Doctoral Dissertation

Integrated Analysis on Household Energy Consumption Behavior across Residential and Transport Sectors: Model Development and Applications

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Declaration

I hereby declare that this dissertation entitled "**Integrated Analysis on Household Energy Consumption Behavior across Residential and Transport Sectors: Model Development and Applications**" has never been previously submitted for a degree in this or other institutions, and the work presented in this dissertation is original unless otherwise acknowledged in the text.

Signed

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Biying YU

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Abstract

There has been a growing interest in the sustainability of energy conservation in major metropolitan areas throughout the world. Many countermeasures have been adopted to achieve this goal. Recently, apart from the technological development and economic control measures, the role of the behavioral sciences is emphasized in dealing with the energy issue, especially for the household energy consumption (in both residential and transport sectors) which has historically been difficult to address by using traditional economic methods because of its autonomy and diversity.

This research is a policy-oriented study which intends to answer the question that how to reduce household energy consumption across both residential and transport sectors from the behavioral perspective. Note that household energy consumption here is defined as actual direct energy used by domestic end uses and for personal travel, while the indirect energy embedded in goods and services purchased by households is excluded. In such context, two streams of analysis are conducted subsequently: spatial analysis which is used to find out the similarities and differences of the household energy consumption patterns in different megacities, and temporal analysis which is for thoroughly understanding the household energy consumption behavior.

Regarding the spatial analysis (*Chapter 4*), Asia region was targeted considering its great amount of potential energy consumption in the future. Four representative megacities, Tokyo, Beijing, Jakarta, and Dhaka were selected and an international questionnaire survey about household energy consumption covering more than 1,000 households was conducted at each city in 2009. Based on the survey data, the respective household energy consumption pattern in each city were compared by using the Heckman's latent index model. The results showed that, energy consumption patterns differed a lot with the economic development level. The

greater maturity the economic development of a city is, the larger effect of car ownership while the smaller effect of self-selection is on the total household energy consumption. This conclusion implied the future trajectory of household energy consumption change in developing countries. Based on the spatial analysis, Beijing is selected as the empirical context in the temporal analysis given its fast development and the guiding role to other developing cities.

For deeply understanding how to reduce household energy consumption, the temporal analysis is conducted in the context of Beijing. Regarding the temporal analysis, household energy consumption is thought to be related to many household decisions. From the long-term viewpoint, the residential location choice might be related to energy consumption, from the middle-term, the ownership of vehicles and domestic appliances is related to energy consumption, and from the short term, the vehicle usage, appliance usage and time allocation are all related to household energy consumption. And all these elements are not independent with each other. In this sense, if we want to know how to change and reduce the energy consumption, we need to clarify how these decision elements interacted with energy consumption first. In order to represent such intertwined relationship, several advanced models have been further developed and a series of policies including telecommuting policy, land-use policy, soft-policy, technology improvement, and the propaganda of social context were proposed to reduce the household energy consumption. Another quasi panel survey was conducted in Beijing in 2010 so as to collect in-depth information about the residents' energy consumption behavior. Based on the data, following analysis was carried out and the efficacy of the aforementioned policies was evaluated.

(*Chapter 5*) Before the model development and policy analysis, a preliminary analysis is first done. Traditionally, the residential energy consumption behavior and travel behavior have been separately treated. However, due to the existence of rebound effects and self-selection effect, it is expected that residential energy consumption behavior and travel behavior might be correlated with each other. With such consideration, this study first built a new type of energy consumption model based on the mixed Multiple Discrete-Continuous Extreme Value (MDCEV) modeling framework so as to verify the rationality of the above assumption. Based on the model results, log-linear competitive relationships among energy expenditure of end uses (including the domestic appliances and vehicles) were found due to the total expenditure budget, and the energy consumption behavior of residential and transport end uses were further revealed correlating with each other due to the unobserved factors. These findings strongly support the necessity of the integrated analysis for household energy consumption across residential and transport sectors.

Under such an integrated context of the household energy consumption in both residential and transport sectors, Chapter 6 to Chapter 9 are further conducted.

(*Chapter 6*) To understand the relationship between household time use and energy consumption, we developed a new resource allocation model based on multi-linear utility functions and endogenously represented zero-consumption for both time and energy within the group decision-making modeling framework. This model explicitly incorporated multiple interactions, including the interaction between time use and energy consumption, the inter-activity interaction, the inter-end-use interaction, and the intra-household interaction. The results showed the applicable validity of the proposed model as well as the significant beings of the various interactions. This model can be applied to quantify how time use policies (e.g., telecommuting, flexible working arrangements, and work-holiday balance) affect the household energy consumption. Here, we only took the telecommuting policy as an example, and its effect on reducing household energy consumption was tested. It was suggested that if changing the householders of the two-person families who are still in employment to be telecommuters (i.e., working at home), almost 16% of the total household energy consumption can be cut down. In addition, since the inter-end-use interaction is significantly influential to the energy consumption, the rationality for describing the energy consumption behavior of domestic end uses and vehicles simultaneously was supported again.

(*Chapter 7*) An integrated model termed as joint mixed Multinomial Logit-Multiple Discrete-Continuous Extreme Value (MNL-MDCEV) model was proposed to jointly describe the residential location choice and household energy consumption behavior referring to the ownership and usage of end uses. In view of the concerns of the self-selection effect which might result in a non-causal association between residential choice and energy consumption behavior in addition to the causal effect, end-use specific self-selection effects were directly accommodated in the model which can help capture the relatively "true" effect of land-use policy on household energy consumption behavior. The effectiveness of the integrated model was confirmed in the empirical analysis. The model results suggested that land-use policy do play a great role in changing Beijing residents' energy consumption pattern, while the self-selection effects cannot be ignored when evaluating the effect of land-use policy. And the self-selection effect was revealed to vary with end uses. Subsequently, the sensitivity analysis of household energy consumption to land use policy was further conducted. It was found that increasing recreational facilities and bus lines in the neighborhood can still greatly promote household's energy-saving behavior after controlling the multiple self-selection effects. Additionally, it was implied that introducing "soft policy" was important to conserve household energy consumption in Beijing and furthermore, the soft policies focusing on electric fan, air conditioner, gas shower, microwave oven and car should be given a priority. The importance of the package policy was also emphasized attributing to the significant complementary effect between the energy consumption behavior in residential and transport sectors.

(*Chapter 8*) To examine the extent to which the technology improvement of major household end uses causes additional utilization on itself and on other end-uses (i.e., rebound effects) in the short-run in Beijing, another integrated model was developed by combining Logit model and a resource allocation model, where the former represented the choice of end-use ownership and the latter described the end-use usage. The rebound effects were finally obtained from calculating the own- and cross-elasticities based on the model prediction. The empirical results showed that for refrigerator, electric fan, gas shower, TV and PC, no rebound occurred; while for air conditioner, clothes washer, microwave oven and car, either a direct rebound effect or an indirect rebound effect existed significantly. The respective average direct rebound effects for them were 60.76%, 106.81%, 100.79%, and 33.61%, suggesting a backfire for the clothes washer and microwave oven, while the respective total rebound effects were 88.95%, 100.36%, 626.58%, and 31.61%. Furthermore, increasing the efficiency of air conditioner and car can reduce the total household energy consumption during the use phase, but opposite for microwave oven.

(*Chapter 9*) It is easy to understand that household energy consumption process is not static considering that the continuously changing market and the social context might significantly affect the household energy use behavior. Therefore, to develop a robust policy system to reduce the total household energy consumption, this study carried out a dynamic simulation to evaluate the collaborative effects of most of the above-mentioned policies (including the land-use policy, soft policy, and the technology improvement/rebate program) by reflecting the change of market end-use diffusion rate and the neighborhood social interaction as well as the existence of household inefficiency consumption. This proposed simulation program comprehensively considered the possible aspects which might be relevant to household energy consumption pattern. It can be calibrated for any urban city and, it also has many potential applications such as assessing the influence of some macro-level policies which seem irrelevant to the household energy consumption issue (i.e., educational policy, population policy, and market policy).

After all the above analysis, we finally concluded this thesis from a systematic perspective (*Chapter 10*). Some recommendations for future research were also outlined.

Keywords:

Household energy consumption behavior; Integrated analysis; Asian megacities; Time use; Multiple interactions; Residential location choice; Self-selection effect; Rebound effects; Mixed MDCEV model; Latent index model; Resource allocation model; Mixed MNL-MDCEV model; Dynamic simulation.

Table of Contents

List of Tables..I

List of Figures III

Chapter 1 Introduction 1

1.1 Background.. 1

1.2 Motivations and Research Issues... 3

1.2.1 Analysis from the Behavioral Perspective 3

1.2.2 Household Energy Consumption Behavior across Residential and Transport Sectors 4

1.2.3 Diverse Energy Consumption Patterns 6

1.2.4 Analysis Framework of Household Energy Consumption 7

1.3 Aims and Objectives.. 8

1.4 Outline of the Thesis.. 9

1.5 Tasks and Major Contributions 12

Chapter 2 Literature Review 15

2.1 Household Energy Consumption Behavior 15

2.2 Policy and Household Energy Consumption.. 19

2.2.1 Land-use Policy and Household Energy Consumption 19

2.2.2 Soft Policy and Household Energy Consumption 21

2.2.3 Technology Innovation and Household Energy Consumption 24

2.3 Spatial Comparative Analysis 29

2.4 Summary 30

Chapter 3 Household Energy Consumption Surveys 33

3.1 International Energy Consumption Surveys 33

3.2 Quasi Panel Survey 36

Chapter 4 Comparative Analysis of Household Energy Consumption Patterns in Different Cities 39

4.1 Introduction 39

4.2 Methodology 42

4.3 Descriptive Statistics of Data 45

4.4 Model Estimation Results 49

4.4.1 Results of Treatment Selection Model 49

4.4.2 Results of Treatment Outcome Models 50

4.4.3 Results of Treatment Effects 53

4.5 Summary and Conclusion 55

Chapter 5 Exploring the Necessity for Joint Representation of Energy Consumption Behavior in Residential and Transport Sectors 59

5.1 Introduction 59

5.2 A Conceptual Framework of Household Energy Consumption Behavior 60

5.3 Modeling Methodology 62

5.3.1 A Kernel Model Structure: MDCEV 62

5.3.2 Representing the Influence of an Outside Goods 65

5.3.3 Mixed MDCEV Model 66

5.4 Aggregate Analysis.. 66

5.5 Estimation Results of MMDCEV Model 69

5.6 Summary and Conclusion.. 75

Chapter 6 Time Use and Household Energy Consumption Behavior..................................... 79

6.1 Introduction 79

6.2 Behavioral Mechanism of Multiple Interactions 80

6.2.1 Time-to-energy Interaction 80

6.2.2 Time-to-time Interaction... 81

6.2.3 Energy-to-energy Interaction 82

6.2.4 Intra-household Interaction.. 82

6.2.5 Behavioral Interaction Modeling 83

6.3 Methodology.. 85

6.3.1 Household Utility Function.. 86

6.3.2 Household Members' Utility Functions... 87

6.3.3 Model Estimation Method 90

6.4 Data 93

6.5 Model Estimation Results 96

6.5.1 Overall Model Performance 97

6.5.2 Intra-household Interaction 97

6.5.3 Time-to-energy Interaction 98

6.5.4 Time-to-time Interaction 99

6.5.5 Energy-to-energy Interaction 99

6.5.6 Utility composition 100

6.5.7 Explanatory Variables 101

6.5.8 Sensitivity Analysis of Telecommuting 102

6.6 Summary and Conclusion 106

Chapter 7 Residential Location Choice and Household Energy Consumption Behavior 113

7.1 Introduction 113

7.2 Modeling Methodology 116

7.2.1 Residential Choice Behavior 118

7.2.2 Energy Consumption Behavior 119

7.2.3 The Integrated Choice Model 122

7.3 Data 125

7.4 Model Estimation Results 128

7.4.1 Overall Model Performance ... 129

7.4.2 Results of Residential Location Choice Sub-model ... 130

7.4.3 Results of Household Energy Consumption Sub-model ... 132

7.4.4 Variance Proportion ... 139

7.4.5 Sensitivity Analysis of Policy Interventions ... 141

7.5 Summary and Conclusion ... 143

Chapter 8 Evaluating the Direct and Indirect Rebound Effects in Household Energy Consumption Behavior ... 149

8.1 Introduction ... 149

8.2 Modeling Methodology ... 151

8.2.1 Definition ... 151

8.2.2 Integrated Model ... 152

8.3 Data ... 157

8.4 Model Estimation Results and Rebound Effects Analysis ... 160

8.4.1 Model Estimation Results ... 160

8.4.2 Analysis of Rebound Effects ... 166

8.5 Summary and Conclusion ... 173

Chapter 9 Policy Application Based on Dynamic Simulation ... 177

9.1 Introduction to the Simulation ... 178

9.1.1 Referring Aspects in the Simulation ... 178

9.1.2 Limitations in the Simulation 178

9.2 Model Structure and Results 179

9.2.1 Model Structure 179

9.2.2 Model Results 180

9.2.3 Policy Sensitivity Analysis 182

9.3 Dynamic Simulation Program 184

9.3.1 Program Interface 184

9.3.2 Technology Improvement/Rebate Module 185

9.3.3 Environmental Awareness Change Module 186

9.3.4 Land-use Change Module 189

9.3.5 Explanatory Variable Change Module 189

9.3.6 Market Change Module 189

9.3.7 Neighborhood Social Interaction Module 190

9.4 Simulation Results 196

9.4.1 Single Policy 197

9.4.2 Policy Package 199

9.5 Summary and Potential Application 202

9.5.1 Summary 202

9.5.2 Potential Application 203

Chapter 10 Conclusions and Future Research 205

10.1 Conclusions 205

10.2 Recommendations for Future Research 213

Appendix 215

A. Sampling Algorithms 215

B. Convergence Diagnostic 216

References 219

Publications 233

List of Tables

Table 2- 1 Empirical evidence of the direct rebound effect for the household end-uses 24

Table 3- 1 Statistics of Japan, China, Indonesia, and Bangladesh 34

Table 3- 2 Information about the survey in each megacity 35

Table 4- 1 Aggregation statistics of survey data 48

Table 4- 2 Estimation results of car ownership model (treatment selection model) 49

Table 4- 3 Estimation results of household energy consumption models (treatment outcome models) 51

Table 4- 4 Treatment parameters and self-selection effect 54

Table 5- 1 Descriptive statistics of household end-use ownership and expenditure 68

Table 5- 2 Explanatory variables introduced in the model 69

Table 5- 3 Estimation results of MMDCEV model 70

Table 5- 4 Correlations among end uses due to unobserved factors 73

Table 5- 5 Proportions of variances explained by the introduced variables 74

Table 6- 1 Elements of likelihood functions 92

Table 6- 2 Activity classification 94

Table 6- 3 Descriptive statistics of the explanatory variables and dependent variables 109

Table 6- 4 Estimation results of time use and energy consumption expenditure 110

Table 7- 1 Statistical relation between energy consumption and residential neighborhoods 126

Table 7- 2 Summary statistics of household end-use ownership and expenditure 127

Table 7- 3 Estimation results of residential location choice sub-model 130

Table 7- 4 Estimation results of household energy consumption behavior sub-model 147

Table 7- 5 Simulation results for the assumed policy scenarios 148

Table 8- 1 Descriptive statistics of the energy intensity and service demand of end-uses ... 158

Table 8- 2 Estimation results of the model performance ... 161

Table 8- 3 Estimation results of the explanatory variables in the model ... 165

Table 8- 4 Prediction accuracy indexes of the model ... 167

Table 8- 5 Rebound effects due to the energy efficiency improvement ... 169

Table 8- 6 Energy consumption change caused by the end-use efficiency improvement ... 173

Table 9- 1 Model estimation results ... 181

Table 9- 2 Market end-use penetration rate regression results ... 190

Table 9- 3 Variables in the SFA ... 192

Table 9- 4 Estimation results of SFA model ... 193

Table 9- 5 The energy consumption change in different scenarios ... 196

Table 9- 6 Information of each policy group ... 197

Table 9- 7 Timing effect on the policy performance ... 201

Table 10- 1 Policy implication based on the whole research ... 201

List of Figures

Figure 1- 1 Energy demand in the world 2
Figure 1- 2 Household energy consumption system 7
Figure 1- 3 Tasks of the thesis 12
Figure 3- 1 The targeted megacities in the energy consumption survey 33
Figure 3- 2 Economic and emission in the four cities 34
Figure 3- 3 The temperature in the four cities 34
Figure 3- 4 Location of the surveyed residential neighborhoods 37
Figure 4- 1 Household energy consumption in treated and untreated households 47
Figure 4- 2 Energy consumption per capita in treated and untreated households 47
Figure 4- 3 The relation between income and household energy consumption 52
Figure 4- 4 Partial utility results 53
Figure 5- 1 Energy related behavior components in residential life 61
Figure 5- 2 Total annual energy consumption per capita (GJ/cap·year) 67
Figure 5- 3 welling structure and energy consumption (GJ/cap·year) 67
Figure 5- 4 Household attributes and energy consumption 67
Figure 6- 1 Model structure 85
Figure 6- 2 The percentage of the interacted utility in the total household utility 98
Figure 6- 3 The percentage of each utility element in the total member's utility 101
Figure 6- 4 Time use change of each member after the telecommuting policy 104
Figure 6- 5 End-use energy consumption change of each member after the telecommuting policy 105
Figure 6- 6 Total energy consumption change of each member 106

Figure 7- 1 The variance portion for end uses 140

Figure 8- 1 Aggregation result of fuel intensity and end-use usage 160

Figure 9- 1 Model derivation 180

Figure 9- 2 Static policy sensitivity analysis (percentage change) 183

Figure 9- 3 Static policy sensitivity analysis (energy consumption MJ change) 183

Figure 9- 4 Simulation interface 184

Figure 9- 5 Dynamic simulation flowchart 187

Figure 9- 6 Inefficiency level of the end uses 194

Figure 9- 7 Annual increasing rate of household energy consumption for single policy 197

Figure 9- 8 Effect of single policy in the end of year 2015 198

Figure 9- 9 Annual increasing rate of household energy consumption for policy package .. 199

Figure 9- 10 Effect of package policy in the end of year 2015 200

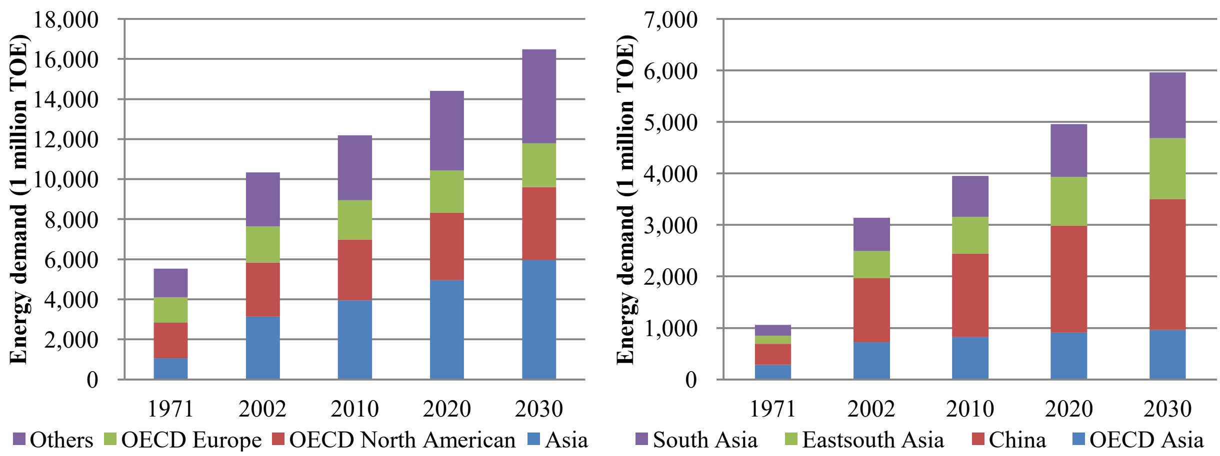
Chapter 1

Introduction

1.1 Background

According to WEO (2009), energy is accounting for 65% of the world's greenhouse gas (GHG) emissions, and by 2030, the Reference Scenario, which assumes no change in government policies, sees world primary energy demand a dramatic 40% higher than in 2007. The unsustainability of current energy trends and the urgent need for action to realize a low-carbon society have been internationally recognized. It is also revealed that non-OECD countries account for over 90% of the increase, their share of global primary energy demand rising from 52% to 63% (see Figure 1-1). China and India represent over 53% of incremental demand to 2030. Coupled with strong growth from ASEAN, it is becoming more and more important how to reduce energy use in Asia. Even though in developing countries energy consumption per capita is much lower than in industrialized countries (e.g., in the ESCAP region, the average per capita energy consumption was only 604 kilogrammes of oil equivalent (kgoe) and that of developing countries 333 kgoe, in comparison to the world average of 1,692 kgoe), household energy consumption is expected to increase throughout the Asian and Pacific region together with economic growth and rising per capita income, and consequently it is important to analyze household energy consumption patterns in order to formulate policies for promotion of sustainable energy consumption (ESCAP, 2009).

To date, the main tools applied to ameliorate the energy problem are technological development (e.g., the improvement of end-use efficiency, the introduction of new type of energy, housing insulation, and ventilation) and economic control measures (e.g., fuel price, tax, subside, and discount). Many countries have devoted substantial public resources to research and development for energy-efficient technologies which are likely to take several decades for diffusion. Energy efficiency, however, depends on both these technologies and the choices of users (Allcott and Mullainathan, 2010). Even if people choose to use advanced technologies, there is still another problem that energy rebound effect might breed, cutting the expected energy saving or inversely increasing energy consumption (i.e., backfire) (Greening et al., 2000; Sorrell et al., 2007; Vera and Denise, 2009). As for economic control measures, with the increase of income, it is expected that monetary incentives will gradually lose its luster. Consequently, there is significant concern that at least for the next few decades these tools will not be sufficient for addressing climate change and energy security issues (Carrie Armel, 2008). Furthermore, such concern is particularly severe among some developing countries, like China and India, as they are enjoying a rapid economic development and meanwhile a high goal for CO_2 reductions in the near future. In this context, some researchers emphasize the role of the behavioral sciences in dealing with the energy problem (Allcott and Mullainathan, 2010), especially for the problem of household energy consumption sector (i.e., including both in-home energy consumption and out-of-home car energy consumption) which has historically been difficult to address by using traditional economic methods (Yu et al., 2011).



Statistics: IEA「World Energy Outlook 2004」

Figure 1- 1 Energy demand in the world

Although the existing research on residential energy consumption behavior or travel behavior has received a great deal of interest, the integrated analysis of energy consumption behavior across both residential and transport sectors does not gain the same level of attention in both academic and practical sides. This is probably due to the idea of the widely adopted sector-oriented policy decision scheme. Whereas, according to the CFA (Consumer Federation of America) survey result, it is surprising that in America, since 2009, the energy consumption caused by domestic end uses has taken just as large a bite out of household budgets as does expenditures for gasoline. Therefore, looking towards a low carbon future, both of the residential and transport energy consumption deserves to be emphasized.

1.2 Motivations and Research Issues

1.2.1 Analysis from the Behavioral Perspective

It is argued that technological development alone will not be enough to reach targeted reductions in GHG emissions, and changes in human behavior are also indispensable. Essentially, effects of technological innovations on reducing energy consumption and then GHG emissions depend on consumers' choices of products – buy or not, what types of products (here refers to domestic appliances and vehicles) consumers buy, and how consumers use their purchased products (e.g., frequency, duration, and distance traveled). When firms develop products, they need to pay careful attention to consumers' preference, which is a decisive factor to determine the success of business. In other words, success or failure of realizing a low-carbon society depends on whether consumers prefer a low-carbon lifestyle and how consumers respond to low-carbon policies (e.g., environmental taxation, urban and transportation planning, regulations, incentive schemes, and enlightenment).

In this sense, the household energy consumption can be viewed as a behavioral process which is comprised of two parts: the choice of end-use ownership and the decision of end-use usage. Motivated by this, to find out the way to reduce household energy use, the household energy consumption behavior referring to the end-use ownership and end-use usage is targeted in this thesis.

1.2.2 Household Energy Consumption Behavior across Residential and Transport Sectors

1.2.2.1 Rebound Effect

With the technological improvement, fewer resources (e.g., time, energy, and money) are needed to produce the same amount of products or services, in this way the resources for household or household members are freed up. However, the saved resources can be reallocated across a variety of activities, which may lead to an increase in household production activities and/or an increase in resource-intensity activities. For instance, after the ownership of time-saving end uses such as an automobile, households may have an incentive to demand more of this service (e.g., drive more and longer distances) or substitute it with other services that are more time intensive, like watching TV or playing computer games at home. In other words, an increase in time efficiency leads to feedback on time use, which is called time rebound effect (Khazzoom, 1980; Binswanger, 2001; Jalas, 2002). Accordingly, if the time is reallocated from less to more energy-consuming activities, household energy use will increase as a result of adopting time-saving end uses. In addition to the time-specific rebound effect, so-called income-effect also has a contribution to the total rebound effect, which makes energy consumption patterns alter simultaneously since many time-saving technologies are always more energy-intensive than other alternatives, implying that more expenditure is needed for them and less is left for others. Another example is the energy rebound effect caused by the energy efficiency improvement of end uses (Greening et al, 2000; Sorrell and Dimitropoulos, 2008). In this context, the monetary cost per unit of service that is produced by this end use declines, which probably in turn stimulates the incremental consumption of that end use or the usage occurrence of other end uses. Finally, the expected energy saving will be partially or fully offset by the extra triggered consumption.

It is not difficult to understand that no matter for the time rebound effect, income effect, or for the energy rebound effect, the reallocation process is not restricted within the residential sector or transport sector, instead, the reallocation might occur across the residential and transport sectors.

1.2.2.2 Self-selection Effect

Another important issue related to household energy consumption is the self-selection effect. In statistics, self-selection arises in any situation in which individuals select themselves into a group. It is commonly used to describe situations where the unique characteristics of the people which make them to select themselves into the group which creates abnormal or undesirable conditions in the group. In the context of fully considering objective factors, the self-selection effect is expected to be caused by household unique subjective characteristics that could impact individual's behavior, such as some motivational factors, environmental awareness, special taste on driving, lifestyle and so on (Cao, 2009). For example, individuals high in environmental self-consciousness are motivated to care about the situation of the environment and reject the energy intensive behaviors. In other words, such kinds of people are more likely to choose energy-saving end uses to fulfill their activities and use them more efficiently, or straightly attend non-energy consuming activities such as jogging in the park instead of running on a treadmill, and commute by bicycle instead of vehicle. While for some people who have specific preference on driving, they might prefer to live in the suburban area and conduct a car-dependent lifestyle.

As you can see that, the self-selection effect is inherent trait of some group of people and this trait might work on all the individual behaviors which include both the residential energy consumption behavior and the travel behavior.

Motivated by the existence of rebound effect and self-selection effect, it seems plausible that the joint representation of household energy consumption behavior across residential and transport sectors is more consistent with the real behavioral mechanism. However, traditionally, these two parts have been separately treated and little has been done to the development of the integrated analysis that simultaneously accommodates both residential and transport energy consumption with the consideration of the rebound effect and self-selection effect from the behavioral perspective. This thesis contributes to identify the necessity and rationality of the integrated analysis by directly dealing with the issue of rebound effect and self-selection effect in the energy realm.

1.2.3 Diverse Energy Consumption Patterns

As Environmental Kuznets Curve (Galeotti et al., 2006) explains, economic maturity and environmental emissions are under a relation of inverted U-shaped curve. With the economic development, the emission first increases and then decrease. This might be one type of trajectory for the household energy consumption pattern change. Many previous findings have proved that the energy consumption pattern in residential or transport sector not only differs with the economic development, but also the climate feature, geographic location, society structure, and so on. But majority of them are focusing on the developed countries.

Due to the importance of Asian effect on the global environment, accumulation of knowledge on its present energy consumption pattern is very essential to assist in formulating adequate measures to cope with the environmental problems foreseen in the future. Furthermore, a great diversity among concerned Asian nations in energy consumption and socioeconomic conditions will make environmental conservation even more complicated. Therefore, the spatial comparative analysis is conducted to explore the diversities of the household energy consumption patterns in Asia.

1.2.4 Analysis Framework of Household Energy Consumption

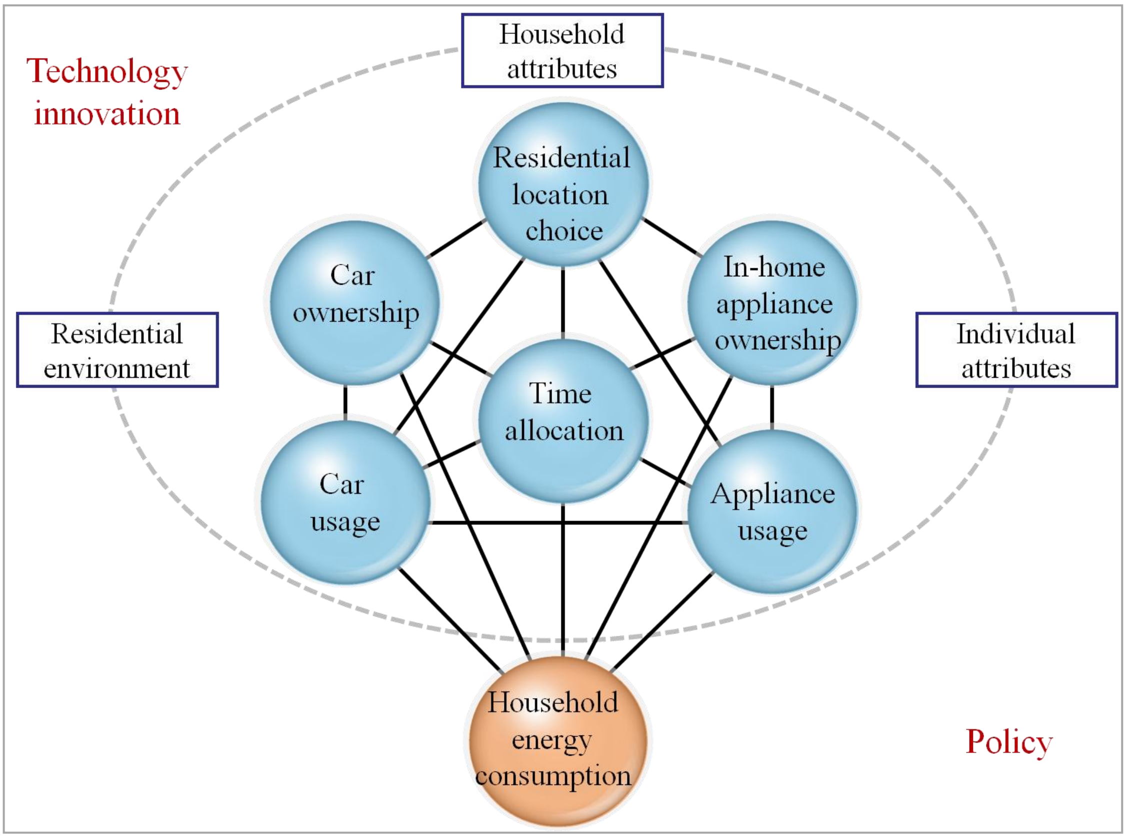


Figure 1- 2 Household energy consumption system

Household energy consumption is related to many other household decisions (see Figure 1-2). Concretely speaking, from the long-term viewpoint, the residential location choice is related considering that the residential environment might influence household energy consumption pattern; from the middle-term, the ownership of car and domestic appliances is related to energy consumption, and from the short term, the car usage, appliance usage and time allocation are related to household energy consumption. And all these elements are not independent with each other. They are all correlated. When the technology innovation happens, or policy is carried out, some of the decision elements in the circle will alter, and then cause the change of household energy consumption behavior which finally influences the total household energy use. In this sense, to fully understand the household energy consumption mechanism, first we need to understand how these decision elements interacted with energy consumption behavior, then the significant policies on energy saving can be identified.

The existing literature has dealt with some of the aspects in Figure 1-2. However, they either focused on the residential sector or the transport sector. Few of them comprehensively considered all the decision aspects under the context of the integrated analysis of the whole household sector. This thesis contributes to deeply explain the household energy consumption from the aforementioned behavioral aspects by systematically looking at the energy use in both residential and transport sectors.

1.3 Aims and Objectives

This research aims to make an effort toward energy policy analysis which can help answer the question that how to reduce household energy consumption across both residential and transport sectors from the behavioral perspective. Concretely speaking, on the one hand, given the considerable energy demand in Asia, we are attempting to understand the Asian energy consumption style so as to provide some knowledge about how to cope with the serious energy and environment problems foreseen in the future; on the other hand, we propose an integrated analysis framework to evaluate the efficacy of telecommuting policy, land-use policy, soft policy, and technology improvement on the energy saving in both the residential and transport sectors. The framework is constructed by first separately addressing the interaction between residential location choice and household energy consumption, the interaction between end-use ownership and/or usage and household energy consumption, and the interaction between time use and household energy consumption, after that combining them together. Given the composite characteristic of this integrated analysis, the research objectives are given in multiple:

- To confirm the necessity of integrated analysis for household energy consumption across both residential and transport sectors;
- To understand household energy consumption pattern from behavioral viewpoint in developing countries;
- To evaluate the effect of time use policy (i.e., telecommuting policy) on household energy consumption saving;
- To evaluate the true effect of the land-use policy on household energy consumption saving;
- To evaluate the effect of the soft policy on household energy consumption saving and its emphasis;
- To evaluate the true effect of technology improvement on household energy consumption saving;
- To provide a robust policy evaluation system to achieve the energy conservation target.

1.4 Outline of the Thesis

To get an overview of the structure of the reminder of this thesis, contents of the individual chapters are briefly listed below:

Chapter 2 gives a review of the existing work in the field of household energy consumption and the energy policies. Chapter 3 introduces two surveys specifically conducted for this research, one is for the spatial dimension analysis and another is for the temporal dimension analysis. After this background introduction, two streams of analysis are conducted subsequently: spatial analysis which is used to find out the similarities and differences of the household energy consumption patterns in different megacities, and temporal analysis which is for thoroughly understanding the household energy consumption behavior.

Chapter 4 aims to explore the diversity of household energy consumption patterns in Asian megacities. Four representative megacities, Tokyo, Beijing, Jakarta, and Dhaka were selected and an international questionnaire survey about household energy consumption was conducted at each city in 2009. Based on the survey data, Heckman's latent index model is further built for each city by separating the effect of car ownership and the effect of self-selection on the total household energy consumption. The interrelation between economic development and car ownership as well as between economic development and self-selection effect is checked based on the spatial comparison results. The comparative result is further used to select the empirical context in the temporal analysis (i.e., Chapter 5 to Chapter 9).

Chapter 5 examines the issue that whether the energy consumption behavior in residential sector and transport sector should be represented simultaneously. First, the concept framework of household energy consumption behavior is described. To follow this concept, the mixed MDCEV model is adopted to jointly describe the energy consumption behavior across residential and transport sectors by incorporating the income effect. Based on the empirical result which is in the context of Beijing, the necessity of joint representation is discussed on the one side from the observed relationship between end uses due to the money budget, on the other hand from the correlation resulting from unobserved factors.

After confirming the necessity of the integrated analysis, the model development and policy analysis are further carried out.

Chapter 6 contributes to the analysis of household time use and energy consumption behaviors. A new household resource allocation model is built, which incorporates multiple interactions (including the interaction between time use and energy consumption, the inter-activity interaction, the inter-end-use interaction, and the intra-household interaction) based on multi-linear utility functions and endogenously represents zero-consumption for both time and energy within the group decision-making modeling framework. The effect of telecommuting policy is evaluated based on the proposed model structure.

Chapter 7 looks at the issue of how residential location choice interacted with household energy consumption behvior by incorporating the end-use specific self-selection effect. An integrated model termed as joint mixed Multinomial Logit-Multiple Discrete-Continuous Extreme Value model is presented here to identify the sensitivity of household energy consumption to land use policy by considering multiple self-selection effects. Different land-use policy scenarios are examined based on the model results and moreover, the importance of the soft policy in the context of Beijing is also discussed.

Chapter 8 examines the extent to which an increase in the energy efficiency of major household end uses causes additional utilization on itself and on other end-uses (i.e., rebound effects) in the short-run in Beijing. An integrated model is first developed by combining Logit model and a resource allocation model, where the former represents the choice of end-use ownership and the latter describes the end-use usage. The model is estimated based on the data collected from a quasi panel survey conducted in 2010. The rebound effects are finally obtained from calculating the own- and cross-elasticities based on the prediction.

Chapter 9 provides a policy evaluation system by directly accommodating the contents of Chapter 7 and Chapter 8. To achieve this, a dynamic simulation program is developed to evaluate the collaborative effect of several types of policies which include the land-use policy, soft policy, and technology improvement by reflecting the change of market end-use diffusion rate and the neighborhood social interaction as well as the existence of household inefficiency consumption. Six modules used to describe the above aspects are designed. Any combination of the policy package can be made by setting different policy years in the program, from which the best policy timing can also be obtained. The effect of three groups of policy packages is tested based on several assumptions. The limitation and potential application of this dynamic simulation are further elaborated.

Chapter 10 provides a summary of the work discussed in this thesis, presents the conclusions, and describes some limitations which might be dealt with in the future research.

Note that household energy consumption in the whole thesis is defined as direct energy used within households and energy used for personal transport and the indirect energy embedded in goods and services purchased by households is excluded.

1.5 Tasks and Major Contributions

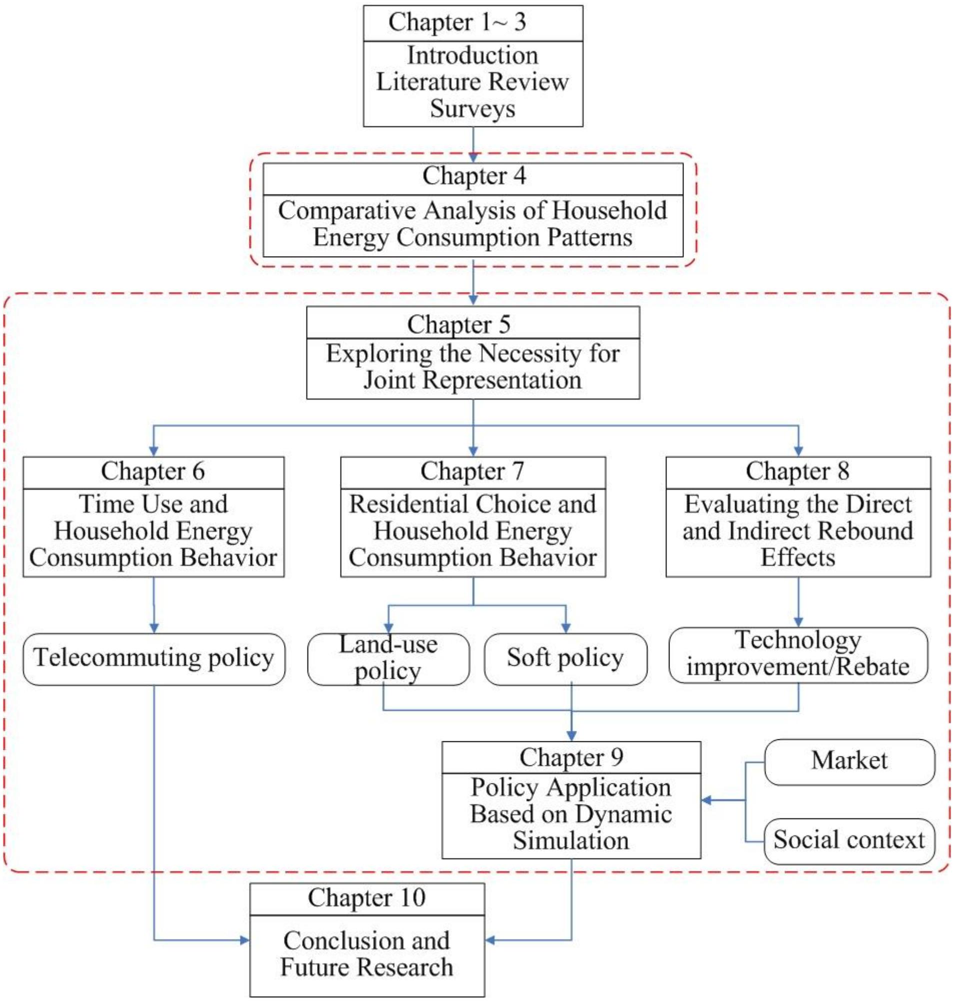


Figure 1- 3 Tasks of the thesis

Two main tasks across the whole thesis can be summarized as: (1) confirm the necessity and rationality of the integrated analysis of energy consumption behavior across residential and transport sectors; (2) identify the effective energy policies in the context of the integrated analysis. Chapter 5 is the premise of the temporal analysis which is specifically arranged for accomplishing the first task. While to fulfill the second task, several sub-tasks are assigned to Chapters 6, 7, 8, 9 (see Figure 1-3).

Comparing with existing studies, several major contributions are made in this thesis. The most significant contribution is the proposal of the integrated analysis of household energy consumption behavior across the residential and transport sectors. This concept can help remind the policy makers about the current morbid sector-oriented policy making rule. Other contributions of this research are summarized by linking to different chapters. Those contributions are based on the principle of theoretical and applicable viewpoints.

To capture the specific household energy consumption pattern in different Asian countries, the effects of car ownership and self-selection on the total household energy use are specifically studied and compared, which can help Asian country to grasp the future direction of the policy crux for household energy saving. (Chapter 4)

A new resource allocation model is proposed to explore the interaction between time use and household energy consumption, which also explicitly accommodates the inter-activity interaction, the inter-end-use interaction, and the intra-household interaction, and meanwhile endogenously represents zero-consumption for both time and energy within the group decision-making modeling framework. This model contributes a lot to the existing methodology used to deal with the effect of time use policy on energy consumption. (Chapter 6)

A mixed MNL-MDCEV model is developed to explain the interaction between residential location choice and household energy consumption. This model is the first instance to include end-use specific self-selection effects when representing the interdependence of residential choice and household energy consumption behavior. The model result can be dedicated to find out a relatively true effect of land-use policy on energy saving in the household. In addition, the importance of the soft policy on household energy use as well as the end-use priority during carrying out the soft policy can be indicated based on the model results. (Chapter 7)

A Logit & resource allocation model is proposed to describe the end-use ownership and/or usage and household energy consumption, by reflecting the rebound effect. This model can be regarded as an alternative tool for evaluating the direct and indirect rebound effects to the existing methods. Besides, the result of this analysis enriches the evidence of the rebound effects associated with household end uses in the developing country. (Chapter 8)

A dynamic simulation is designed to evaluate the collaborative effects of the land-use policy, soft policy, and the technology improvement by incorporating the change of market end-use diffusion rate and the neighborhood social interaction as well as the existence of household inefficiency consumption. This might be the first attempt to develop such a comprehensive policy evaluation system, which can be further applied to deal with many other policies, such as educational policy, population policy, and market policy. (Chapter 9)

Chapter 2

Literature Review

How to obtain the sustainable energy consumption pattern has been widely discussed in the whole world. To make clear the state-of-art of the existing studies and the uniqueness of the current research, this chapter gave a comprehensive review on the relevant topics. Section 2.1 depicts the technique evolution for the analysis on household energy consumption and the necessity of the analysis from the behavioral perspective. Section 2.2 specifically looks at the policies related to household energy consumption which include the land-use policy, soft policy, technology innovation, and telecommuting policy. A brief introduction about the spatial comparative analysis is given afterwards in Section 2.3 and then this chapter ends up with a short summary.

2.1 Household Energy Consumption Behavior

A series of studies have been done with respect to household energy consumption. Existing studies can be classified into two types: aggregate analysis and disaggregate analysis.

Earlier tasks tended to be based on aggregate analysis, which deals with energy consumption at a national, regional or sector level and do not distinguish energy consumption depending on individual end-uses (e.g., Schipper and Ketoff, 1983; Sawachi, 1994; Ishida, 1997; Miura, 1998; Unander et al., 2004; Zhang, 2004; Lenzen et al., 2006; Achao and Schaeffer, 2009). For example, household energy consumption at the national level is usually explained by macroeconomic indicators (e.g., GDP, employment rates, and price indices), climatic conditions, housing construction/demolition rates, and number of appliances in the residential sector. The advantage of this type of analysis is that it can be easily formulated to examine the effects of long-term changes or transitions of macroeconomic indicators on energy consumption and general trends, primarily for the purpose of determining supply requirements (Swan and Ugursal, 2009). However, it is difficult to know whether and how households could respond to the policies derived from aggregate analysis.

In the 1980s, researchers began to pay attention to the development of disaggregate approaches of energy consumption, which are currently commonly used in most developed countries because they can clearly present the effects of those influential socio-economic factors on the household energy use. Some researchers identified that the core determinants for the increase of household energy consumption are the rise of household income and household size (Irorlmonger et al., 1995; Vringer and Blok, 1995; Weber and Perrels, 2000; O'Neill and Chen, 2002; Pachauri, 2004; Moll et al., 2005). However, the energy consumption pattern can be totally different even for the households with the same level of income and household size. This implies that in addition to the above two main determinants, the roles of other factors cannot be ignored, either. For example, age structure may have direct consequences since energy consumption tends to change over the lifespan (Yamasaki and Tominaga, 1997). Also, for urban households and rural households, the energy consumption patterns are different. The urban residents' domestic energy use is much higher than that of rural residents, while it is inverse for residents' energy consumption caused by the ownership and usage of vehicle (Wei et al., 2007). However, these studies either focus on the total energy use or separately focus on residential or transport energy consumption. Additionally, most of them failed to account for the household energy consumption behavior referred to the ownership and usage of end uses in the household.

Essentially, as a choice behavior, total direct household energy demand can be broken down into a discrete component involving choices over several alternative end uses and a corresponding continuous component describing demand conditional on those choices.

Hitchcock (1993) proposed an integrated descriptive framework for energy use behavior and highlighted the importance of simultaneously representing households' purchase (ownership) and use behavior, which is driven by households' needs, as well as the importance of the residential and household attributes. New forecasting models were, therefore, developed to examine the interrelated choice of end-use ownership and energy use (e.g., Dubin and McFadden, 1984; Weber and Perrels, 2000; Bin and Dowlatabadi, 2005; Wei et al., 2007; Chiou et al., 2009; Leahy and Lyons, 2010). For example, Shimoda et al. (2004) represented the residential energy consumption by simulating energy use for each household sector (i.e., space heating, cooking, electric appliances, and private cars). Alternatively, Leahy and Lyons (2010) examined domestic energy use and appliance ownership in Ireland. Based on logit model, analyses revealed how household characteristics can help explain the ownership of energy-consuming appliances. Using OLS (ordinary least squares) regression models, the factors affecting residential energy demand conditional on appliance ownership were further explored. They found a high level of statistical and economic significance for many appliance ownership variables in the energy use regressions discussed above. This implies that if energy use was modeled without controlling the endowment of appliances, the model would be mis-specified and might consequently lead to incorrect inferences. Dubin and McFadden (1984) jointly modeled the demand for electric appliances and the demand for electricity. Chiou et al. (2009) proposed integrated energy consumption models with consideration of choice behaviors related to car/motor ownership, type, and usage. As can be seen, these studies either treat each household energy use sector independently, or only focus on domestic energy consumption or vehicle consumption, which ignored the interrelation between residential and transport energy behavior.

Regarding to the model development, several discrete and discrete-continuous choice models have been proposed in literature to represent ownership and usage behavior (e.g., Train and Lohrer, 1983; Mannering and Winston, 1985; De Jong, 1990; Mansouri et al., 1996; Linciano, 1997; West, 2004; Feng et al., 2005; Fuks and Salazar, 2008; Chiou et al., 2009; Leahy and Lyons, 2010). However, there are two main shortcomings for them. One is that the methods used are mainly standard discrete choice models (e.g., multinomial logit, nested logit, mixed logit or probit model) for representing ownership behavior and linear regression models for calculating the usage which is a simple statistically-oriented model. In order to explain the complex energy consumption behavior, some sophisticated behaviorally-oriented models need to be proposed. The other point is that traditional discrete and discrete-continuous models usually deal with choice situations in which a household can choose only one alternative from a range of mutually exclusive alternatives in a choice set. Using such models will become problematic when investigating the choice situation of multiple end-uses, where households own and use several types of end uses simultaneously to satisfy various functional needs of households. The analysis of such choice situations requires models to recognize the multiple discreteness in the choice set of appliances owned by a household. Such models have been developed recently in several fields (see Bhat (2008) for a review). Among these, Bhat (2005) introduced a simple and parsimonious econometric approach to handle the multiple discreteness. Bhat's model, labeled the multiple discrete-continuous extreme value (MDCEV) model, is analytically tractable in the probability expressions and is practical even for situations with a large number of discrete consumption alternatives.

Energy consumption in the household sector is the outcome of various household behaviors, such as choice of residential area, ownership and usage of domestic appliances and vehicles, time use behavior. It is expected that behaviorally-oriented modeling approaches might be more feasible and rational for deeply understanding the inherent elements. Unfortunately, little has been done to the development of the integrated model that simultaneously accommodates both residential and transport energy consumption with the consideration of the time rebound effect, income effect, and energy rebound effect. In addition, the behavioral influence has also been ignored.

2.2 Policy and Household Energy Consumption

2.2.1 Land-use Policy and Household Energy Consumption

In recent years, the focus on urban spatial structures has attracted considerable attention in many realms like landscape ecology (McGarigal, 2004; Yang and Lo, 2002; Yeh and Li, 2001), transportation (Hickman and Banister, 2007; Næss, 2005), and community design (Clifton et al., 2007; Randall and Baetz, 2001). However, little is known about the role of urban spatial structure on household energy usage challenges. Essentially, residential spatial structures are considered to be efficient in the sense that they reduce the households' in-home time or the need for travel, but not always without energy consumption in other terms. Owens (1992) shed light on the relation between land-use planning and energy consumption which mainly refers to the transport and space heating and cooling. Some interesting questions were posed in his paper, for example: After settled down in a new compact neighborhood, long trips might be replaced by shorter journeys, but would these now be by car instead of by energy efficient rail? Would time and energy saved by daily trips simulate other forms of consumption or travel, such as watching TV longer with the AC open or conducting more leisure driving in the countryside during vacations? Enlightened by these questions, there is a need to understand the dynamics of the whole household energy consumption system by considering the influence of residential environment and concomitant socioeconomic variables.

In reality, behavioral theories have pointed out the importance of relationships between longer-term choices, such as residential location choices, and shorter-term choices, such as daily travel choices (Ben-Akiva and Atherton, 1977; Domencich and McFadden, 1975). Under this context, considerable scholars contributed to mine the aforementioned relationship. Generally speaking, two types of approaches dominate. One is that land-use attributes are considered pre-determined and exogenous, and are used as independent variables to explain energy consumption behavior. This approach is very popular in earlier research and also the current studies which deal with the residential energy consumption issue (Chang et al., 2010; Dunphy and Fisher, 1996; Hickman and Banister, 2007; Kaza, 2010; Larivi`ere and Lafrance, 1999; Permana et al., 2008). This stream of studies looked into the travel behavior or residential electricity, water use condition on the known residential environment, which means a one-directional causal impact is pre-assumed. The other is that accommodating the endogeneity of long-term residential location choices with short-term energy consumption choices through the integrated modeling framework. This type is more and more prevalent in recent research especially in transportation domain (Bhat and Chatman, 2009; Guo, 2007; Eliasson and Mattsson, 2000; Joh et al., 2008; Næss, 2005; Pinjari et al., 2009; Waddell, 2001). Compared with the first type, the inter-relationship that may exist among different time dimension decisions (i.e., long-term, medium-term, and short-term) is realized and it is said that individuals/households adjust with combinations of short-term travel-related and long-term location choice-related behavioral responses to land-use and transportation policies (Waddell, 2001). For instance, Ben-Akiva and Lerman (1991) introduced the multidimensional nested logit model to consider both residential location and travel behavior choices, in which the latter choice is conditioned on the former one, and the model was estimated by maximizing the joint probability. Pinjari et al. (2009) built an ambitious joint model of residential location and household time use behavior. In contrast, to date, only few studies shed light on the integrated analysis of multi-time-dimension choices related to residential energy consumption behavior, let alone the whole household energy consumption decisions. One paper written by Dubin and McFadden (1984) displayed an integrated model of electricity end-use ownership and usage by convincing that the medium-term and short-term choices are not independent. Similarly, Leahy and Lyons (2010) examined domestic energy use and appliance ownership in Ireland. As for the long-term residential location choice and short-term household energy consumption behavior, it seems to be scarce.

Overall, the importance of residential location choice on explaining residential or transport energy demand is emphasized, but the association caused probably by the expenditure or time budget, or some common unobserved attributes (e.g., the energy saving consciousness, specific preference or others), among each part of household energy consumption is overlooked. In other words, the land-use policy development under the context of integrated energy consumption analysis for both residential and transport sectors does not gain enough attention in the current academic and practical areas.

2.2.2 Soft Policy and Household Energy Consumption

It is thought that the soft policy (e.g., environmental education, the provision of information about energy-saving behavior, and an evaluation platform for households to monitor their energy consumption and emissions) might be effective to make households lead an efficient lifestyle. There is now growing interest in better understanding the role of some unobserved characteristics like attitudes and lifestyle preference as a driver for various behaviors. From the concept of some literature (Ajzen and Fishbein, 1980; Fransson and Gärling, 1999; Nordlund and Garvill, 2003), it is known that attitudinal factors like environmental awareness may stimulate the energy efficient behavior and also compact location choice. People high in environmental self-consciousness are motivated to care about the situation of the environment and reject the energy intensive behaviors. On the contrary, people low in environmental self-consciousness might be more likely to use energy intensively and not so inclined to high-density neighborhoods. Recently, Yu et al. (2011) verified the importance of unobserved factors on explaining household energy consumption behavior. For the purpose of understanding the soft policy effect, many researchers straightly collected the attitudinal and/or preference and/or lifestyle factors in the survey and incorporated them into the model together with the socio-demographics and neighborhood characteristics (Kitamura et al., 1997; Bagley and Mokhtarian, 2002), it is still unlikely that all the demographic and lifestyle attitudes that indeed have substantive impact on households' behavior can be included in the questionnaire. Therefore, the concept of "self-selection effect" is proposed to somehow capture the effect of those unobserved factors which have collective influence on the household energy consumption behaviors and the relevant decisions. Take the residential location choice and energy consumption behavior as an example to deeply explain the self-selection effect.

Concerning the integrated residential and energy consumption analysis, one possible issue is the causal impact VS non-causal association which is also termed as "self-selection effect", between the above two behavioral aspects. In the common sense, the assumed integrated structure between residential location choice and household energy consumption are generally expressed in the following mathematical form:

$$\left.\begin{aligned} RLC &= f(RE, Z) + \pi \\ HEB &= g(RE, X) + \varepsilon \end{aligned}\right\} \Rightarrow \text{Integrated probability} \tag{2.1}$$

where, *RLC*, *HEB* are the residential location choice and household energy consumption behavior, respectively; *RE* is residential environment; *Z*, *X* indicate the other observed variables such as household and individual socio-demographics, π, ε denotes the collective influence of all unobserved variables on *RLC*, *HEB*, respectively. Combining the probability of *RLC* and *HEB* together, we can obtain the integrated probability. The problem here is that the endogeneity bias is easy to occur due to the correlation among *RE* and π or *RE* and ε

(see Mokhtarian and Cao (2008) for details). For instance, when part of the observed *RE* and unobserved attitude variables are directly correlated, the mathematical form is like:

$$\left.\begin{aligned} RLC &= f(RE, RE(AT), Z) + \pi(AT) \\ HEB &= g(RE, RE(AT), X) + \varepsilon(AT) \end{aligned}\right\} \Rightarrow \text{Integrated probability} \tag{2.2}$$

in which the attitude (*AT*) in π and ε partly explains or causes *RE*. Due to these specific attitudes, households self-select into a neighborhood and then pursue their energy consumption pattern which is consistent with those attitudes. In this sense, the effect of *RE* attributes on residential location choice and household energy consumption is not only the causal impact, but also the non-causal association which is caused by intervening attitude elements. Such kind of non-causal association is the most frequently form of self-selection effect (i.e., unobserved factor derived) discussed in other disciplines and also the type included in this thesis. The term self-selection has been used for a long time in the transport, labor economics (Heckman, 1974), health (Holly et al. 1998), and migration (Borjas, 1987) and planning literature. Some studies have proved that the planning result without controlling for self-selection effect caused by unobserved attributes tends to produce a biased estimation of the influence of the residential environment on individual/household behavior (see Cao and Chatman, 2012; Cervero, 2007; Handy et al., 2004; Zhou and Kockelman, 2008; only for the review related to travel behavior). In other words, after explicitly controlling the self-selection effect, the extent to which the residential environment itself on residential location choice and household energy consumption behavior can be figured out.

Self-selection effect not only exists in the residential location choice and household energy consumption behavior, but also other decisions associated with household energy consumption, such as the end-use ownership and usage dimensions. Due to the similar mechanism, here no more explanation is given. But another issue need to emphasize is that, the self-selection effect might vary with end uses. For example, households who do not like cooking may choose to reside in the neighborhood with good catering facilities (e.g., restaurants and/or supermarkets) and use less cooking-related end uses, while households with a preference on driving may prefer to live in suburban area so as to satisfy their desire of driving. Obviously, these two effects are distinct. This implies that the soft policy might have different influence on varied end uses, and therefore, how it works on different types of end uses should be clarified.

Unfortunately, there is little analysis which considers the self-selection effect when dealing with the integrated analysis of household energy consumption. Consequently, our study is devoted to fill this gap and to find out the efficacy of soft policy.

2.2.3 Technology Innovation and Household Energy Consumption

Improving technology efficiency is among the favorite strategies to achieve the goal of conserving energy. However, it is widely argued that efficiency improvements do not actually produce the expected savings, given that an efficiency improvement of a specific end use always leads to a decline in the cost of per-unit service, which in turn causes a feedback to incremental usage of that end use and/or the demand for other end uses. This so-called rebound effect partially or fully offsets the initial reduction of energy consumption, posing a series of concerns about the real effectiveness of technology-oriented policies. Three types of rebound effects have been identified, including a direct rebound effect, an indirect rebound effect and an economy-wide effect (Greening et al., 2000).

2.2.3.1 Direct Rebound Effect

Most of the current evidence on the direct rebound effect is targeted on space heating, cooling devices and personal vehicles, while for other household appliances, the evidence is very sparse. From Table 2-1, we can see that the direct rebound effect on residential space

Table 2- 1 Empirical evidence of the direct rebound effect for the household end-uses

Paper	Country	Direct rebound effect
Residential space heating		
Douthitt (1986)	Canada	Short-run: 0~17% ; Long-run: 35~60%
Schwarz and Taylor (1995)	US	Long-run: 1.4%~3.4%
Nesbakken (2001)	Norway	Short-run: 15~55% (average 21%)
Guertin et al. (2003)	Canada	Long-run: 29%~47%
Bra¨nnlund et al.(2007)	Swedish	5%
Residential space cooling		
Hausman (1979)	US	Short-run: 4% ; Long-run: 26.5%
Dubin et al. (1986)	US	1~26%
Guertin et al. (2003)	Canada	Long-run: 38%
Jin (2007)	South Korea	57‐70%
Private transport		
Johansson and Schipper (1997)	12 OECD	Long-run: 5%~55%
West (2004)	US	Short-run: 87%
Dargay (2007)	UK	Short-run: 10% ; Long-run: 14%
Small and Van Dender (2007)	US	Short-run: 4.5% ; Long-run: 22.2%
Sorrell and Dimitropoulos (2007)	UK	Upper bound : Short-run: 20%~25% &Long-run: 80%
Frondel et al. (2008)	Germany	Long-run: 56~66%
Hymel et al. (2010)	US	Short-run: 4.7% ; Long-run: 24.1%
Matiaske et al. (2011)	Germany	Nonlinear rebound effect
Other household end-uses		
Guertin et al. (2003)	Canada	Long-run: 34%~38% for water heating; 32%~49% for electric appliances and lighting
Bra¨nnlund et al.(2007)	Swedish	Short-run:49% for domestic appliances
Jin (2007)	South Korea	71.7‐84.0% for refrigerator, but including the income effects
Davis (2007)	USA	<5% for clothes washer
Freire-González (2010)	Spain	Short-run: 35% and long-run: 49% for all electric end-uses

Note: see Greening et al. (2000), Binswanger (2001), and Sorrell et al. (2009) for more detail review.

heating devices is significant but with a great dispersion. Overall, previous estimates are in the range 0%~55% for the short-run rebound effect and 1.4%~60% for the long run, indicating that any technological improvement will be between 40%~98% effective in reducing energy consumption for space heating. In contrast, there is much less evidence on the direct rebound effect for space cooling (e.g., air conditioners). The most frequently mentioned studies in the previous literature are those of Hausman (1979) and Dubin et al. (1986). They found a similar result for the rebound effect between 1%~26% in the US.

Guertin et al. (2003) suggested a total of 38% long-term take-back for a 100% increase in the energy efficiency of cooling end use in Canada. On the other hand, Jin (2007) found that South Korea presented a rebound as high as 57%~70%, which is much larger than for the US and Canada. Because of the high proportion of private transport energy consumption across the whole world, scholars have increasingly explored the rebound effect in personal automotive transportation. Sorrell et al. (2007, 2009) suggested that for OECD countries, the upper bound of the short-run direct rebound effect is 20%~25%, and 87% over the long run. However, there is great variation between the estimates, and hence a "best guess" for the long-run direct rebound effect ranging from 10% to 30% is given on the basis of ample reviews. Relatively little evidence on the direct rebound effect for other main end uses in the household (e.g., refrigerator, lighting, clothes washer, gas shower, TV, PC, microwave oven, etc.) has been found, owing largely to the lack of data. Several studies calculated the elasticity of household electricity consumption with respect to energy price, which can be regarded as a proxy for the direct rebound effect of all electricity end uses (Guertin et al., 2003; Freire-González, 2010). A take-back of 32%~49% for a 100% increase in efficiency is derived in this manner. Davis (2007) successfully estimated the direct rebound effect for the clothes washer itself; nevertheless, a minor rebound effect (i.e. <5%) is indicated.

2.2.3.2 Indirect Rebound Effect

The empirical evidence on all types of indirect rebound effects is very limited compared with the evidence on the direct rebound effect. Generally, the indirect rebound effect is estimated together with the economy-wide effects because both of them are associated with equilibrium adjustments. There is very little evidence about the secondary effect referring to the trade-offs between energy savings and demand for services produced by other household end uses. The limited findings available suggest that such secondary effects from energy efficiency improvements in consumer technologies are relatively small (Greening and Greene, 1998; Schipper and Grubb, 2000). However, Sorrell (2007) pointed out that although these arguments might be plausible, they are not supported by the results of several quantitative studies. On the other hand, the case of a shift from car travel to cycling was cited to show that secondary effects could be substantial and may even exceed the direct energy savings.

2.2.3.3 Methodologies for Estimating Rebound Effect

In summary, three main categories of approaches have been utilized for estimating rebound effects (Bhattacharyya and Timilsina, 2009; Sorrell et al., 2009).

(1) Econometric models: This type of method typically represents the rebound effects by calculating elasticities, meaning the percentage change in energy consumption following a percentage change in the technological efficiency or price of a service, holding the other measured variables constant. Currently, the widely accepted empirical evidence for direct rebound effects as well as part of evidence for the indirect rebound effects is derived from these models. Econometric models can be further classified into statistically oriented models (e.g., linear/log-linear regressions, AID system, household production functions, etc.) and behaviorally oriented models (e.g., discrete/continuous models only for the direct rebound effect, translog utility functions). For the statistically oriented models, only the statistical relationship between variables can be obtained rather than a behavioral explanation (Davis, 2007; Guertin et al., 2003; Reister and Edmonds, 1981). While for the behaviorally oriented models, few relevant discrete/continuous models have addressed the interactions between the consumption of different end uses when efficiency changes, though models based on the translog utility functions can fill this function for continuous decision only (Dubin et al., 1986; Frondel, 2004; West, 2004).

(2) Quasi-experimental approach: This method estimates the rebound effects by directly

measuring the demand of the energy service before and after an energy efficiency improvement (Frondel and Schmidt, 2005; Meyer, 1995). However, as mentioned by Sorrell et al. (2009), the methodological quality of the majority of such studies is relatively poor because most of them only conduct the simple before–after comparisons without presetting a control group or explicitly controlling for confounding variables. In addition, sample selection bias and small sample size are other weaknesses of this approach.

(3) Input–Output approach: This method is a disaggregated approach and is able to capture the direct rebound effect, indirect rebound effect, as well as the economy-wide effect through intersector transactions (Kok, et al., 2006; O'Doherty and Tol, 2007). The rebound effect calculated by price elasticity can be easily obtained through this type of model. However, the requirements for the data are very demanding and technological diversity is difficult to capture within a given sector (Bhattacharyya and Timilsina, 2009).

2.2.3.4 Targeting Area

The previous evidence of rebound effects is mainly based on OECD countries and is unlikely to be representative of situations in developing countries. Essentially, rebound effects may be expected to be larger in developing countries because of the relative low average income as well as the unsaturated demand for energy services (Hymel et al., 2010; West, 2004). However, this is only supported by the limited empirical evidence available. Hence, two studies from developing countries deserve a mention. Roy (2000) looked at the effect of technical efficiency gains on energy use in the domestic, transport, and industrial sectors in India. For the domestic sector, the case of rural lighting was analyzed and it was shown that an energy saving of approximately 50% would be taken away if the old kerosene lamps were changed to solar-powered battery lamps. Concerning the private transport sector, a direct rebound effect depicted by the elasticity of fuel to income was 48.7% in the short term and

101% (i.e., backfire) in the long term, which is much higher than the effect in OECD countries. Ouyang et al. (2010) addressed the rebound effect from a macroeconomic perspective and they presumed a rebound effect of 30~50% in Chinese households by reference to the effects in other countries.

Based on the above literature review, it is obvious that the existence of rebound effects and their values vary remarkably between targeting countries and end uses. Therefore, the impact of the rebound effect has to be gauged individually when evaluating the effect of technology innovation on energy conservation, given that each country and sector might have very different consumption characteristics and patterns, especially in the developing countries.

2.3 Spatial Comparative Analysis

Cross-country comparison research has been conducted widely in developed countries to investigate national differences in household energy consumption patterns (Genjo *et al*., 2005; Schipper and Ketoff, 1983). Following the footprint of developed countries, analyses in Asian developing countries gradually rise since the last decade. As mentioned by Nakagami (2006), in Asian countries, future large increases in energy consumption appear unavoidable, especially in tropical regions (e.g., Indonesia and Malaysia), whose potential demand for cooling is extremely large. The existing research on household energy consumption in Asian developing countries shows that in the past 15 years, the diffusion of various end-uses in households has contributed a lot to the increase of energy consumption, like electricity and gasoline (Genjo *et al*., 2005; Murata *et al*., 2008; Saidur *et al*., 2007; Tyler, 1996). However, the study in the context of Asia is very limited, and one of the main reasons is the scarcity of the data.

In order to provide detailed information on energy consumption, household level surveys are conducted which are always organized by national Bureau of Statistics. These surveys can be divided into two types: consumer expenditure (CEX) survey (e.g., USA, the Netherlands, Sweden, Japan and UK) and household energy consumption survey (e.g., Canada and Japan). As we see, household level survey is very widespread in developed countries, while for developing countries it is limited. Due to the important role of Asia on the global energy consumption increase, it is necessary to carry out such kind of household energy consumption surveys in Asia especially in developing countries, so as to derive more accurate information for energy research and relevant policy decisions. Under such consideration, in this study, we conduct an international household energy consumption survey in Tokyo, Beijing, Jakarta, and Dhaka, cross-sector information not only containing residential sector but also transport sector referring to personal travel are collected to fully understand the household energy consumption patterns in Asian megacities.

2.4 Summary

To date, massive studies have been found to deal with the energy consumption issue related to the residential sector or the transport sector. Unfortunately, the importance of the analysis from the behavioral perspective is not fully realized. Furthermore, the necessity of the joint representation of residential energy consumption and transport energy consumption is always not recognized in the existing research. Consequently, this thesis aims to conduct an integrated analysis of the household energy consumption behavior across residential and transport sectors. Under such a broad context, the energy policy analysis is further carried out in this thesis based on several proposed models. Multiple research issues are reviewed in this section which is related to the land-use policy, soft policy and technology innovation.

According to the behavioral mechanisms mentioned in Figure 1-2, it is expected that the land-use policy might work on household energy saving due to the interdependence between residential location choice and household energy consumption behavior. In addition, it is argued that the true effect of land-use policy might be biased when the self-selection effects are ignored. However, little is known about the respective role of urban spatial structure and the self-selection effects (associated with the soft policy) on the total household energy use. This thesis develops an integrated model to find out the true effect of land-use policy as well as to understand how the soft policy works on the household energy consumption.

On the other hand, though the technology innovation is thought to be effective to reduce the energy use, it always meets with the query that whether the rebound effect exists. Based on the review result, a lot of evidence verified the significant rebound effect. Whereas, it is mainly focus on the space heating/cooling devices or private vehicles in the context of OECD countries, and the methodology used to gauge the indirect rebound effect is very limited. This thesis proposes an integrated model to evaluate both the direct and indirect rebound effect, which can finally help obtain the true effect of the technology improvement on energy saving.

To achieve the macro target of the energy conservation, single policy might be not enough. A policy system should be proposed. However, after the broad review of the existing ideas and methodologies, it is found that scarce work did this, especially the policy system design under the concept of the integrated analysis on the household energy consumption behavior across both residential and transport sectors. To reach this goal, after the single policy analysis, this thesis further sheds light on the collaborative efficacy of land-use policy, soft policy, technology improvement/rebate program, and time controlling policy, on the household energy consumption including the residential energy consumption and travel related energy use.

Chapter 3

Household Energy Consumption Surveys

To support this study, two surveys were carried out: international energy consumption surveys and a quasi panel survey. The former survey is for the spatial dimension analysis while the latter one is for the temporal dimension analysis.

3.1 International Energy Consumption Surveys

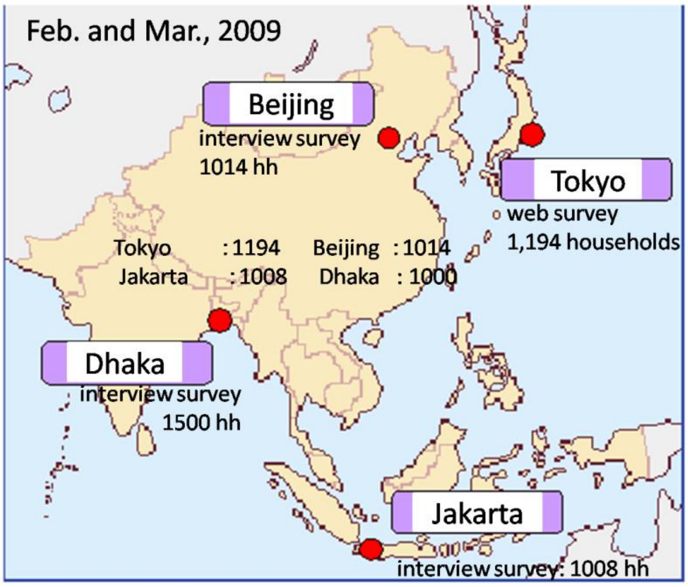
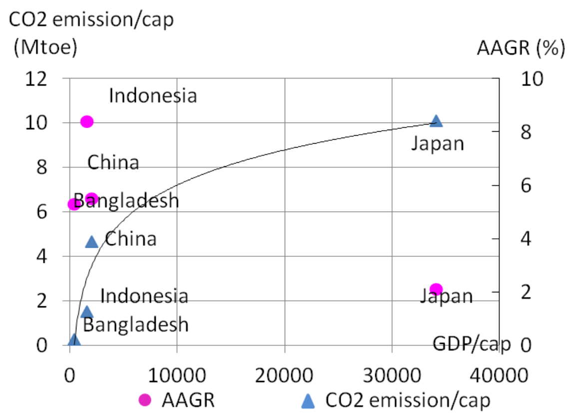


Figure 3- 1 The targeted megacities in the energy consumption survey

By considering the economic development level, geographic location, climate feature, current energy consumption and the transportation structure, four representative cities were chosen to conduct the household energy consumption survey: Tokyo, Beijing, Jakarta, and Dhaka, the respective capital city of Japan, China, Indonesia, and Bangladesh (see Figure 3-1). Concerning the economic development level (see Figure 3-2), these four countries belong to four non-overlapped leagues, which can proxy either the highly-developed cities, or relatively less developed cities. Additionally, diverse energy supply markets (the available energy resource), transportation system (a variety of travel modes), as well as the climate features (see Figure 3-3) shaped their own energy consumption patterns. In view of the aforementioned aspects, we decided to use these four megacities to depict the Asian style energy consumption pattern. The basic statistics are given in Table 3-1.



(AAGR: average annual energy consumption growth rate.)

Figure 3- 2 Economic and emission in the four cities

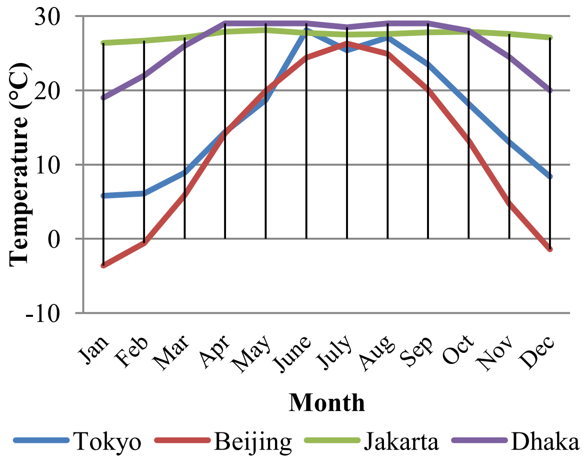


Figure 3- 3 The temperature in the four cities

Table 3- 1 Statistics of Japan, China, Indonesia, and Bangladesh

Items	Japan	China	Indonesia	Dhaka
Population (Million)	127.33	1331.46	229.97	162.22
GDP (billion 2000 USD)	4872.22	2937.55	258.49	78.23
TPES/Population (toe/capita)	3.71	1.70	0.88	0.18
CO_2/Population (tCO_2/capita)	8.58	5.13	1.64	0.31
CO_2/GDP (kg CO_2/2000 USD)	0.22	2.33	1.46	0.65

Note: TPES means total Primary Energy Supply

Statistics: IEA 「Energy Statistics 2009」

Table 3-2 lists the details of the survey in each city. A carefully designed questionnaire survey was conducted in Tokyo through web and through face-to-face interview in Beijing, Jakarta, and Dhaka in March 2009. In each city, a pilot survey was done to improve the questionnaire contents. In Tokyo, the web survey was implemented with the help of a major web survey company in Japan (having more than 1.4 million registered panels), thus the age, gender and residential distributions across the whole population were guaranteed. In Beijing, Jakarta, and Dhaka, candidate households located in the urban area were randomly chosen and those who agreed to participate in the survey were asked to fill in the questionnaires. In order to improve the survey quality, the respondents' answers were checked by a face-to-face interview when collecting the questionnaires. The questionnaire contents were specifically designed for each city.

Table 3- 2 Information about the survey in each megacity

Survey Name	Household Energy Consumption Behavior Survey	
Survey Period	February ~ March in 2009	
Survey Sites	Tokyo, Beijing, Jakarta, and Dhaka	
Respondent	Urban households	
Survey Method	Tokyo: web-based questionnaire survey Other three megacities: face-to-face interview survey	
Survey Content	• Attributes of respondent • Household/housing attributes • Ownership and usage of domestic appliances and private vehicles • Monthly energy consumption in different seasons	
Collected Sample	Tokyo: 1194 Beijing: 1024 Jakarta: 1009 Dhaka: 1000	
Survey Content		
Energy Consumption	Electricity Gas Water Kerosene Gasoline Diesel	Monthly energy consumption in different seasons - Tokyo, Beijing, Dhaka Spring (Mar ~ May) Fall (Sep ~ Nov) Summer (June ~ Aug) Winter (Dec ~ Feb) - Jakarta Dry season (Nov ~ Apr) Wet season (May ~ Oct)
Domestic appliances	Refrigerator Air-conditioner Space heater Washer Shower	- Holding number in the household, - Type, size, capacity, efficiency, made year, energy saving level, fuel type, etc., - Frequency and/or duration of usage per week in different seasons.
Out-of-home vehicle	Private car Motorcycle	- Holding number in the household, - Type, made year, displacement, fuel intensity, number of passengers, use purpose, fuel type, etc.; - Driving frequency, VMT.
Social-demographic /economics attributes	Respondent	Gender, age, education, and environmental consciousness, travel mode, travel time.
	Household	Household size, income, composition of members, housing area, dwelling type, and distance to public transit station.

The data collected in this international energy consumption survey will be used in Chapter 4 and Chapter 5

3.2 Quasi Panel Survey

In order to deeply understand the household energy consumption behavior, the capital city of China, which is experiencing rapid economic and population growth, was chosen to be the target area of the temporal analysis. Over the last decades, more and more people in Beijing are living in high-rise buildings and owning/using various electric appliances and vehicles, implying that the Beijing residents are enjoying energy-intensive modern life. It is required to take some effective measures to transform such energy-intensive life style. However, little has been done with respect to the Beijing residents' energy consumption behavior.

A quasi panel survey was conducted there in the summer of the year 2010. This survey was designed to collect the information about the energy consumption in residential and transport sectors as well as the residential environment and time use for different activities. The questionnaire contents were improved based on a pilot survey. The candidate households in 10 residential districts located in the central city area, the inner city area, and the outer city area (almost covered each orientation in Beijing), were first randomly visited (see Figure 3-4). Those who agreed to participate in the survey (nearly 2,000 households) were asked to fill in questionnaires. Two days later the well trained surveyors visited those respondent households again with small gifts and checked their answers on the spot with the respondents together. Because some respondents did not have time to fill in the questionnaire, and some of them were not at home, consequently, we retrieved 775 valid questionnaires with complete records (i.e., all the essential questions like the efficiency, usage, and time use were answered). The questionnaire contents include the following six parts.

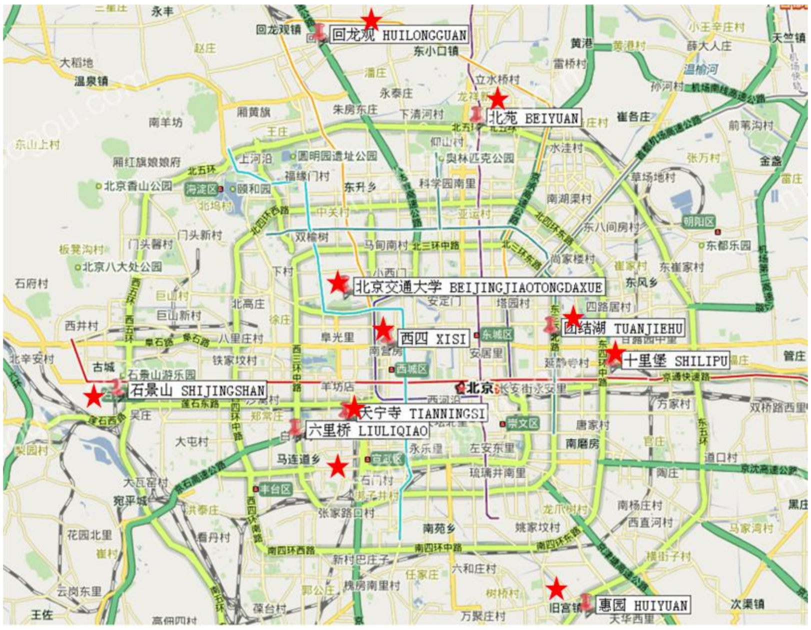


Figure 3- 4 Location of the surveyed residential neighborhoods

(1) Ownership and usage of domestic appliances and cars: attributes (e.g., type, size, capacity, and efficiency), frequency and/or duration of usage per week in four seasons. By multiplying the efficiency with the usage, the approximate energy consumption of each end use can be derived.

(2) Energy consumption: monthly energy consumption (e.g., kwh, m^3, and L) or monetary expenditure spent on electricity, gas, and gasoline in four seasons.

(3) Residential environment attributes: distance, frequency of visit, major travel mode, and travel time to the nearest railway station (or bus stop), supermarket, large-scale shopping mall, park, hospital, kindergarten, and schools (from elementary school to high school).

(4) Household and housing attributes: household size, income, composition of members, housing area and dwelling type.

(5) Individual attributes: each household member's gender, age, education level, ownership of car and driving license, employment status, daily commuting/schooling mode, travel

time to/from work/school, depart time to work/school and arrival time from work/school, sleep time and get-up time.

(6) Time use: time allocation across different activities in a weekday and a weekend day for the main household members (older than 7 years old). And the accompanying group for each activity: whether they participated in the activity independently or shared with other household members.

This survey is a retrospective survey which asked households to answer the above information at two time points: one is the current situation, and the other is a previous time point (i.e., year 2001 for households who did not experience residential re-location within the last 10 years, and the year before the re-location for households who moved within the last 10 years). Compared with the international survey, besides the end uses previously mentioned, some end uses for recreational activities and for cooking, such as TV, PC, microwave oven were also targeted in this survey. And three extra contents were included: the individual attributes for every member in the household, the concrete information about the residential environment, and the activity-travel behavior for each member.

Data collected in this survey will be analyzed in Chapter 6, Chapter 7, Chapter 8, and Chapter 9.

Chapter 4

Comparative Analysis of Household Energy Consumption Patterns in Different Cities

4.1 Introduction

In recent years, Asian region is consuming increasing amounts of energy. Since 1990, consumption has risen by two thirds, largely driven by middle-income economies such as China and India, where energy has been used to fuel rapid economic growth. Furthermore, to 2030 the increase of energy consumption in Asia is estimated to account for 46% in the total world energy increase (ESCAP, 2009).

Household energy consumption is expected to increase throughout the Asian region together with rising per capita income, living standards, and lifestyles, and consequently it is important to analyze household energy consumption behavior in order to formulate policies for promotion of sustainable energy consumption (ESCAP, 2009). Household energy consumption includes residential energy consumption caused by the usage of cooling, heating, electric appliances (e.g., electricity, gas, kerosene) and transport energy consumption caused by the private vehicle usage, like gasoline. Statistics shows that residential energy consumption in Asian countries has significantly increased with the growing penetration rate of different appliances during the last decade (the annual growth of household electricity is 3.8 percent which is much higher than 2.0 percent of OECD countries). Regarding to the transport energy consumption, strong economic growth coupled with low car ownership rates and rising incomes has turned Asia into a gold mine for the automotive industry. The annual growth rate of Asian transport energy demand to 2020 is projected to be 4.33 percent (the world level is 2.14 percent) (Urban Transport Energy Efficiency 2006). Moreover, in some

Asian countries (e.g., Japan, Korea, Indonesia), transport energy consumption caused by private vehicle travel accounts for nearly 50% of the total household energy consumption, which suggests that the car ownership choice has a significant influence on the household energy consumption behavior (World Energy Outlook 2006). Accordingly, accumulation of knowledge on the energy consumption patterns, as well as the relationship between car ownership and household energy consumption in Asian cities is very essential to assist in formulating adequate measures to cope with the environmental problems foreseen in the future.

In general, households select whether to own a car or not based on their social-demographic attributes, travel needs, attitudinal factors (e.g., environmental awareness, special taste on driving) and so on. The objective factors like social-demographic attributes can be easily captured through the survey; however the subjective psychological factors like environmental awareness are difficult to derive exactly. In order to deeply understand the relationship between car ownership and household energy consumption behavior in Asian cities, self-selection is proposed to disentangle the effect of car ownership on household energy consumption. As mentioned in the first chapter, in the context of fully considering objective factors, the self-selection is expected to be the unique subjective characteristics of households, such as some motivational factors, environmental awareness, special taste on driving and so on. Regarding to the effect of self-selection on household energy consumption behavior, it covers two parts: the direct effect on vehicle travel and the indirect effect on residential energy consumption behavior. For instance in reality, some people may choose to use public transportation instead of buying a car due to their high environmental concern which would also influence the residential energy consumption behavior, such as the ownership (choosing to buy energy efficient types) and usage (leading an energy-saving lifestyle) of domestic appliances. While certain individuals might have a special taste on driving, in this case the household will choose to buy a car regardless of other limitations, and put a heavier use on it which increases the gasoline consumption but meanwhile alters the time allocation for different activities which may change the residential energy consumption pattern. Consequently, the observed difference in household energy consumption between car owning households and no car households is a comprehensive product of car ownership, self-selection on transport energy consumption behavior, and self-selection on residential energy consumption behavior. As a result, the predicted increase of household energy consumption caused by the change of car ownership would be biased if households' self-selection help determine the car ownership and usage.

Under such circumstances, aiming at exploring diversities of household energy consumption behavior, this study selects four representative megacities with varied economic development level in Asia, including Tokyo, Beijing, Jakarta, and Dhaka, the capital of Japan, China, Indonesia, and Bangladesh, respectively. An international household energy consumption survey was conducted in each city in 2009. Based on the comprehensive survey data, aggregation analysis and Heckman's latent index model (Heckman, 1976, 1979) are conducted to explore the diverse cause-effect relationships in these four megacities among car ownership, household attributes, end-use ownership, and energy consumption. Besides, the relative effects of car ownership and self-selection on household energy consumption are separated and quantified by using the latent index model.

The remaining part of this chapter is organized as follows. The next section elaborates the model structure and the way to calculate the self-selection effect. Section 5.3 shows some descriptive statistics of the data. The model estimation results and the comparative analysis based on the results are explained in Section 5.4. This chapter ends up with a brief summary and conclusion.

4.2 Methodology

A common approach to dealing with selection bias is to use a latent index model, which relates the treatment to the likelihood of potential treatment outcomes. This approach is often called Heckman's latent index model (Heckman, 1976). In this study, the treatment group denotes that households choose to own a car, while the non-treatment group indicates that households choose not to own a car. Household's prior selection into whether to own a car or not is first decided, and then household energy consumption is represented, conditional on the prior selection. More specifically, households receive treatment (own a car) if the utility of doing so is positive and do not receive treatment (do not own a car) if the utility is negative. Potential-outcome equations (household energy consumption) are specified as follows:

Consider a model of potential outcomes:

$$Y_i^1 = \alpha^1 + \sum_k \beta_k^1 x_{ik}^1 + e_i^1, \text{ } if \text{ } D_i = 1 \tag{4.1}$$

$$Y_i^0 = \alpha^0 + \sum_k \beta_k^0 x_{ik}^0 + e_i^0, \text{ } if \text{ } D_i = 0 \tag{4.2}$$

where, Y_i^1 and Y_i^0 are the potential outcomes (refer to household energy consumption in this chapter) in two possible "states" (own a car ($D_i = 1$, i.e., the receipt of treatment) and do not own a car ($D_i = 0$, i.e., no receipt)) for household *i*, respectively; x_{ik}^1 and x_{ik}^0 are the *k*th explanatory variables with parameters β_k^1 and β_k^0; α^1 and α^0 are constant terms; e_i^1 and e_i^0 are error terms; D_i is a dummy variable, indicating where a car is owned or not, is defined below.

$$D_i = \begin{cases} 1, \text{ } if \text{ } D_i^* \geq 0 \\ 0, \text{ } if \text{ } D_i^* < 0 \end{cases} \tag{4.3}$$

$$D_i^* = \mu + \sum_q \theta_q z_{iq} + \varepsilon_i \tag{4.4}$$

Here, D_i^* is a latent variable used to generate D_i, z_{iq} is the *q*th explanatory variable with parameter θ_q, μ is a constant term and ε_i is an error term. A binary probit model is developed to predict households' car ownership choice in this study.

With the above equations, total household energy consumption can be expressed as

$$Y_i = D_i Y_i^1 + (1-D_i)Y_i^0. \quad (4.5)$$

Note that Y_i^1 or Y_i^0 is observed for each household, not both. The information about various expected differences from the receipt of treatment is denoted by $\Delta_i \equiv Y_i^1 - Y_i^0$.

To estimate the above latent index model, Heckman (1976) proposed a two-step procedure, and Heckman *et al*. (2001) described the detailed procedure, which is briefly summarized as follows (Zhou and Kockelman, 2008):

Step1: Estimate a binary probit model to obtain θ_q for the treatment decision (own a car or not) and then use the estimated θ_q to calculate the selection correction terms (the expectation of the control variables, see equations (4.6) and (4.7)).

$$E(\varepsilon_i \mid \mu, \theta_q, z_{iq}, D_i = 1) = \frac{\phi(\mu + \sum_q \theta_q z_{iq})}{\Phi(\mu + \sum_q \theta_q z_{iq})} \quad (4.6)$$

$$E(\varepsilon_i \mid \mu, \theta_q, z_{iq}, D_i = 0) = -\frac{\phi(\mu + \sum_q \theta_q z_{iq})}{1 - \Phi(\mu + \sum_q \theta_q z_{iq})} \quad (4.7)$$

where, ϕ and Φ are the probability density function and cumulative density function of a standard normal distribution, respectively.

Step2. Treat the selection correction terms as new explanatory variables and add them into equations (4.1) and (4.2).

$$Y_i^1 = \alpha^1 + \sum_k \beta_k^1 x_{ik}^1 + \gamma^1 \frac{\phi(\mu + \sum_q \theta_q z_{iq})}{\Phi(\mu + \sum_q \theta_q z_{iq})} + e_i^1, \mathit{if}\ D_i = 1 \quad (4.8)$$

$$Y_i^0 = \alpha^0 + \sum_k \beta_k^0 x_{ik}^0 + \gamma^0 \left(-\frac{\phi(\mu + \sum_q \theta_q z_{iq})}{1 - \Phi(\mu + \sum_q \theta_q z_{iq})}\right) + e_i^0, \; if \; D_i = 0 \tag{4.9}$$

where, γ^1 and γ^0 are the parameters explaining the influence of selection correction terms on treatment outcomes (i.e., household energy consumption).

To disentangle the influences of the car ownership itself and self-selection, two important concepts articulated in Heckman *et al*. (2001) are introduced here: average treatment effect (ATE) and the effect of treatment on the treated (TT). A treatment effect, loosely speaking, is the value added or the difference in outcome when a household undergoes treatment (own a car) relative to not undergoing treatment (not own a car). ATE represents the average increase in household energy consumption of moving a randomly-selected household from a no car state to holding a car state (treatment) without considering the effect of self-selection. This effect represents the direct influence of the car ownership on energy consumption behavior. TT is the expected outcome gain from the treatment for the group of households who select the treatment option. In this study, it indicates the average additional energy consumption of households who own a car by taking self-selection into account. TT represents the total influence of the car ownership on energy consumption behavior including the self-selection effect on residential and transport behavior. Therefore, the effect of self-selection is the difference between TT and ATE.

In sample selection models, point estimates for ATE and TT can be derived using the following equations (refer to Heckman *et al*. 2001 for detailed derivation). Let $\Delta_i \equiv Y_i^1 - Y_i^0$ represent the increase in household energy consumption (GJ) due to car ownership change. The ATE conditional on $X = x_i$ can be expressed as

$$ATE(x_i) = E[\Delta_i | X = x_i] = \alpha^1 - \alpha^0 + \sum_k \beta_k^1 x_{ik}^1 - \sum_k \beta_k^0 x_{ik}^0 \tag{4.10}$$

The unconditional estimate for ATE is

$$ATE = E[\Delta_i] = \int ATE(X)dF(X)$$

$$\approx \frac{1}{n}\sum_{i=1}^{n} ATE(x_i) = \frac{1}{n}\sum_{i=1}^{n}(\alpha^1 - \alpha^0 + \sum_k \beta_k^1 x_{ik}^1 - \sum_k \beta_k^0 x_{ik}^0) \quad (4.11)$$

Here, n is the sample size. Conditional on $X = x_i, Z = z_i,\ D_i = 1$, TT can be expressed as:

$$TT(x_i, z_i, D_i = 1) = E[\Delta_i | X = x_i, Z = z_i, D_i = 1]$$

$$= \alpha^1 - \alpha^0 + \sum_k \beta_k^1 x_{ik}^1 - \sum_k \beta_k^0 x_{ik}^0 + E(e_i^1 - e_i^0 | (-\mu - \sum_q \theta_q z_{iq}) \le \varepsilon_i) \quad (4.12)$$

This parameter is conditional on the joint distribution of X and Z, so the unconditional estimate is

$$TT = E[\Delta_i | D_i = 1] = \int TT(X, Z, D_i = 1)dF(X, Z | D_i = 1) \approx \frac{1}{m}\sum_{i=1}^{n} D_i TT(x_i, z_i, D_i = 1)$$

$$= \alpha^1 - \alpha^0 + \sum_k \beta_k^1 x_{ik}^1 - \sum_k \beta_k^0 x_{ik}^0 + (\rho_i^1 \sigma_i^1 - \rho_i^0 \sigma_i^0)\frac{\phi(\mu + \sum_q \theta_q z_{iq})}{\Phi(\mu + \sum_q \theta_q z_{iq})} \quad (4.13)$$

where, m is the sample size of the treatment group; $\rho_i^s = corr(e_i^s, \varepsilon_i)$ and σ_i^s is the standard deviation of e_i^s (s = 1, 0); $\rho_i^s \sigma_i^s = \gamma^s$ which is the coefficient for selection correction term introduced into equations (4.1) and (4.2).

It is worth noting that although these estimates are derived under an assumption of tri-variate normality across the three error terms, a Monte Carlo experiment showed that the estimates for ATE and TT have very low bias (a few percent) even when the data deviate from the normality assumption (Cao, 2009).

4.3 Descriptive Statistics of Data

The data collected in the international energy consumption survey is applied in this chapter. Aggregate analysis of energy consumption, household attributes, and end-use ownership in treated and untreated households are first carried out based on the data collected in the international surveys, from which we can get the general features of the four megacities. Figures 4-1 and 4-2 together with Table 4-1 show the average values of annual energy consumption, household attributes, and the ownership of several kinds of end uses by disentangling the treated households and the untreated households in the four cities. In order to remove outliers, both 2.5% of the maximum and minimum values for each data sample are excluded in the analysis. In Dhaka because the gas cost is fixed and there is no gasoline data, the energy consumption analysis does not include these two parts. The aggregate statistics reveals some similarity and differences among these four cities. Differences are as follows: 1) Tokyo has the highest car ownership share (nearly 60%), followed by Beijing and Jakarta (about 35%), and Dhaka is the least motorized city with auto share less than 10%. 2) In Tokyo and Jakarta, residential energy consumption, especially electricity consumption, regardless of total or per capita, is obviously larger than other two cities, whereas, in Beijing and Jakarta more than half of energy consumption comes from gasoline consumption, that is to say, there are more heavy users of electricity in Tokyo, more heavy users of gasoline in Beijing, and more heavy users of both in Jakarta. 3) Attributing to the heavy use of gasoline in Beijing and Jakarta, the total energy consumption in car owning households are much higher than no car households, which is different from the relatively stable situation shown in Tokyo. In other words, car ownership is more sensitive to household energy consumption in developing cities than in developed cities. Similarity is that for all these four cities, the electricity and gas consumption are significantly different between treated and untreated households, which means the difference in energy consumption caused by car ownership not only consists in out-of-home energy consumption, but also in residential energy consumption.

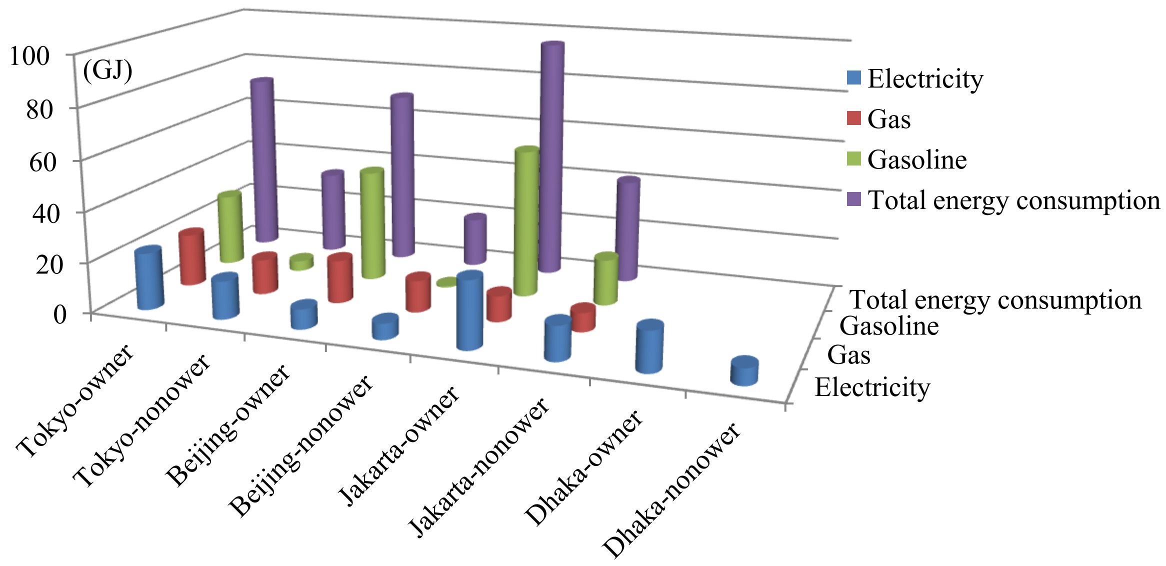


Figure 4- 1 Household energy consumption in treated and untreated households

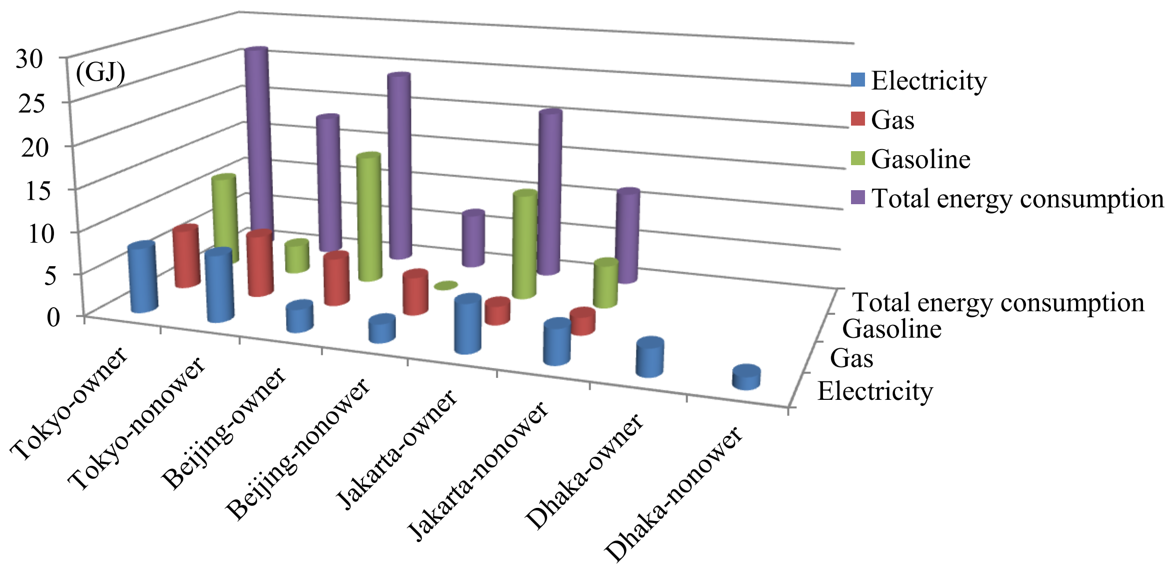


Figure 4- 2 Energy consumption per capita in treated and untreated households

Household attributes of treated and untreated households in these four cities vary a lot: the average household size in Jakarta and Dhaka is larger than in Tokyo and Beijing, while the annual income is opposite; the average of household annual income, household size, floor area, the percentage of highest education level above bachelor are explicitly larger in treated households than in untreated households.

Table 4- 1 Aggregation statistics of survey data

Category		Tokyo	Beijing	Jakarta	Dhaka
Car ownership share (%)		57.8	37.2	38.9	7
Household attributes (own car)	Income (Thousand dollar)	85~90	11~12	8~9	5~6
	Household size(capita)	2.9	3.2	4.9	4.9
	Floor area (m^2)	84.1	86.4	145.8	157.8
	Dwelling structure, iron (%)	50.6	65.1	30.7	90.9
	Education $\geq$ bachelor (%)	61.8	63.3	55.8	90
	Residential duration (years)	15.9	10.1	11.7	5
	Access to transport station (km)	0.5	1	1.6	0.9
Household attributes (no car)	Income (Thousand dollar)	60~70	8~9	3~4	2~3
	Household size(capita)	1.91	3.04	3.75	4.5
	Floor area (m^2)	55.9	66.5	84.4	44.9
	Dwelling structure, iron (%)	64.9	58	47.5	39.3
	Education $\geq$ bachelor (%)	58.8	47	25.9	26.6
	Residential duration (years)	17.8	11	10.2	7.1
	Access to transport station (km)	0.5	1.3	2.2	0.78
End-use ownership (own car) (%)	Refrigerator	100 (1.2)	98 (1)	95 (1.1)	95 (1.4)
	AC	99 (2.8)	96 (1.6)	69 (1.3)	45 (0.8)
	Fan	—	72 (0.9)	91 (2)	100 (5.9)
	Washer	100 (1.1)	95 (0.9)	79 (0.8)	0.2(3)
	Bike	82 (1.74)	74 (1.4)	52 (0.8)	—
	Motorcycle	14 (0.2)	—	80 (1.1)	18 (0)
End-use ownership (no car) (%)	Refrigerator	99 (1.1)	93 (0.9)	79 (0.8)	41 (0.5)
	AC	97 (1.7)	87 (1.3)	31 (0.4)	5 (0.1)
	Fan	—	66 (1.1)	92 (1.9)	92 (2.4)
	Washer	99 (1)	89 (0.8)	58 (0.6)	0(0)
	Bike	69 (1.2)	86 (1.5)	37 (0.5)	—
	Motorcycle	7 (0.1)	—	59 (0.8)	6 (0.2)

Note: the number in parentheses is the mean ownership of the appliance or traffic instrument.

In Tokyo the penetration rates of most durable consumer goods like refrigerator, air-conditioner, and clothes washer are already saturated. In contrast, in developing countries, it is likely that household energy consumption will continue to rise attributable to prevalence of durable goods and the great population growth. With the increasing income, more and more households in developing countries will likely increase the appliance ownership and energy use over the coming decade, especially for Dhaka, because of the lowest penetration of most appliances. Another finding is that the motorcycle ownership rate is very high in Jakarta and the energy use of motorcycle accounts for nearly 50% of the total energy consumption in the households without a car, which is a typical phenomenon in Southeast Asian developing countries (e.g., Vietnam, Malaysia). Besides the traits mentioned above, there is a similarity among these four cities that is the ownership rate of energy intensive end uses are higher in treated households than untreated households. And this might be one reason to explain the difference of energy consumption between these two types of households in varied cities.

Based on the aggregate analysis, we can know that households observed receiving treatment (owning a car or cars) often present different characteristics from those not receiving the treatment in each city. Consequently, clarifying the influential factors for treated and untreated households is essential to understand relationship of car ownership and household energy consumption behavior.

4.4 Model Estimation Results

4.4.1 Results of Treatment Selection Model

Table 4- 2 Estimation results of car ownership model (treatment selection model)

Explanatory variable	Tokyo		Beijing		Jakarta		Dhaka	
Constant term	-4.686	**	-4.992	**	-7.489	**	-5.348	**
Log(Income)	0.290		0.492	**	0.816	**	0.384	*
Household size	0.431	**	0.121	**	0.153	**	-0.115	
Education level	0.064	**	0.240	**	0.407	*	1.185	
Distance to bus/subway stop	0.052		0.040	*	0.024	*	-0.012	
Car license ownership	0.674	**	-0.227		0.036		1.162	**
Number of Observations	823		732		791		673	
Initial Log-Likelihood	-570.460		-507.384		-548.279		-466.488	
Converged Log-Likelihood	-459.263		-444.947		-391.198		-64.751	
Rho-squared	0.195		0.123		0.286		0.861	
Sample size	823		732		791		673	

Note: **. significant at the 1% level; *. significant at the 5% level.

A binary probit model was employed to describe the choice of whether to buy a car as well as to control the selection bias in treated and untreated households (i.e., equations (4.3) and (4.4)). The explanatory variables include household annual income, household size, highest education level (whether above bachelor), accessibility (distance to bus/ subway station), and car license ownership. The model estimation results are shown in Table 4-2. It is revealed that the significant factors differ across cities: in Tokyo, household size, education level, and car license ownership significantly affect car ownership choice, while in Jakarta and Beijing, besides household size and education level, income and accessibility are also validated to be significant. In Dhaka, only income and car license ownership work. The estimation results mentioned above might be interpreted as follows: in Tokyo, the high average income level makes buying a car for every household more easily than other cities, in other words, income is no longer a main factor to decide whether to buy a car in developed cities. In addition, it might because of the good accessibility to transport station in Tokyo (i.e., average 0.5km, variance of 0.2km compared to Beijing 6.1km, Jakarta 4km, Dhaka 1km), the factor "Distance to bus/subway stop" is found not significant here. Due to the varied requirements of larger families, it is reasonable that household size positively impacts the probability of owning a car. Higher education level is always related to a better job, consequently resulting in a higher probability to have a car. Based on the coefficient estimates of this probit model, the sample correction terms are calculated based on equations (5.6) and (5.7), and used to estimate the following treatment outcome models (i.e., household energy consumption models).

4.4.2 Results of Treatment Outcome Models

Treatment outcome models (i.e., equations (4.8) and (4.9)) for household energy consumption were estimated, corresponding to the two treatment-specific groups (i.e., those holding a car, versus those with no car). For Tokyo, Beijing and Jakarta, the dependent variable is total household energy consumption including residential (electricity, gas) and transport (gasoline) consumption, while for Dhaka, it is electricity consumption (GJ) due to the lack of data. Explanatory variables consist of household attributes, end-use ownership, and the selection correction term. Preliminary analysis results suggest that education level, ownership of fridge and washer are statistically insignificant in both equations for these four cities, therefore, these are not included in the final model. Since calculation of Heckman's treatment parameters requires the same number of explanatory variables in each of the two equations, variables that are statistically insignificant in just one of the equations are retained in both models, and in order to do the comparative analysis among four cities, the explanatory variables are fixed the same for each city. Estimation results are shown in Table 4-3.

Table 4- 3 Estimation results of household energy consumption models (treatment outcome models)

	Tokyo		Beijing		Jakarta		Dhaka	
Dependent variable	Total energy		Total energy		Total energy		Electricity	
Explanatory variable								
Treatment (Car owning state)								
Constant	6.188		56.400		-191.333	**	-16.954	
Log(Income)	-0.479	**	1.176	*	31.286	**	2.956	
Household size	17.689	**	4.076	**	8.278	**	1.485	**
Dwelling structure	0.868		-1.025	*	17.035		-5.596	**
Residential years	0.049		0.300	**	-0.460		-0.335	
Floor area	-0.056	*	-0.017	*	0.080		0.045	**
Ownership of AC	1.690	*	-1.645		14.782	**	0.551	
Correction term	5.972		6.592	**	25.614	*	0.480	
Number of Observations	476		272		387		22	
Rho-squared	0.440		0.134		0.406		0.901	
Non treatment (No car state)								
Constant	-13.953	**	14.095	**	-38.397	**	.0123	
Log(Income)	1.491	**	-1.126		12.918	**	0.029	**
Household size	17.157	**	1.914	**	3.189	**	0.992	**
Dwelling structure	-0.503	*	3.239		-12.702	*	1.105	*
Residential years	-0.043		0.046	*	0.161		-0.008	
Floor area	-0.006		0.007		0.024		0.030	**
Ownership of AC	2.746	**	0.487	**	19.730	**	-0.310	
Correction term	0.525	*	3.971	*	13.070		-0.918	
Number of Observations	347		460		404		651	
Rho-squared	0.671		0.116		0.294		0.427	

Note: **. significant at the 1% level; *. significant at the 5% level.

The results show that the statistically significant variables differ among cities, furthermore, the significant factors and their influential effects vary between treated and untreated households in all cities. The most obvious difference is that in Tokyo, income negatively impacts the energy consumption in treated households, while opposite in untreated households. This status can be explained by the well-known Environmental Kuznets Curve (Lopez, 1994): income and environmental emissions are under a relation of inverted U-shaped curve. In other words, environmental emissions increase with the rising income at first, but when the income reaches a certain level, environmental emissions turn to decrease. Such decreasing trend might be caused by the improvement of technological efficiency, the advance of environmental awareness, and other changes of the society. For these four cities, see Figure 4-3, according to the Kuznets Curve, our results show that currently Tokyo might be on the right side of the curve, while the other three cities might be on the left side. Household size is positively correlated to household energy consumption regardless of the household type in all these four cities. The ownership of air conditioner also has a positive influence on energy consumption in Tokyo, Beijing and Jakarta. The selection correction term is proved to significantly affect the household energy consumption in the car owning households in Beijing and Jakarta as well as no car households in Tokyo and Beijing.

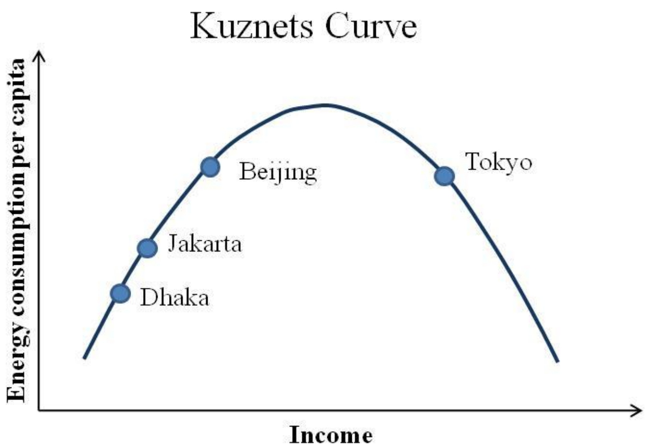
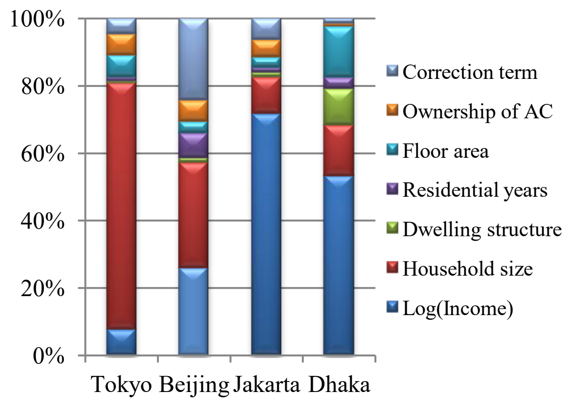
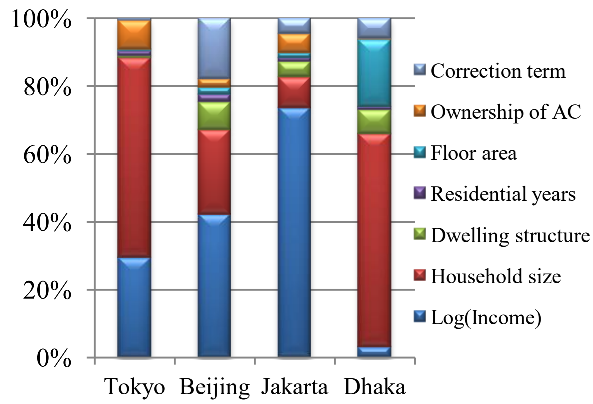


Figure 4- 3 The relation between income and household energy consumption

In order to clarify the most influential factors to household energy consumption in Tokyo, Beijing, Jakarta, and Dhaka, the partial utility (absolute value) is calculated by multiplying the coefficient and the mean of each variable together (see Figure 4-4). The partial utility can be understood as a contribution of each variable to the dependent variable. Based on this index, the most influential factors in treated households are identified: household size in Tokyo and Beijing, income in Jakarta and Dhaka, respectively. While the top influential factors in untreated households are: household size in Tokyo and Dhaka, income in Beijing and Jakarta. Overall, the top two influential factors are income and household size no matter in treated or untreated households, which is consistent with the previous research (Moll *et al.*, 2005; O'Neill and Chen, 2002; Pachauri, 2004). The partial utility of selection correction term in Beijing and Jakarta is relatively larger than other two cities, that is to say, the increase of household energy consumption caused by the difference of subjective psychological variables, such as the environmental awareness, is greater in Beijing and Jakarta.



(a) For treated households



(b) For untreated households

Figure 4- 4 Partial utility results

4.4.3 Results of Treatment Effects

Table 5-4 shows the treatment parameters and the self-selection effects. The ATE of Tokyo is estimated to be 13.15 GJ per year, which means a randomly selected household is expect to increase its energy consumption by 13.15 GJ per year after buying a car, as compared to no car state. Given the average observed total household energy consumption “56.05 GJ” per year in Tokyo, “13.15 GJ” represents more than 23% increase in yearly energy consumption. Likewise, the ATE of Beijing is 42.42 GJ, which means more than 100% increase in yearly energy consumption compared to the average observed “37.75 GJ”, and for Jakarta, the ATE is 49.31, amounting to 72.8% increase. Due to the lack of data, here the ATE of Dhaka reflects that a randomly selected household is expect to increase its electricity consumption by 0.67 GJ per year after buying a car as compared to no car state. This result shows that the ownership of car not only leads to different gasoline consumption in each household, but also changes the residential energy consumption, in other words, the interrelationship between residential and transport energy consumption behavior is confirmed. However, due to the small sample size of treatment group in Dhaka, this conclusion should be further validated by using other city’s data in the next step.

Table 4- 4 Treatment parameters and self-selection effect

Treatment Parameters	Tokyo	Beijing	Jakarta	Dhaka
ATE	13.15	42.42	49.31	0.67
TT	14.59	48.99	62.97	0.97
ATE/TT	90.13%	86.59%	78.31%	69.07%
Self-selection Effect	9.87%	13.41%	21.69%	30.93%

The TT was estimated to be 14.59 GJ in Tokyo, suggesting that a household owning a car can be expected to exhibit 14.59 more yearly energy consumption (GJ) than having no car state, ceteris paribus. Based on the size of these two effects (ATE and TT), the impacts of the “car ownership” on annual household energy consumption (i.e., the GJ increase due to owning a car, rather than no car state) is estimated to be 90.13% of the as-observed differences in treated and untreated households. This implies that the total effect of self-selection including on residential and transport energy consumption behavior accounts for nearly 10% of observed energy consumption (GJ) differences across households owning a car versus no car households. Essentially, if all no car households buy a car may be expected to yield higher energy consumption increase than analysts may perceive at first glance. Likewise, the TT is estimated to be 48.99 GJ in Beijing, 62.97 GJ in Jakarta, and 0.19 GJ in

Dhaka. The impacts of "car ownership" on annual household energy consumption can be computed: 86.59% in Beijing, 78.31 % in Jakarta, and 69.07% in Dhaka, which infers that the self-selection effect accounts for 13.41% in Beijing, 21.69% in Jakarta, and 30.93% in Dhaka. This result reveals that the greater maturity of economic development of a city (reflected by average income level derived from the survey data), the smaller effect of self-selection on household energy consumption behavior. In developed cities, because of the overall relatively higher environmental awareness, the household energy consumption difference caused by attitudinal factors is much less significant than in developing cities.

4.5 Summary and Conclusion

In order to understand the energy consumption patterns of different cities, as well as examine the effects of car ownership and self-selection on household energy consumption behavior, this chapter presents a comparative analysis of household energy consumption across an array of household attributes and end uses owned by households in Tokyo, Beijing, Jakarta and Dhaka, the four representative megacities in Asian region. For the sake of disentangling the effects of car ownership and self-selection on household energy consumption behavior, Heckman's latent index model is applied here for each megacity to explore the causal effect of car ownership on household energy consumption behavior and its relative contribution to the total influence by using the data we collected from the international survey. Moreover, the effect of the car ownership itself and the effect of self-selection are separated. Three main conclusions can be derived from the aggregation analysis and the model estimation results.

First, the statistically significant variables to household energy consumption behavior vary among cities; furthermore, in the same city the influential factors are different within car owning households and no car households. Whereas, the top two influential factors in Tokyo, Beijing, Jakarta, and Dhaka, are all income and household size.

Second, it is found that the effect of car ownership itself on the increase of household energy consumption accounts for 90.13% in Tokyo, 86.59% in Beijing, 78.31% in Jakarta, and 69.07% in Dhaka. This considerable influence in these four cities provides a supportive evidence for the truth that changes in car ownership stimulate great changes in household energy consumption behavior. Moreover, the effect of self-selection on the increase of household energy consumption accounts for 9.87% in Tokyo, 13.41% in Beijing, 21.69% in Jakarta, and 30.93% in Dhaka. This result implies that the greater maturity of economic development of a city, the smaller effect of self-selection on household energy consumption behavior. In addition, due to the existence of self-selection, the car ownership and household energy use should be analyzed together instead of separately treated, furthermore, the role of "soft policies" such as popularizing high level education, reinforcing propagation of environmental protection, etc. are emphasized in both developed cities and developing cities, especially the latter. Overall, comparative results show that although both the car ownership and self-selection influence household energy consumption behavior, the car ownership tends to play a dominant role no matter in which city.

Finally, it is at least confirmed that there is interaction between residential and transport energy consumption behavior based on the result of Dhaka. The change of car ownership not only leads to different gasoline consumption in each household, but also alters the residential energy usage (based on the result of Dhaka). Therefore, instead of deriving future total energy needs by simply summing up the forecasting of residential demand and transport demand as existing studies do, a joint representation of energy consumption behavior across residential and transport sectors should be considered so as to properly predict the energy demand.

Having examined the energy consumption pattern in each city by considering car ownership and self-selection, more accurate prediction of energy demand can be achieved, furthermore, concrete policy development based on the comparative results can be carried out in the next step. Nevertheless, for the aim of comparison among four cities, the common factors like income, household size are selected into the model, while some specific factors like motorcycle ownership are not included, therefore, in order to fully understand the household energy consumption patterns in each city, all the factors should be covered. This is left to be the next-step analysis. In addition, the selection model here just involves two treatments, whereas it's better to represent car ownership as a multiple treatments, such as no-car state, one-car state, two-car state and so on. Due to the linear limitation of the outcome models and the potential bias caused by the two step estimation, other advanced methods could be further applied to describe the effects of self-selection and car ownership on household energy consumption.

Considering the rapid development and the guiding role to other developing cities which can be found from the abovementioned results, Beijing is selected as the empirical context in the subsequent analysis in this thesis.

Chapter 5

Exploring the Necessity for Joint Representation of Energy Consumption Behavior in Residential and Transport Sectors

5.1 Introduction

Existing studies have dealt with the joint representation of energy usage caused by different domestic end uses (e.g., electric appliance, heating, cooling), or that of different vehicles (e.g., passenger car and motorcycle) (Aydinalp et al., 2002; Shimoda, 2004; Chiou et al., 2009). However, due to the existence of household budget constraints (e.g., time and money), it is expected that residential and transport energy consumption behavior might be correlated with each other. Shift to own/use energy-saving technologies for domestic appliances (or vehicles) might lead to the increase in the transport (or residential) energy consumption. Increasing evidence has shown that with the development of energy technologies or the implementation of policies (e.g., fuel tax), households have to adjust their consumption behavior in terms of monetary expenditures allocated to various households' activities, consequently resulting in that the change of energy consumption patterns (Sanchez et al., 2006; Fetters, 2008; Vera and Denise, 2009; Ferdous et al., 2010). Therefore, it seems important to jointly represent residential and transport energy consumption behavior, reflecting the influence of household budget constraints.

With the above consideration, this chapter aims to：1) clarify the effectiveness of the mixed multiple discrete-continuous extreme value (MMDCEV) model, which was proposed by Bhat (2005, 2008) and is able to deal with the choices of multiple alternatives simultaneously, in representing household energy consumption behavior; 2) confirm the rationality of the joint representation of energy consumption behavior across residential and transport sectors, 3) identify influential factors to household energy consumption behavior referring to the end-use ownership and usage.

The remaining part of this chapter is organized as follows. The next section presents a conceptual framework related to household energy consumption behavior. The mixed MDCEV model used in this study is illustrated in Section 4.3. Section 4.4 explains the survey data. Results of model estimation are shown and influential factors are examined in Section 4.5. This chapter is concluded in Section 4.6 along with a discussion about future research issues.

5.2 A Conceptual Framework of Household Energy Consumption Behavior

Household energy consumption comes from uses of appliances at home and vehicles outside to support various activity participations, which play an important role in meeting various household and individual needs. Traditionally, the energy consumption behaviors in residential and transport sectors have been separately treated. This might be influenced by the idea of the widely adopted sector-oriented policy decision scheme. However, since ownership and usage of appliances at home and vehicles result in the reduction of disposal household income, residential and transport energy consumption might be interrelated with each other, suggesting that any behavioral change might lead to the alteration of energy consumption pattern. Such interrelationships might be observed with respect to ownership and/or usage of various appliances (e.g., refrigerator, air-conditioner, and washing machine) and vehicles (e.g., passenger car and motorcycle), implying that some multi-dimensional modeling approaches are required. A joint representation that reflects the aforementioned interrelationships also has an important implication to clarify the rebound effects (Vera and Denise, 2009). For example, these days, energy-saving technologies have been actively developed and have even become an indispensible part of products to win the competition among manufactures. However, the introduction of energy-saving technology does not mean that household energy consumption will be automatically reduced. One of the worrying concerns is that households might become environmentally insensitive to their energy consumption behavior and as a result, total amount of energy consumption might even increase, i.e., the rebound effects might occur. Since energy-saving technologies in different appliances and vehicles have not been equally developed and households might show different preferences for these new technologies, the sources of the rebound effects might vary across appliances and vehicles as well as households. The above concerns motivate us to develop an integrated model to cover both residential and transport energy consumption. In addition, household attributes are important determinants to household energy use. Therefore, representing the residential and transport energy consumption pattern jointly by regarding household energy consumption as a synthesis of attributes, energy related behaviors and resource is reasonable. These are summarized in Figure 5-1.

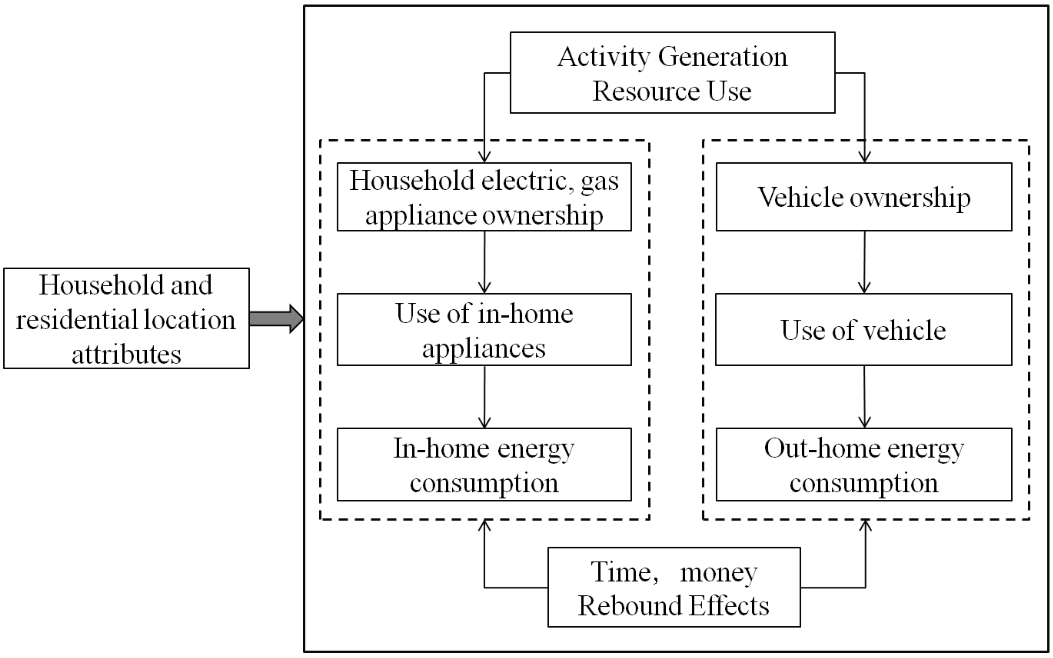


Figure 5- 1 Energy related behavior components in residential life

5.3 Modeling Methodology

The methodology adopted in this chapter uses a resource allocation modeling framework, in which the household income is apportioned to several categories (including savings) identified in the previous section. Concretely speaking, the MDCEV model proposed by Bhat (2005, 2008) is utilized here, which is a utility-maximizing resource allocation model. The model describes the households' expenditures on different types of end uses and services that are used to satisfy households' needs and desires. Different from the traditional discrete-continuous models explained previously, MDCEV model can deal with the choices of multiple alternatives simultaneously. This section presents the model formulation.

5.3.1 A Kernel Model Structure: MDCEV

Assume that there are K different end uses that a household can potentially allocate its money to. Let x_k be the consumption quantity of end use k $(k = 1,2,\cdots,K)$. The utility that a household derives from energy consumption is specified as the sum of the utilities obtained from spending money on each end use, as shown below.

$$U(x) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} \varphi_k \left\{ \left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\} \tag{5.1}$$

Here, $U(x)$ is the total utility derived from allocating a non-negative amount of the total budget to each consumption (or expenditure) end use (or alternative) k, including savings. With the above utility function, it is assumed that a household maximizes its utility subject to its budget constraint that $\sum_{k=1}^{K} e_k = E$, where E is the total budget (e.g., expenditure, disposal income, or available time), and $e_k = p_k x_k$, p_k is the unit energy price of end use k. As a result, the linearly competitive relationship among end uses is reflected in the model. Note that only one type of budget constraints can be represented. This study only deals with household monetary budget constraint. In fact, using the monetary budget constraint can at least partially represent the influence of time budget because the longer the time households allocate to activities, the more the energy households may consume. φ_k is the baseline utility for money spent on end use k, and α_k and γ_k are parameters which are introduced next.

The parameter α_k represents a satiation parameter, which plays a role of expressing the characteristic of the diminishing marginal utility with increasing consumption of end use k. Depending on the value of α_k, various types of non-linear relationships among various end uses can be accommodated. When α_k = 1 for all *k*, this indicates the absence of satiation effect (i.e., the marginal utility becomes constant), meanwhile, illustrates the competitive relation between end use *k* and other end uses is linear. As α_k moves downward from the value of 1, the satiation effect for alternative k increases. When $\alpha_k \rightarrow 0$, the utility function for end use k collapses to $U_k = \gamma_k \varphi_k \text{In}\left(\frac{x_k}{\gamma_k} + 1\right)$, suggesting the existence of log-linear relationship. α_k can also take a negative value and, when $\alpha_k \rightarrow -\infty$, this implies immediate and full satiation (i.e., infinite decrease in the marginal utility).

The parameter γ_k ($\gamma_k > 0$) is a translation parameter that serves to accommodate corner solutions (zero consumption) for end use *k*. However, it also plays the role of the above satiation parameter. Values of γ_k closer to zero imply higher rate of diminishing marginal utility (or lower consumption) for a given level of the baseline preference.

The baseline preference can be represented as a random utility specification as follows:

$$\Phi(z_k, \varepsilon_k) = \varphi(z_k) \cdot exp\ (\varepsilon_k) \tag{5.2}$$

where, z_k is a set of attributes characterizing end use *k* and the decision-maker, and ε_k is an error term that captures the influence of unobserved factors on the baseline utility φ_k.

The exponential form for the error term guarantees the positivity of the baseline utility conditional on that $(\mathrm{z_k}) > 0$. To ensure this latter condition, $(\mathrm{z_k})$ is further specified as $\exp(\beta' \ \mathrm{z_k})$, which then leads to the following form of the baseline random utility.

$$\varphi(z_k, \varepsilon_k) = exp\left(\beta' \ z_k + \varepsilon_k\right) \tag{5.3}$$

Note that a constant term can be introduced into equation (5.3) to represent the average influence of various unobserved factors on household energy consumption.

Then, the random utility function is reconstructed as:

$$U(x) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} [\exp\left(\beta' \ z_k + \varepsilon_k\right)] \left\{\left(\frac{x_k}{\gamma_k} + 1\right)^{\alpha_k} - 1\right\}. \tag{5.4}$$

The above utility specification leads to a surprisingly simple closed-form expression for the discrete-continuous joint probability (i.e., likelihood) (of consuming zero quantities for certain end uses and consuming some amounts for the remaining end uses). When the error term ε_k follows an i.i.d. Gumbel distribution, the probability that an individual chooses *M* alternatives from *K* end uses is determined by equations (5.5) and (5.6) (see, Bhat, 2005, 2008), respectively, where the former is expressed in the form of the consumption amount and the latter in the form of monetary expenditure. From these two equations, it is obvious that the competitive relationships among choices of ownership for each end use can also be explicitly explained by the term $\left[\frac{\prod_{i=1}^{M} e^{V_i/\sigma}}{\left(\sum_{k=1}^{K} e^{V_k/\sigma}\right)^M}\right]$.

$$P(x_1^*, x_2^*, x_3^*, \cdots, x_M^*, 0,0, \cdots, 0) = \frac{1}{p_1} \frac{1}{\sigma^{M-1}} \left[\prod_{i=1}^{M} f_i\right] \left[\sum_{i=1}^{M} \frac{p_i}{f_i}\right] \left[\frac{\prod_{i=1}^{M} e^{V_i/\sigma}}{\left(\sum_{k=1}^{K} e^{V_k/\sigma}\right)^M}\right] (M-1)! \tag{5.5}$$

$$P(e_1^*, e_2^*, e_3^*, \cdots, e_M^*, 0,0, \cdots, 0) = \frac{1}{\sigma^{M-1}} \left[\prod_{i=1}^{M} c_i\right] \left[\sum_{i=1}^{M} \frac{1}{c_i}\right] \left[\frac{\prod_{i=1}^{M} e^{V_i/\sigma}}{\left(\sum_{k=1}^{K} e^{V_k/\sigma}\right)^M}\right] (M-1)! \tag{5.6}$$

Here σ is a scale (σ can be normalized to one if there is no variation in unit prices across end uses), and $f_i = \left(\frac{1-\alpha_i}{x_i^* + \gamma_i}\right)$, $c_i = \left(\frac{1-\alpha_i}{e_i^* + \gamma_i p_i}\right)$, $V_k = \beta' \ z_k + (\ _{\mathrm{k}} - 1)\ln\left(\frac{e_k^*}{p_k} + 1\right) - \ln p_k$ $(k = 1,2,3, \cdots, K)$ when the α-profile (γ_k=1) is used, and $V_k = \beta' \ z_k - \ln\left(\frac{e_k^*}{\gamma_k p_k} + 1\right) - \ln p_k$ $(k = 1,2,3, \cdots, K)$ when the γ-profile ($_{\mathrm{k}} \rightarrow 0$) is used.

5.3.2 Representing the Influence of an Outside Goods

Thus far, the discussion has assumed that there is no outside numeraire goods (i.e., no essential Hicksian composite goods). If an outside goods which is always consumed is present, label it as the first goods with a unit price of one (see Bhat, 2008). In this study, the money derived from income deducting the energy expenditure is regarded as the outside goods, which is termed as disposal money. For identification, let $\varphi(x_1, \varepsilon_1) = e^{\varepsilon_1}$. Then, the utility function is modified as follows:

$$U(x) = \frac{1}{\alpha_1} exp(\varepsilon_1) x_1^{\alpha_1} + \sum_{k=2}^{K} \frac{\gamma_k}{\alpha_k} [exp\left(\beta' z_k + \varepsilon_k\right)] \left\{\left(\frac{x_k}{\gamma_k} + 1\right)^{\alpha_k} - 1\right\} \tag{5.7}$$

Note that the translation parameter γ_1 is absent for the outsides goods, because the first goods is always consumed. In the "no-outside goods" case, as described in the above sub-section, it is generally not able to simultaneously estimate $_k$ and $_k$ for the inside goods k (k=2,3, $\cdots$, K). Instead, one can estimate one of the following three utility forms. In reality, one can select the most appropriate form that fits the data best based on statistical considerations.

-profile ($_k$=1): $U(x) = \frac{1}{\alpha_1} exp(\varepsilon_1) x_1^{\alpha_1} + \sum_{k=2}^{K} \frac{1}{\alpha_k} [exp\,(\beta' z_k + \varepsilon_k)]\{(x_k + 1)^{\alpha_k} - 1\}$

-profile ($_k \rightarrow 0$): $U(x) = \frac{1}{\alpha_1} exp(\varepsilon_1) x_1^{\alpha_1} + \sum_{k=2}^{K} \gamma_k\, [exp\left(\beta' z_k + \varepsilon_k\right)] ln\left(\frac{x_k}{\gamma_k} + 1\right)$

Constant : $U(x) = \frac{1}{\alpha} exp(\varepsilon_1) x_1^{\alpha} + \sum_{k=2}^{K} \frac{\gamma_k}{\alpha} [exp\left(\beta' z_k + \varepsilon_k\right)] \left\{\left(\frac{x_k}{\gamma_k} + 1\right)^{\alpha} - 1\right\}$

(5.8)

The above specifications can be extended to describe the "with outside good" case. The probability expression for the expenditure allocation on various goods (with the first goods being the outside goods) is identical to equation (5.6), while the probability expression for consumption of the goods (with the first goods being the outside goods) is given below.

$$P(x_1^*, x_2^*, x_3^*, \cdots, x_M^*, 0,0, \cdots, 0) = \frac{1}{\sigma^{M-1}} \left[\prod_{i=1}^{M} f_i\right] \left[\sum_{i=1}^{M} \frac{p_i}{f_i}\right] \left[\frac{\prod_{i=1}^{M} e^{V_i/\sigma}}{\left(\sum_{k=1}^{K} e^{V_k/\sigma}\right)^M}\right] (M-1)! \tag{5.9}$$

The expressions for the term V in equations (5.6) and (5.9) are as follows for each of the three utility forms in equation (5.8).

-profile ($_k$=1): $V_k = \beta' z_k + (\alpha_k - 1) ln(x_k^* + 1) - lnp_k \ \ (k \geq 2);$

$V_1 = (\alpha_1 - 1)\ln(x_1^*),$

-profile ($_k \rightarrow 0$): $V_k = \beta' z_k - ln\left(\frac{x_k^*}{\gamma_k} + 1\right) - lnp_k \ \ (k \geq 2); V_1 = (\alpha_1 - 1)\ln(x_1^*),$

Constant : $V_k = \beta' z_k + (\alpha - 1) ln\left(\frac{x_k^*}{\gamma_k} + 1\right) - lnp_k \ \ (k \geq 2); V_1 = (\alpha - 1)\ln(x_1^*).$

(5.10)

5.3.3 Mixed MDCEV Model

The previous section assumed that the ε_k terms are independently and identically distributed across alternatives, and are distributed standard Gumbel. However, sometimes the alternatives are interrelated with each other due to some unobserved factors. Therefore, the mixed MDCEV (MMDCEV) model are further developed by assuming the ε_k (k=2, 3,…, K) following the multivariate normal distribution (see Bhat (2005) for details).

We use the maximum likelihood inference approach to estimate the parameters of the mixed MDCEV model. The scrambled version of the Halton sequence is adopted to draw the value of error terms from their population normal distributions.

5.4 Aggregate Analysis

Here, aggregation analyses are first carried out based on the survey data, from which we can get some general features (see Figures 5-2, 5-3, 5-4). Figure 5-2 shows the total annual energy consumption per capita. It can be seen that more than half of the total energy consumption is caused by gasoline consumption in Beijing, and electricity-oriented energy consumption shows the least share.

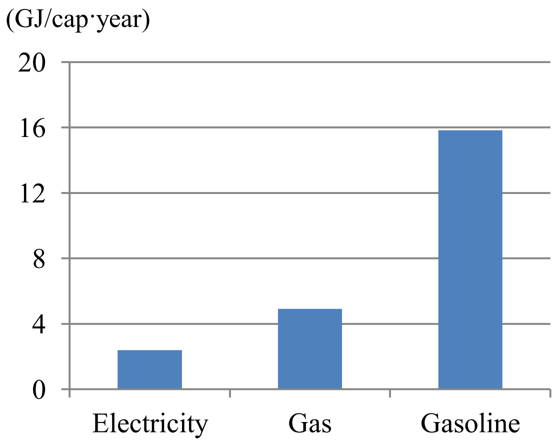


Figure 5- 2 Total annual energy consumption per capita (GJ/cap·year)

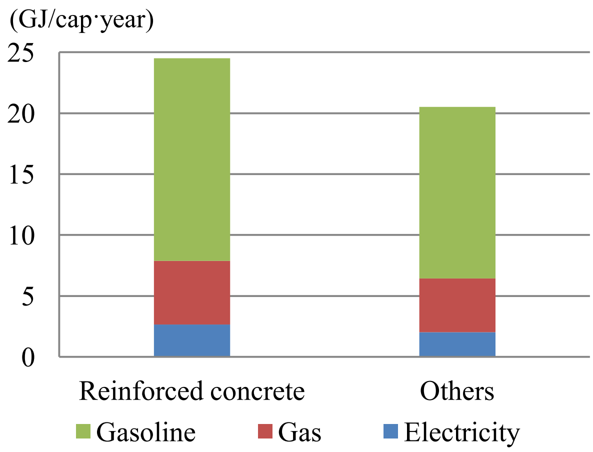
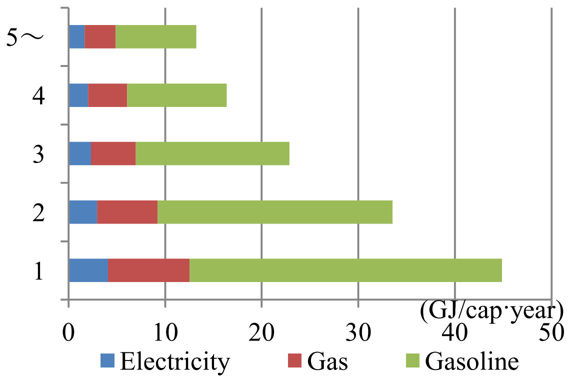
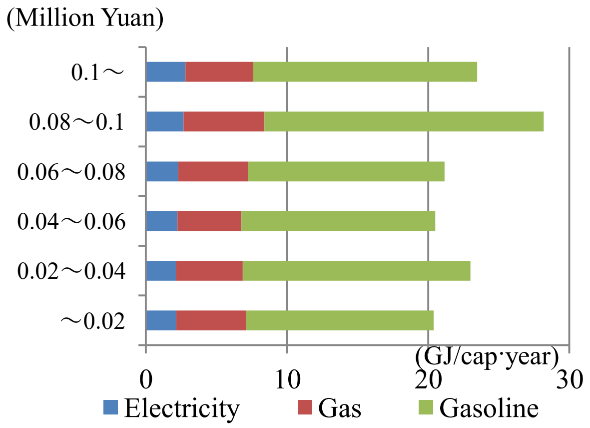


Figure 5- 3 welling structure and energy consumption (GJ/cap·year)



(a) Household size and energy consumption (GJ/cap·year)



(b) Household income and energy consumption (GJ/cap·year)

Figure 5- 4 Household attributes and energy consumption

Figures 5-3 and 5-4 show the relationships between some representative household attributes (including dwelling structure type, household size and income) and energy consumption. For reinforced concrete dwellings, more energy use is observed in comparison to other types. There is a significant relationship between household energy consumption and household size. As the household size increases, the energy consumption per capita decreases, and furthermore, residential energy consumption decreases slowly (the average decreasing ratios of electricity and gas are 19% and 21%, respectively) while transport energy consumption tends to decrease steeply (the average decreasing ratio of gasoline is 28%). Different from some existing studies (O'Neill and Chen, 2002; Pachauri, 2004; Moll et al., 2005), the absence of a relation between income and energy consumption is remarkable. In order to explore the essential relationship between influential factors and household energy consumption, disaggregate model is further developed based on the survey data.

Table 5- 1 Descriptive statistics of household end-use ownership and expenditure

End-use type	Percentage of household owning (%)	Annual operating cost (Yuan)	Energy consumption (GJ)
Refrigerator	91%	146.1	2.97
AC	78%	443.5	9.02
Fan	46%	28.4	0.58
Clothes washer	89%	56.9	1.16
Electrical shower	38%	244.9	4.98
Gas shower	41%	805.4	18.11
Car	32%	5814.8	33.36

Table 5-1 provides descriptive details of household end-use ownership and expenditure. The second column indicates the percentage of individuals owing each type of end use, the third and fourth columns indicate the average annual energy expenditure and consumption caused by each type of end use, respectively. Some findings can be derived from the statistics in these three columns. Refrigerator and clothes washer have a higher penetration rate but lower annual expenditure and energy consumption in comparison to other end uses. Even though the penetration rates of gas shower and car are lower, their operating cost and energy consumption are much bigger than those of other end uses. In spite of the different transformation coefficients from expenditure to energy for electric, gas and gasoline end uses, the energy consumption and the monetary expenditure are reflecting the same trend of end uses' utilization. Therefore, it is feasible to measure the energy consumption by monetary expenditure.

5.5 Estimation Results of MMDCEV Model

The above aggregation analyses revealed some rough relationships between energy consumption and its potential factors. To identify influential factors at the household level, in this section, we apply the mixed MDCEV model. Here, the dependent variables are the end-use ownership for the discrete part and the monetary expenditure for the continuous part. The explanatory variables used to describe end-use ownership and usage were selected based on a preliminary analysis, as shown in Table 5-2, including individual attributes, household attributes, and residential attributes.

Table 5- 2 Explanatory variables introduced in the model

Explanatory variables	Description
Individual attributes	
Education	Dummy variable of the highest education level: 1 for higher education (bachelor or above), 0 otherwise.
Energy-saving Consciousness	Ordinal variable: 1, 2, 3, 4 1 - residents are not willing to save energy at all 2 - residents are not willing to save energy 3 - residents are willing to save energy 4 - residents are strongly willing to save energy
Household attributes	
Income	Continuous variable: Average annual income of household (YUAN: RMB)
Household size	Continuous variable: Number of household members
Housing area	Continuous variable: Area of the current residence
Residential attributes	
Residential duration	Duration living in the current house (years)
Iron structure of dwelling	Dummy variable: 1 - iron-type dwelling, 0 - otherwise
Household type	Dummy variable: 1 - owned by residents, 0 - otherwise
Access	Continuous variable: distance to bus stop or subway station

The estimation results are presented in Table 5-3. Disposal money and 7 expenditure categories (expenditures of refrigerator, air conditioner (AC), fan, clothes washer, gas shower, electric shower, and vehicle) are regarded as alternatives (i.e., end uses), where the ownership refers to whether a household owns an end use under question and the usage relates to how much the household uses in terms of monetary expenditures. Here, disposal money, indicating the remaining income after deducting the energy expenditures of domestic appliances and vehicles, serves as the outside goods that is always consumed. After several trials of model estimations, we found that the model with the satiation parameter $_k$ approaching to zero and translation parameter $_k$ being unity gives the best model fit, which suggests the existence of log-linear competitive relationships among expenditures of end uses.

Table 5- 3 Estimation results of MMDCEV model

Explanatory variables	Refrige-rator	AC	Fan	Clothes washer	Electric shower	Gas shower	Vehicle
Baseline preference constants							
Constant	-5.741**	-6.115**	-11.075**	-7.884**	-7.659**	-10.451**	-11.785**
	(-7.462)	(-10.550)	(-13.343)	(-7.224)	(-9.282)	(-12.190)	(-15.442)
Household attributes							
Income	-0.190**	0.034	-0.377**	-0.223**	-0.407**	-0.010	0.171**
	(-4.549)	(1.057)	(-8.668)	(-4.031)	(-8.731)	(-0.205)	(3.639)
Household size	-0.061	-0.235**	0.440**	0.015	-0.101	-0.631**	0.149
	(-0.492)	(-2.672)	(3.708)	(0.095)	(-0.657)	(-4.061)	(1.294)
Housing area	0.007*	0.007*	0.008	0.006	0.011**	-0.003	0.021**
	(1.692)	(1.910)	(1.567)	(0.944)	(2.261)	(-0.725)	(5.640)
Residential attributes							
Residential duration	0.031*	0.044**	0.003	0.015	-0.021	0.065**	0.028
	(1.699)	(2.860)	(0.172)	(0.549)	(-0.876)	(3.271)	(1.284)
Iron structure of dwelling	0.301	1.035**	-0.952**	0.272	0.505	-0.269	-1.438**
	(1.095)	(4.941)	(-3.503)	(0.756)	(1.445)	(-0.876)	(-5.458)
Household type	0.470	0.993**	-1.175**	0.177	-0.326	0.441	0.157
	(1.127)	(3.644)	(-3.428)	(0.393)	(-0.868)	(1.277)	(0.487)
Access	-0.120	-0.120	0.181	0.002	0.254	0.002	0.329**
	(-1.036)	(-1.445)	(1.368)	(0.017)	(1.219)	(0.001)	(2.349)
Individual attributes							
Education	0.541*	-0.069	0.179	0.390	-0.327	0.617*	0.046
	(1.694)	(-0.324)	(0.680)	(1.060)	(-1.078)	(1.937)	(0.173)
Energy-saving Consciousness	-0.116	-0.868**	0.547**	-0.280	-0.443**	0.181	-0.663**
	(-0.678)	(-6.490)	(2.809)	(-1.124)	(-2.294)	(0.972)	(-4.030)
Error term							
Standard deviation	0.500**	0.122 *	0.459**	0.012	0.348	0.296*	0.335*
	(2.139)	(1.798)	(2.175)	(0.273)	(1.600)	(1.699)	(1.701)
Initial log -likelihood	-30394.6		Converged log-likelihood		-21189.2		
Rho-square	0.3029		Adjusted rho-square		0.3000		
Sample size	608						

Note: **. significant at the 5% level. *. significant at the 10% level. The values in parentheses are t-statistics.

The constant terms related to the baseline preference (elements of the β vector) in the first row are estimated by treating the disposal money alternative as the base category (i.e., the parameters in the disposal money alternative are all assumed to be zero). As pointed out by Ferdous et al. (2010), these constants do not have any substantive interpretations and simply capture generic tendencies of spending on each category. However, all baseline preference constants are negative. This indicates that a much higher percentage of households spend a nonzero amount of their budget on the disposal money relative to other alternatives.

The coefficients of explanatory variables in MMDCEV model are the same for both ownership and usage behavior. A positive (negative) coefficient of an explanatory variable means that an increase in the explanatory variable increases (decreases) the likelihood of the household budget being allocated to that expenditure category.

Household income: As household income increases, the probabilities of owning AC and vehicle, and the proportions of the total income expended on them (i.e., expenditures) increase, whereas the probabilities of owning refrigerator, fan, clothes washer, and shower, and their expenditures decrease. This might reflect the fact that households with higher income more prefer the luxurious AC and vehicle to other types of end uses. This observation can be transferable to explaining the relationship between household income and energy consumption.

Household size: The household size coefficients are positive for fan, negative for AC and gas shower, suggesting that households with more members show a higher preference for ownership and usage of less energy-intensive end uses (i.e., fan) than energy-intensive ones (i.e., AC and gas shower). This may be because larger families might have less disposal income, consequently leading them to invest in more affordable end uses to meet their functional needs. There is no significant impact of household size on ownership and usage of vehicle.

Housing area: As housing area increases, the ownership and usage of all end uses increase except gas shower. In particular, housing area has a significantly positive effect on energy consumption behavior of vehicle. This suggests that housing area plays a different role from household income in explaining the ownership and usage of different end uses.

Residential duration and household type play an important role in the ownership and usage of domestic appliances, but they do not have an obvious effect on the ownership and usage behavior of vehicles. With the increase of residential duration, the probability of owning refrigerator, AC and gas shower and the expenditure increase. This might be interpreted as longer residential duration always goes with more old end uses which consume intensive energy. Household type has a positive effect on ownership and usage of AC while negative effect on fan, implying that there is a complementary relationship between these two end uses for households who own their house. Iron structure of dwelling shows a significant influence on ownership and usage of AC, fan and vehicle. In order to compensate the large expenditure on AC, the probability to own and the money spent on a vehicle retrench. The access factor related to household's residential location has no obvious impact on the residential energy consumption behavior, but has a negative influence on energy consumption behavior of owing/using vehicles. The longer distance to bus stop or subway station, the larger the probability of buying/using a vehicle.

Household members' highest education level does not have a significant influence on energy consumption behavior except the refrigerator and gas shower. The energy-saving consciousness is an attitudinal factor that motivates households to show the environmentally friendly behavior. It is estimated that individuals who are willing to save energy own and use energy-intensive end uses (e.g., AC and vehicle) less than other people. This attitudinal factor affects both residential energy consumption behavior and travel behavior.

Some of the household and personal attributes, such as income, housing area, iron-type dwelling, the energy-saving consciousness, significantly influence both residential energy consumption behavior and travel behavior. This means that a change in socio-demographic characteristics or dwelling type results in the change of both residential and transport energy use patterns, providing an important evidence of the necessity of the joint representation.

Based on the standard deviation of the error terms introduced in the baseline preference function, it is found that the ownership and usage of refrigerator, AC, fan, gas shower, and vehicle is significantly affected by the unobserved factors. Furthermore, the correlation between the energy consumption behavior of different end uses due to unobserved factors is identified (see Table 5-4), especially for the refrigerator and AC, electrical shower and clothes washer, electrical shower and fan within the residential sector; car and refrigerator, car and AC, car and gas shower across the residential and transport sectors.

Table 5- 4 Correlations among end uses due to unobserved factors

	Refrigerator	AC	Fan	Clothes washer	Electrical shower	Gas shower	Car
Refrigerator	1						
AC	<u>0.318</u>	1					
Fan	-0.087	-0.105	1				
Clothes washer	0.039	0.109	0.208	1			
Electrical shower	-0.090	0.106	<u>0.370</u>	<u>0.317</u>	1		
Gas shower	-0.241	-0.095	0.140	-0.059	0.172	1	
Car	<u>0.412</u>	<u>0.301</u>	0.096	0.061	-0.109	<u>-0.426</u>	1

To further clarify the effect of each explanatory variable, next, we calculate the proportion of variance explained by each explanatory variable in the total variance of the baseline preference for both ownership and usage as follows. The calculation is based on the assumption that all explanatory variables are independent. Note that this assumption is already made when the model was estimated.

$$\{\mathrm{S_j}\}\% = \frac{\mathrm{var}(\ {}_{\mathrm{k}}\mathrm{x_{ijk}})}{\mathrm{var}(\sum_{\mathrm{k}}\ {}_{\mathrm{k}}\mathrm{x_{ijk}})} = \frac{{}_{\mathrm{k}}^{2}\mathrm{var}(\mathrm{x_{ijk}})}{\sum_{\mathrm{k}}\ {}_{\mathrm{k}}^{2}\mathrm{var}(\mathrm{x_{ijk}})} \tag{5.11}$$

Here, x_{ijk} indicates the kth explanatory variable of household i that is used to describe the utility of end-use type j.

The calculated variance proportions are shown in Table 5-5, where the insignificant variables are removed. It is obvious that the influential degrees of some observed factors vary largely with end uses. For refrigerator, fan, clothes washer and electric shower, the most influential factor is household income while the energy-saving consciousness is most influential to AC, household size to gas shower, and housing area to vehicle.

Table 5- 5 Proportions of variances explained by the introduced variables

	Refrigerator	AC	Fan	Clothes washer	Electrical shower	Gas shower	Vehicle
Income	13.99%		32.71%	23.23%	40.99%		7.52%
Household size		2.00%	4.39%			15.66%	
Housing area	3.40%	3.32%			6.18%		23.12%
Residential duration	1.84%	3.50%				8.16%	
Iron structure		8.07%	4.27%				10.81%
Household type		8.06%	7.06%				
Access							5.53%
Education level	2.53%					3.38%	
Consciousness		15.76%	3.92%		2.75%		6.39%
Correlated unobserved factors	17.28%	3.98%	9.39%			10.48%	7.61%
Other unobserved factors	56.78%	53.78%	33.62%	68.12%	36.04%	58.27%	37.36%
Total unobserved factors	74.06%	57.77%	43.01%	68.62%	43.68%	68.75%	44.97%

The calculated variance proportions also show that unobserved factors can explain 43.01%~74.06% of the total variance related to the ownership and usage behavior of residential end uses, especially for refrigerator, AC, clothes washer and gas shower, the percentages rise up to 57.77%~74.06%. In contrast, in case of the ownership/usage of vehicle, only 44.97% of the total variance is explained by unobserved factors. As argued by Gärling et al. (2002) and Abrahamse et al. (2005), factors affecting households' consumption patterns can be classified into macro-level factors (e.g., technological developments, economic growth, social factors, and cultural developments) and micro-level factors (e.g., social-demographic attributes, motivational factors, abilities and opportunities). The macro-level factors can be regarded as contextual variables at the city or national level that are common to all respondents in each city, and they are all omitted in this study because a micro-level (i.e., household) model is adopted. In addition, as for the micro-level factors, this study also ignored the potential influences of some social factors like life-style and life stage (e.g., Lutzenhiser, 1993; Weber, 2000), cultural factors (e.g., Lutzenhiser, 1992; Abrahamse et al., 2005), and motivational factors (e.g., Seligman et al., 1979; Heberlein and Warriner, 1982; Spangenberg, 2002). Since unobserved factors play a higher role in explaining energy consumption behavior, this study re-confirmed the importance of collecting as sufficient information (e.g., psychological, habitual, structural or cultural variables) related to these unobserved factors as possible. Introducing additional explanatory variables into the model could improve the model accuracy on one hand, while it might result in that more variables are significantly correlated with each other, leading to the collinearity issue, on the other hand. Such issue should be properly treated during the modeling processes. However, no matter how detailed information can be collected from households, it is impossible to perfectly predict household energy consumption behavior, suggesting that the model should allow the presence of error terms in the utility function. To properly capture the sources of error terms, one can apply, for example, the Multilevel MDCEV model (see Chikaraishi et al., 2009), which can flexibly divide any error term into two or more unobserved components. Calibration of such error structure is also helpful for modelers to identify what types of additional explanatory variables should be included in the model.

5.6 Summary and Conclusion

This chapter presents a comprehensive analysis of household expenditures across an array of domestic and transport end uses owned and used by households based on the mixed

Multiple Discrete-Continuous Extreme Value (MMDCEV) model proposed by Bhat (2005), using the survey data collected in Beijing, China in 2009, in which more than 1,000 households participated. In the model, household energy consumption behavior is indirectly described using the relevant monetary expenditure.

First, the empirical analysis confirmed the effectiveness of MDCEV model to simultaneously describe residential energy consumption behavior and travel behavior. Furthermore, on the one hand, log-linear competitive relationships are found among expenditures of end uses, while on the other hand, the correlation between the end uses caused by the unobserved factors are also verified. That is to say, the relationship between residential and transport energy consumption behavior is identified. The above correlation also suggests that, for example, reduction of residential energy consumption due to the introduction of energy-saving end uses results in the increase of disposal household income, which may however lead to the increase of gasoline consumption by vehicle. In this sense, to reduce household energy consumption, government should focus on the mutual influence between residential and transport energy consumption. Such consideration is expected to provide a new viewpoint for designing policies. For example, the Japanese government is promoting the purchase of eco-friendly electric appliances through the legalized “eco-point” scheme, which allows consumers to spend the credits gained from buying one appliance on the other types of appliances. However, currently, such credits cannot be spent on the purchase and/or usage of vehicles. It might also be a good idea to extend the “eco-point” scheme to cover both domestic and travel related end uses. Interestingly, some electricity, housing, and automobile companies in Japan already developed joint management systems of electricity fees of both domestic appliances and electric cars. Such systems can assist households to save and use electricity in a more efficient way[1]. It is therefore not unrealistic to integrate the above "eco-point" scheme and electricity management systems for the sake of more effectively promoting the diffusion of eco-friendly domestic end uses and vehicles.

Second, model estimation results provide additional insights about the influence of household attributes, housing attributes, and residential location on households' consumption behavior of different types of end uses. Some of the household and personal attributes, such as income, housing area, iron-type dwelling, the energy-saving consciousness, significantly affect the energy consumption behavior in both residential and transport sectors. Among the observed factors, the most influential factors differ across end uses. For refrigerator, fan, clothes washer, and electric shower, household income plays the greatest role, while the energy-saving consciousness is most influential to air-conditioner, household size to gas shower, and housing area to vehicle. Based on our results, it can be predicted that with the increase of income and the prevalence of nuclear families, people will prefer to own and use more energy-intensive end uses (e.g., gas shower, air-conditioner, and vehicle), which will contribute a lot to the increasing energy consumption. Therefore, it becomes more and more important in future how to effectively control households' purchase and usage behavior for energy-intensive end uses (especially the ones mentioned above).

Finally, it is revealed that the unobserved factors play a much more important role in explaining energy consumption behavior than the observed attributes of households and their members. That is to say, besides the observed factors mentioned in our study, a lot of other factors need to be introduced to understand the energy consumption behavior (e.g., social factors, cultural factors, psychological factors, and life stage).

Having elaborated the main conclusions, there are several research issues that should be

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[1] http://company.nikkei.co.jp/news/news.aspx?scode=7203&NewsItemID=20101019NKM0223&type=2 (Accessed on Feb. 10, 2011);

identified. First, in the MDCEV model, the ownership and usage of each end use are explained by the same coefficients. Considering that decisions on the ownership and usage may involve different behavioral dimensions (e.g., time scales, frequencies, efforts, and focuses), factors affecting these two decisions may not necessarily be the same. Model development from such consideration should be attempted. Second, since the MDCEV model must have a budget constraint, household energy consumption behavior has to be described indirectly in the form of monetary expenditure. Behaviorally, this model is suitable because it is natural and understandable to assume that households attempt to minimize their monetary expenditure rather than minimizing the energy consumption. This however requires the transformation from monetary expenditure to energy consumption for the analysis of energy policies. This transformation task remains as an unresolved issue. Third, from policy-making perspective, it seems important to further explore the influences of neighborhood design aspects (e.g., parking availability, garage spaces, public transport accessibility, and accessibility to other daily life facilities) on the household energy use. Forth, in order to effectively reduce household energy consumption, it seems also important to explore how households respond to impacts of the indirect household energy consumption (e.g., Engelenburg et al., 1994; Nijdam et al., 2005) on the environment. Finally, to promote household's energy-saving consumption behavior, it seems essential for firms and government to understand how households respond to the development of energy-saving technologies and the implementation of low-carbon policies.

Chapter 6

Time Use and Household Energy Consumption Behavior

6.1 Introduction

Time and energy are two major inputs into household daily life. Time use on different activities might be interrelated because of individuals' limited time resources. The time spent on one activity will surely reduce the available time for participating in other activities in a given time period (e.g., a day, a week). Such interdependence might be also observed with respect to individuals' or households' energy consumption due to their limited monetary budgets. Furthermore, for example, more time spent at home might result in increased energy consumption on various domestic appliances, and more time spent on out-of-home activities might lead to increased gasoline consumption for car users. In this sense, time use on activities and energy consumption on end uses is likely to be interrelated with each other, too. In case of household behavior, interdependencies among household members might further occur due to the influence of time and monetary budgets, altruism and egoism, etc.

This chapter contributes to the analysis of household time use and energy consumption behaviors. Specifically, the objective of this paper is to analyze the household energy consumption by simultaneously considering the temporal dimension, meanwhile incorporating (1) interaction between energy and time dimensions (termed as time-to-energy interaction); (2) intra-personal interactions between in-home and out-of-home activities as well as end uses (termed as time-to-time interaction, and energy-to-energy interaction, respectively); (3) intra-household interaction between different members. For the purpose of analysis, a household resource allocation model based on several multi-linear utility functions (Zhang et al., 2002, 2005a) is built to explicitly depict all the above mentioned behavioral aspects. Considering that time use and energy consumption are all nonnegative (i.e., censored), the zero-consumption on time use and energy is endogenously addressed as well. To our knowledge, this study presents the first instance of the formulation and application of such a comprehensive methodological framework for jointly modeling the time-to-energy interaction, time-to-time interaction, energy-to-energy interaction and the intra-household interaction. To examine the effectiveness of the proposed model and to explore influential factors, a household questionnaire survey was conducted in Beijing in 2010 to collect the information about household energy consumption of the main durable end uses and the time use of each household member across different activities on weekdays and weekends. The model is estimated based on this data. Note that household energy consumption here is defined as actual direct energy used by domestic end uses and for personal transport within a year, while the indirect energy embedded in goods and services purchased by households is excluded.

The remaining part is organized as follows. The interaction mechanisms are interpreted in Section 6.2. The next section presents the structure of the proposed model. Survey data is introduced in Section 6.4. Results of the model estimation are shown and explained in Section 6.5. This chapter is concluded in Section 6.6.

6.2 Behavioral Mechanism of Multiple Interactions

6.2.1 Time-to-energy Interaction

Behaviorally, the interaction between time use and energy consumption are twofold: direct and indirect relationships. Concerning the direct side, the longer time spent on activity B, the higher possibility to consume end uses related to activity B more and spend more money on this activity, and vice versa. A specific phenomenon worth mentioning here is the rebound effect, including time rebound effect and energy rebound effect. If the saving time caused by the adoption of time-saving end use is reallocated from less to more energy-consuming activities, the time rebound effect exists (Binswanger, 2001; Jalas, 2002). While for the energy rebound effect (Greening et al, 2000; Sorrell and Dimitropoulos, 2008), it means that an improvement of end-use energy efficiency makes households want to enjoy the service produced by that end use longer, which partially offsets the expected saving or even increases the energy use. In this case, individual's decision on the time allocation is also influenced by the extension of the usage on that service (e.g., more efficient air conditioner makes people decide to spend more time at home and accordingly change the time use behavior). Consequently, a bidirectional direct relationship can be seen between time use and energy consumption. Regarding the indirect relationship, the self-selection effect is posed here to describe the phenomenon that some specific factors (e.g., motivation, lifestyle preference, and driving inclination) make households/individuals self select to their preferable time allocation patterns and energy consumption patterns (Holly et al., 1998; Mokhtarian and Cao, 2008). Take the attitudinal factor "environmental awareness" as an example, individuals high in environmental self-consciousness are more likely to join the activities with low energy intensity and purchase/use energy-saving end uses to fulfill these activities, or participate in non-energy consuming activities. In such case, an indirect effect resulting from intervening factors (e.g., awareness) on both the time use and energy consumption occurs. The above discussion suggests that a covariant interrelationship is plausible to exist between time use and energy consumption.

6.2.2 Time-to-time Interaction

For the time use behavior, since an individual has to perform various activities within the available time (e.g., 24 hours, and one week), he/she needs to decide how to trade off the time allocated to the participated activities. The more time he/she spends on one activity, the less time he/she could spend on other activities. Such intra-personal trades-off between activities in the time dimension is called time-to-time interaction. For instance, by assuming the correlation among activities caused by the unobserved factors, Bhat (2005) pointed out that there is a strong covariance between the in-home social activity and in-home recreational activities. Zhang et al. (2005b, 2007) revealed significant inter-activity interactions by considering the observed utilities derived from allocating time on the activities.

6.2.3 Energy-to-energy Interaction

Similar to the time-to-time interaction, the intra-personal interaction between end uses in the energy expenditure dimension (i.e., energy-to-energy interaction) could also be observed considering that available money is another scarce resource. Traditionally, the energy consumption behaviors for different end uses have been separately treated (Chiou et al., 2009; Leahy and Lyons, 2010). However, since ownership and usage of appliances at home and vehicles result in the reduction of disposal household income and time, residential and transport energy consumption might be interrelated, and so do the consumption for all end uses within the same sector, suggesting that any behavioral change might lead to the alteration of household energy consumption pattern. Recently, Yu et al. (2011) jointly represented the energy consumption behavior referring to the ownership and usage of domestic and out-of-home end uses. Log-linear competitive relationships were found among varied end uses (including both domestic and out-of-home end uses). However, they did not deal with the temporal dimension simultaneously.

6.2.4 Intra-household Interaction

Individuals in the same household could allocate their time and expenditure to certain activity and end uses independently to satisfying his/her needs, or they could share with other members. Change in the time of one activity (or energy expenditure on one end use) performed by a member gives rise to the change in the time (expenditure) available not only to his/her competing activities (end uses), but also to other members' activities (usage of end uses). In reality, various types of intra-household interactions can be observed related to joint activity participation, household resource (e.g., time and money) allocation, and role specification (Kato and Matsumoto, 2009; Timmermans, 2006; Zhang and Fujiwara, 2006). In the context of the household time allocation, the intra-household interactions have been confirmed through a lot of ways (Golob and McNally, 1997; Lu and Pas, 1997; Zhang et al., 2005b). Regarding the household energy consumption issue, car usage is a typical example. If two or more household members share the same car, then intra-household interactions take place (Zhang et al., 2009). Similar interactions can be found for other end uses.

6.2.5 Behavioral Interaction Modeling

Generally speaking, three types of models can deal with the aforementioned interactions among varied behaviors: (1) models assuming the interaction is derived from the unobserved components (i.e., error terms included in the model), like the mixed model and the multivariate model (Bhat, 2005; Ferdous et al., 2010); (2) models introducing other dependent variables as parts of explanatory variables in a linear form based on simultaneous-equation modeling approaches (Golob and McNally, 1997; Kang and Scott, 2008); (3) models describing the interactions between different behavioral aspects and/or between household members by reflecting the human decision-making mechanisms, such as the nested structure model (Gliebe and Koppelman, 2002, 2005), resource allocation model based on the multi-linear function (Zhang et al, 2002, 2005a, 2009). The first two groups of models are all exploring the statistical interrelation and consequently share the most serious problem of statistical models, i.e., having no behavioral rationality. In contrast, the third group of models is behaviorally oriented. For example, in the nested logit model, the interaction between choice aspects at the upper and lower levels is illustrated with the help of an inclusive value (or logsum variable: maximum expected utility), and the multi-linear utility function represents inter-subject interactions and relative importance (or relative influence) of different subjects (e.g., household members and activities) in the decision-making process. The present research belongs to the third group which adopts the resource allocation model to represent the interactions among diverse behaviors. However, this method is always bothered with the non-zero consumption problem. For example, in Zhang et al.'s papers, they built up comprehensive models which can embrace several behavioral interactions, but they dealt with the zero-consumption as a part of continuous values. However, the truth is that individuals choose whether to participate in each activity, and decide whether to spend money, indicating that zero-consumption is also a result of decision, which might differ with the decisions on continuous choices. In this sense, it is also better to solve the zero-consumption problem within the same model framework by reflecting the behavioral mechanism. To do this, one way is to build complicated mixed multiple discrete-continuous models which exogenously include both the participation and allocation behaviors (Spissu et al., 2009). Another way is to endogenously tackle the zero-consumption by adopting some easily manipulated estimators (e.g., Kuhn-Tucker conditions, and Amemiya (1974) estimator). For instance, Kato and Matsumoto (2009) described the household time and expenditure allocation behavior through a nonlinear Tobit model which utilized the Kuhn-Tucker conditions to help figure out the zero-consumption problem. However, they adopted an additive-type utility function and consequently did not include any inter-activity interaction in the model which made the modeling process less realistic.

Based on the above review, complex relation structures have been sketched out. Though these behavioral interactions have been separately mentioned in existing studies, none of them jointly accommodate all these mechanisms in a unified and consistent modeling framework. As a first attempt, the present research is aiming to extend the existing resource allocation model into the household energy consumption behavior domain by representing multiple behavior interactions, and endogenously solving the zero-consumption problem.

6.3 Methodology

In this study, a household resource allocation model is built to describe the aforementioned behavioral mechanisms. For ease of understanding, the model structure is drawn in Figure 6-1, and is explained following the up-to-down process in the subsequent sections.

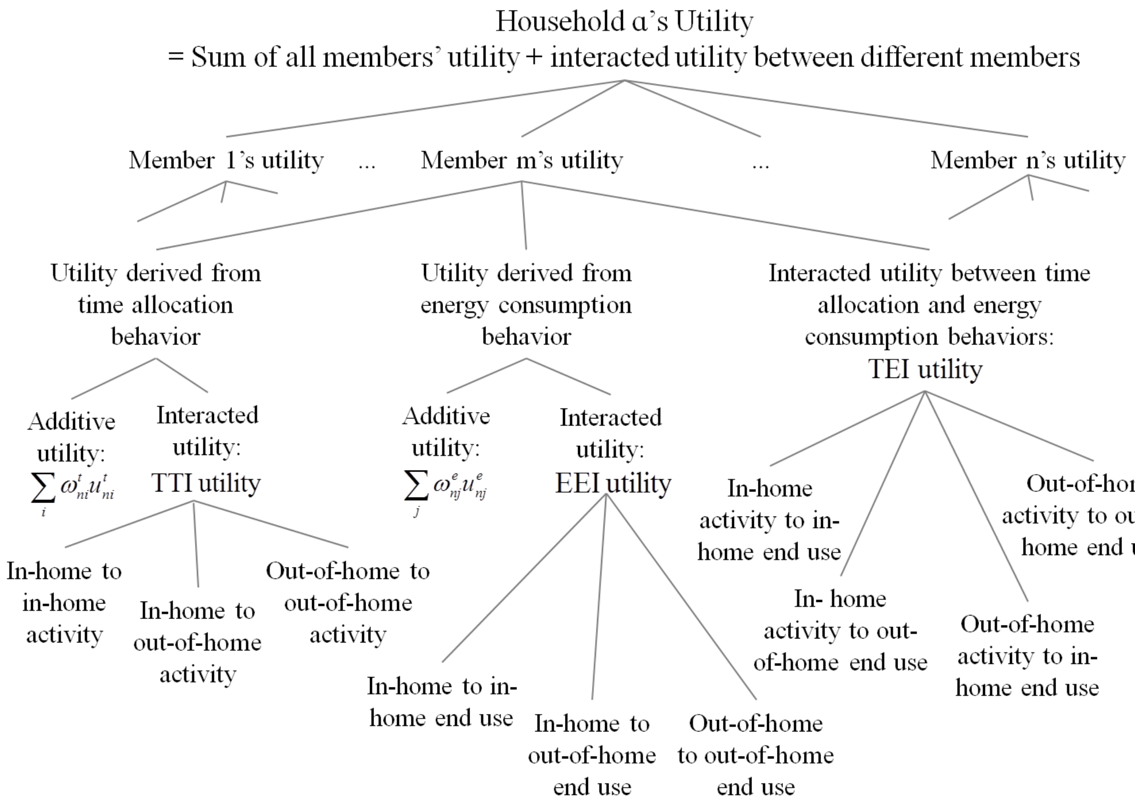

Figure 6- 1 Model structure

It is assumed that the overall household utility is comprised of each member's utility as well as the interacted utility between different members. While each member's utility is further defined by the utility of allocating time to each activity and allocating money to each end use, as well as the utility derived from the interaction between time use and energy consumption behavior (i.e., TEI utility). By considering the time-to-time interaction, the utility derived from time allocation behavior for each member is divided into two components: the additive utility for all activities and the interacted utility between different activities (i.e., TTI utility). Likewise, due to the energy-to-energy interaction, the utility derived from energy consumption behavior is separated into the additive utility for all end uses and the interacted utility between different end uses (i.e., EEI utility). Concerning the TTI utility, EEI utility, and the TEI utility, it is not difficult to understand that the respective interacted utility probably differs across activities, end uses, and the combinations of activity and end use. In other words, it would be better to set activity-specific interaction term and end-use-specific interaction term. However, taking into account the complexity of the model which is exponentially positively related to the number of involved interaction terms, the TTI, EEI, and TEI are only divided by the location type (i.e., in-home and out-of-home) (see the bottom layer in Figure 1). The mathematical description of each stage is introduced following the up-to-down process in the subsequent sections.

6.3.1 Household Utility Function

Here, the household a's utility U_a is defined by a multi-linear group utility function, which consists of household members' utilities (u_n: n indicates a member). The theoretical roots can be found in "group decision theory" (Eliashberg and Winkler, 1981; Keeney, 1972; Messer and Emery, 1980; Zhang et al., 2005a, 2005b).

It is assumed that the household attempts to maximize its utility by considering each member's time budgets and the total household expenditure constraint. Hence, the model structure can be formulated as follows:

$$max \quad U_a = \sum_n u_n + \sum_n \sum_{m>n} \lambda u_n u_m \tag{6.1}$$

subject to

$$\sum_i (t_{ni}^{ind} + t_{ni}^{sha}) = T_n$$

$$\sum_j (\sum_n e_{nj}^{ind} + e_{nj}^{sha}) \leq Y$$

$$t_{ni}^{ind} \geq 0, \quad t_{ni}^{sha} \geq 0, \quad e_{nj}^{ind} \geq 0, \quad e_{nj}^{sha} \geq 0$$

where λ is a parameter used to reflect the intra-household interaction, *i* denotes the activity type, and *j* denotes the end-use type. The time allocation on activities and the expenditure spent on end uses are further distinguished by companion type (i.e., independent and joint): t_{ni}^{ind} and t_{ni}^{sha} are member *n*'s independent and shared time allocated to activity *i*, respectively; e_{nj}^{ind} and e_{nj}^{sha} are member *n*'s independent and shared expenditure on end use *j*, respectively. T_n is the total available time for member *n* and different members might have different available time. Y is the total available expenditure for the whole household.

6.3.2 Household Members' Utility Functions

Likewise, the same type of multi-linear function is adopted to represent each member's utility u_n, in which the time allocation and energy expenditure allocation behavior is included as well as the time-to-time interaction (TTI), energy-to-energy interaction (EEI), and time-to-energy interaction (TEI). The utility function is defined as below:

$$u_n = \sum_i \omega_{ni}^t u_{ni}^t + \text{TTI utility} + \sum_j \omega_{nj}^e u_{nj}^e + \text{EEI utility} + \text{TEI utility} \tag{6.2}$$

where ω_{ni}^t and ω_{nj}^e indicate the importance of activity *i* and end use *j* to member *n*, respectively.

The interacted utilities are further divided by location type (i.e., in-home and out-of-home) (see equations (6.3-a), (6.3-b), (6.3-c)).

$$\begin{aligned}\text{TTI utility} = {} & \mathrm{II}_n^t \sum_{\mathrm{I}i} \sum_{\mathrm{I}i' > \mathrm{I}i} \omega_{n\mathrm{I}i}^t u_{n\mathrm{I}i}^t \omega_{n\mathrm{I}i'}^t u_{n\mathrm{I}i'}^t + \mathrm{OO}_n^t \sum_{\mathrm{O}i} \sum_{\mathrm{O}i' > \mathrm{O}i} \omega_{n\mathrm{O}i}^t u_{n\mathrm{O}i}^t \omega_{n\mathrm{O}i'}^t u_{n\mathrm{O}i'}^t \\ & + \mathrm{IO}_n^t \sum_{\mathrm{I}i} \sum_{\mathrm{O}i} \omega_{n\mathrm{I}i}^t u_{n\mathrm{I}i}^t \omega_{n\mathrm{O}i}^t u_{n\mathrm{O}i}^t \end{aligned} \tag{6.3-a}$$

$$\begin{aligned}\text{EEI utility} = {} & \mathrm{II}_n^e \sum_{\mathrm{I}j} \sum_{\mathrm{I}j' > \mathrm{I}j} \omega_{n\mathrm{I}j}^e u_{n\mathrm{I}j}^e \omega_{n\mathrm{I}j'}^e u_{n\mathrm{I}j'}^e + \mathrm{OO}_n^e \sum_{\mathrm{O}j} \sum_{\mathrm{O}j' > \mathrm{O}j} \omega_{n\mathrm{O}j}^e u_{n\mathrm{O}j}^e \omega_{n\mathrm{O}j'}^e u_{n\mathrm{O}j'}^e \\ & + \mathrm{IO}_n^e \sum_{\mathrm{I}j} \sum_{\mathrm{O}j} \omega_{n\mathrm{I}i}^e u_{n\mathrm{I}i}^e \omega_{n\mathrm{O}j}^e u_{n\mathrm{O}j}^e \end{aligned} \tag{6.3-b}$$

$$\begin{aligned}\text{TEI utility} = {} & \mathrm{II}_n^{te} \sum_{\mathrm{I}i} \sum_{\mathrm{I}j} \omega_{n\mathrm{I}i}^t u_{n\mathrm{I}i}^t \omega_{n\mathrm{I}j}^e u_{n\mathrm{I}j}^e + \mathrm{IO}_n^{te} \sum_{\mathrm{I}i} \sum_{\mathrm{O}j} \omega_{n\mathrm{I}i}^t u_{n\mathrm{I}i}^t \omega_{n\mathrm{O}j}^e u_{n\mathrm{O}j}^e \\ & + \mathrm{OO}_n^{te} \sum_{\mathrm{O}i} \sum_{\mathrm{O}j} \omega_{n\mathrm{O}i}^t u_{n\mathrm{O}i}^t \omega_{n\mathrm{O}j}^e u_{n\mathrm{O}j}^e + \mathrm{OI}_n^{te} \sum_{\mathrm{O}i} \sum_{\mathrm{I}j} \omega_{n\mathrm{O}i}^t u_{n\mathrm{O}i}^t \omega_{n\mathrm{I}j}^e u_{n\mathrm{I}j}^e \end{aligned} \tag{6.3-c}$$

where II_n^t, OO_n^t, IO_n^t denote the in-home activity to in-home activity interaction, out-of-home activity to out-of-home activity interaction, and in-home activity to out-of-home activity interaction, respectively. Similarly, II_n^e, OO_n^e, IO_n^e denote the in-home end use to in-home end use interaction, out-of-home end use to out-of-home end use interaction, and in-home end use to out-of-home end use interaction, respectively. II_n^{te}, OO_n^{te}, IO_n^{te}, OI_n^{te} denote the respective interaction terms between different activities (in-home and out-of-home activities) and end uses (in-home and out-of-home end uses). In such way, we can capture the interaction between in-home behavior and out-of-home behavior straightforwardly. $\mathrm{I}i, \mathrm{I}j, \mathrm{O}i, \mathrm{O}j$ mark the in-home activity *i*, in-home end use *j*, out-of-home activity *i* and out-of-home end use *j*, respectively. u_{ni}^t and u_{nj}^e signify the sub-utility of member *n* allocating the time to activity *i* and the energy expenditure to end use *j*, which both include two parts: independent portion and shared portion. Following previous studies (Zhang et al., 2002, 2005a, 2005b, 2009), the utility elements are specified as logarithmic functions:

$$u_{ni}^t = \rho_{nit}^{ind} In(t_{ni}^{ind} + 1) + \rho_{nit}^{sha} In(t_{ni}^{sha} + 1) \tag{6.4}$$

$$u_{nj}^{e} = \rho_{nje}^{ind} In(e_{nj}^{ind} + 1) + \rho_{nje}^{sha} In(e_{nj}^{sha} + 1) \tag{6.5}$$

$$t_{ni}^{sha} = t_{n'i}^{sha}, \quad e_{nj}^{sha} = e_{n'j}^{sha} \tag{6.6}$$

$$\rho_{nit}^{k} = \exp(\theta_{nit}^{k} x_{ni} + \varepsilon_{nit}^{k}), \quad k = ind, sha \tag{6.7}$$

$$\rho_{nje}^{k} = \exp(\theta_{nje}^{k} z_{nj} + \varepsilon_{nje}^{k}), \quad k = ind, sha \tag{6.8}$$

Note that the shared activities or consumption of end uses may be synchronized or non-synchronized. In the former case, household members participate in the activity or use the end uses together. In the latter case, household members share the activity or end use partially. Since this study only deals with the synchronized activities, $t_{ni}^{sha} = t_{i}^{sha}$ and $e_{ni}^{sha} = e_{i}^{sha}$ hold for any involved member *n*.

To guarantee the computability of the logarithm function and the positivity of the utility function, we add one to the time and energy expenditure in equations (6.4) and (6.5). Besides, ρ_{nit}^{k} and $\rho_{nje}^{k} (k = ind, sha)$ are introduced to represent the heterogeneous preferences for time use on activity *i* and energy expenditure on end use *j*. Two types of heterogeneity are included in them: one stems from the observable attributes of household member *n* (e.g., age, gender, occupation, and education level) and activity-specific or end-use specific factors captured in x_{ni} and z_{nj}; the other derives from the error terms ε_{nit}^{k} and ε_{nje}^{k} which describe the influence of unobservable factors (e.g., attitude, social context, and lifestyle preference) on activity *i* and end use *j*. θ_{nit}^{k} and θ_{nje}^{k} are vectors of unknown parameters for x_{ni} and z_{nj}. The exponential form is applied to ρ_{nit}^{k} and ρ_{nje}^{k} so as to insure the positive sign of the utility function.

6.3.3 Model Estimation Method

Concerning the phenomenon that households may not participate in all activities and meanwhile only use end uses they own, indicating that the time allocation and energy expenditure on activity i and end use j are censored. The Kuhn-Tucker conditions are adopted in this study to deal with the zero observations problem (See Ransom, 1987; Wales and Woodland, 1983; etc. for more econometric implications).

First, the Lagrangian is formed and then Kuhn–Tucker (KT) conditions are applied. Specifically, the Lagrangian function is:

$$\begin{aligned} L &= \sum_n u_n + \sum_n \sum_{m>n} \lambda u_n u_m \\ &+ \sum_n \Gamma_n^t (T_n - \sum_i t_{ni}^{ind} - \sum_i t_{ni}^{sha}) + \Gamma^e \left(Y - \sum_j \left((\sum_n e_{nj}^{ind}) + e_{nj}^{sha} \right) \right) \end{aligned} \tag{6.9}$$

where Γ_n^t is the Lagrangian multiplier associated with the time constraint for household member n (that is, it can be viewed as the marginal utility of total time budget), and Γ^e is the Lagrangian multiplier associated with the energy expenditure constraint. Subsequently, an alternative KT first-order conditions are given by

$$\Delta_{nit}^{ind} = \ln\left(\frac{\widehat{\Omega}_{n1t}^{ind}}{\widehat{\Omega}_{nit}^{ind}} \right) + \ln\left(\frac{t_{ni}^{ind} + 1}{t_{n1}^{ind} + 1} \right) - (\theta_{nit}^{ind} x_{ni} - \theta_{n1t}^{ind} x_{n1}) \begin{cases} = \widehat{\varepsilon}_{it}^{ind} & if\ t_{ni}^{ind} > 0 \\ \geq \widehat{\varepsilon}_{it}^{ind} & if\ t_{ni}^{ind} = 0 \end{cases} \tag{6.10}$$

$$\Delta_{nit}^{sha} = \ln\left(\sum_n \frac{\hat{\Omega}_{n1t}^{ind} \exp(\theta_{n1t}^{ind} x_{n1})}{t_{n1}^{ind} + 1} \right) + \ln\left(\sum_n \frac{t_{ni}^{sha} + 1}{\hat{\Omega}_{nit}^{sha} \exp(\theta_{nit}^{sha} x_{ni})} \right) \begin{cases} = \widehat{\varepsilon}_{it}^{sha} & if\ t_{ni}^{sha} > 0 \\ \geq \widehat{\varepsilon}_{it}^{sha} & if\ t_{ni}^{sha} = 0 \end{cases} \tag{6.11}$$

$$\Delta_{nje}^{ind} = \ln\left(\sum_n \frac{\widehat{\Psi}_{n1e}^{sha} \exp(\theta_{n1e}^{sha} z_{n1})}{e_{n1}^{sha} + 1} \right) + \ln \frac{e_{nj}^{ind} + 1}{\widehat{\Psi}_{nje}^{ind} \exp(\theta_{nje}^{ind} z_{nj})} \begin{cases} = \widehat{\varepsilon}_{je}^{ind} & if\ e_{nj}^{ind} > 0 \\ \geq \widehat{\varepsilon}_{je}^{ind} & if\ e_{nj}^{ind} = 0 \end{cases} \tag{6.12}$$

$$\Delta_{nje}^{sha} = \ln\left(\sum_n \frac{\widehat{\Psi}_{n1e}^{sha} \exp(\theta_{n1e}^{sha} z_{n1})}{e_{n1}^{sha} + 1} \right) + \ln\left(\sum_n \frac{e_{nj}^{sha} + 1}{\widehat{\Psi}_{nje}^{sha} \exp(\theta_{nje}^{sha} z_{nj})} \right) \begin{cases} = \widehat{\varepsilon}_{je}^{sha} & if\ e_{nj}^{sha} > 0 \\ \geq \widehat{\varepsilon}_{je}^{sha} & if\ e_{nj}^{sha} = 0 \end{cases} \tag{6.13}$$

$i = \mathrm{I}i$ or $\mathrm{O}i$, $j = \mathrm{I}j$ or $\mathrm{O}j$

where,

$$\hat{\Omega}^k_{n\mathrm{I}it} = \omega^t_{n\mathrm{I}i}(1 + \mathrm{II}^t_n \sum_{\mathrm{I}i' \neq \mathrm{I}i} \omega^t_{n\mathrm{I}i'}\hat{u}^t_{n\mathrm{I}i'} + \mathrm{IO}^t_n \sum_{\mathrm{O}i} \omega^t_{n\mathrm{O}i}\hat{u}^t_{n\mathrm{O}i} + \mathrm{II}^{te}_n \sum_{\mathrm{I}j} \omega^e_{n\mathrm{I}j}\hat{u}^e_{n\mathrm{I}j} + \mathrm{IO}^{te}_n \sum_{\mathrm{O}j} \omega^e_{n\mathrm{O}j}\hat{u}^e_{n\mathrm{O}j}) \cdot \begin{cases} 1 & \text{if } k = ind \\ (1 + \lambda \sum_{m \neq n} \hat{u}_m) & \text{if } k = sha \end{cases} \tag{6.14}$$

$$\hat{\Omega}^k_{n\mathrm{O}it} = \omega^t_{n\mathrm{O}i}(1 + \mathrm{OO}^t_n \sum_{\mathrm{O}i' \neq \mathrm{O}i} \omega^t_{n\mathrm{O}i'}\hat{u}^t_{n\mathrm{O}i'} + \mathrm{IO}^t_n \sum_{\mathrm{I}i} \omega^t_{n\mathrm{I}i}\hat{u}^t_{n\mathrm{I}i} + \mathrm{OO}^{te}_n \sum_{\mathrm{O}j} \omega^e_{n\mathrm{O}j}\hat{u}^e_{n\mathrm{O}j} + \mathrm{OI}^{te}_n \sum_{\mathrm{I}j} \omega^e_{n\mathrm{I}j}\hat{u}^e_{n\mathrm{I}j}) \cdot \begin{cases} 1 & \text{if } k = ind \\ (1 + \lambda \sum_{m \neq n} \hat{u}_m) & \text{if } k = sha \end{cases} \tag{6.15}$$

$$\hat{\Psi}^k_{n\mathrm{I}je} = \omega^e_{n\mathrm{I}j}(1 + \lambda \sum_{m \neq n} \hat{u}_m) \cdot (1 + \mathrm{II}^e_n \sum_{\mathrm{I}j' \neq \mathrm{I}j} \omega^e_{n\mathrm{I}j'}\hat{u}^e_{n\mathrm{I}j'} + \mathrm{IO}^e_n \sum_{\mathrm{O}j} \omega^e_{n\mathrm{O}j}\hat{u}^e_{n\mathrm{O}j} + \mathrm{II}^{te}_n \sum_{\mathrm{I}i} \omega^t_{n\mathrm{I}i}\hat{u}^t_{n\mathrm{I}i} + \mathrm{IO}^{te}_n \sum_{\mathrm{O}i} \omega^t_{n\mathrm{O}i}\hat{u}^t_{n\mathrm{O}i}) \tag{6.16}$$

$$\hat{\Psi}^k_{n\mathrm{O}je} = \omega^e_{n\mathrm{O}j}(1 + \lambda \sum_{m \neq n} \hat{u}_m) \cdot (1 + \mathrm{OO}^e_n \sum_{\mathrm{O}j' \neq \mathrm{O}j} \omega^e_{n\mathrm{O}j'}\hat{u}^e_{n\mathrm{O}j'} + \mathrm{IO}^e_n \sum_{\mathrm{I}j} \omega^e_{n\mathrm{I}j}\hat{u}^e_{n\mathrm{I}j} + \mathrm{OO}^{te}_n \sum_{\mathrm{O}i} \omega^t_{n\mathrm{O}i}\hat{u}^t_{n\mathrm{O}i} + \mathrm{OI}^{te}_n \sum_{\mathrm{I}i} \omega^t_{n\mathrm{I}i}\hat{u}^t_{n\mathrm{I}i}) \tag{6.17}$$

$k = ind, sha$.

For the derivation of these equations, two assumptions are pre-set. First, we assume that the error components in the household member's utility function are common if the activity is jointly participated or the end-use usage is shared by household members. Second, it is assumed that for time use and energy consumption, there are always outside goods for these two behaviors, that is to say, there is always an activity that every individual has to participate in, and an end use that everyone needs to consume. The outside goods can either be an independent portion or a shared portion. The error terms for the outside goods are not introduced in the model structure. By taking the outsides goods as reference, the above equations can be derived.

The utility terms in equations (6.14) ~ (6.17) are the corresponding ones whose error terms have been thrown out. The error terms in equations (6.10) ~ (6.13) $\widehat{\varepsilon}^{ind}_{it}$, $\widehat{\varepsilon}^{sha}_{it}$, $\widehat{\varepsilon}^{ind}_{je}$,

$\widehat{\varepsilon}_{je}^{sha}$ (i=Ii *or* Oi, j=Ij *or* Oj) are the composite products which have merged with the error terms in the utility components in equations (6.14) ~ (6.17). Although in this way, these error terms become very complicated and are difficult to explain, it is always operable from a mathematical viewpoint, in addition, the interaction comes from the unobserved factors are not the interest in this analysis. How to clarify the error terms is left as a future research issue.

Table 6- 1 Elements of likelihood functions

$t_{ni}^{k} > 0$	$P_{nit}^{k} = \frac{1}{\sigma_{it}^{k}} \cdot \phi\left(\frac{\Delta_{nit}^{k}}{\sigma_{it}^{k}}\right) \quad (i = \mathrm{I}i \text{ or } \mathrm{O}i,\ k = ind \text{ or } sha)$
$t_{ni}^{k} = 0$	$P_{nit}^{k} = \Phi\left(\frac{\Delta_{nit}^{k}}{\sigma_{it}^{k}}\right) \quad (i = \mathrm{I}i \text{ or } \mathrm{O}i,\ k = ind \text{ or } sha)$
$e_{nj}^{k} > 0$	$P_{nje}^{k} = \frac{1}{\sigma_{je}^{k}} \cdot \phi\left(\frac{\Delta_{nje}^{k}}{\sigma_{je}^{k}}\right) \quad (j = \mathrm{I}j \text{ or } \mathrm{O}j,\ k = ind \text{ or } sha)$
$e_{nj}^{k} = 0$	$P_{nje}^{k} = \Phi\left(\frac{\Delta_{nje}^{k}}{\sigma_{je}^{k}}\right) \quad (j = \mathrm{I}j \text{ or } \mathrm{O}j,\ k = ind \text{ or } sha)$

Note: ϕ and Φ denote the probability density function and cumulative density function of standard normal distribution

.

By assuming $\widehat{\varepsilon}_{it}^{ind}$, $\widehat{\varepsilon}_{it}^{sha}$, $\widehat{\varepsilon}_{je}^{ind}$, $\widehat{\varepsilon}_{je}^{sha}$ (i=Ii *or* Oi, j=Ij *or* Oj) are independent with each other and follow the normal distribution with mean zero and variances $(\sigma_{it}^{ind})^2$, $(\sigma_{it}^{sha})^2$, $(\sigma_{je}^{ind})^2$, $(\sigma_{je}^{sha})^2$ (i=Ii *or* Oi, j=Ij *or* Oj), respectively, the probability elements for time use on each activity and the energy expenditure on each end use can be derived (see Table 6-1 for details). The unknown parameters are estimated by maximizing the total likelihood of the whole sample. As it can be seen, the total likelihood is not only comprised of the probability of allocating non-zero continuous amount of time (expenditure) on each activity (end use), but also the probability of zero consumption which implies a discrete choice decision of not participating in the activity (not owning the end use).

After the introduction to the whole model framework, it can be easily found that the proposed model makes up the shortcomings of Kato (2009)'s and Zhang et al. (2002, 2005a, 2005b, 2009)'s models. Apart from solving the non-negativity problem, multiple interactions are also represented, providing a better understanding to the energy consumption issue by considering the temporal dimension.

6.4 Data

The data collected in the quasi panel survey is utilized in this chapter. Through a careful data coding and input process, the data was sort out. It is found that almost 90% of the surveyed households are with the household structure of single, single with parent(s), couple, nuclear, or couple with parent (the number of household members is no more than 3). Since the more members are involved in the model, the more complicated its structure is. Therefore, to simplify the model structure and estimation, we only focus on this 90% portion (i.e., the households with more than 3 members are not targeted here), which is the minimal collection of family membership but with a comprehensive coverage of the sample data. Finally, after excluding the outliers (e.g., the data with the total time for all activities in one day greater than 24 hours, or with zero hour for maintenance activity), a total of 611 households are adopted as the sample. Among these households, 19.3% is single family, 46.3% is two-person family, and the remaining 34.4% is three-person family (in total, there are 1,314 household members).

The initial 12-category activities in the questionnaire are further grouped into 6 categories for each member (see Table 6-2). Time allocation during one survey week to each of the 6 types of activities is used as the dependent variables in the time use component of the model system. The total time across all these 6 categories is considered exogenous.

Table 6- 2 Activity classification

Type of activity	Abbreviation	Corresponding activities in the survey	Description
In-home maintenance activity	IHM	Meal preparation, dining, washing clothes, house cleaning, and other in-home activities	Household chores, personal care, meal preparation, dining, washing, cleaning, etc.
In-home work/study	IHW	In-home work/study	Work or study at home
In-home leisure activity	IHL	In-home leisure	Resting, reading, listening to music, watch TV, internet browsing etc.
Out-of-home dining activity	OHD	Out-of-home dining	Have lunch or dinner (not include the meals in the cafeteria of workplace) outside
Out-of-home leisure activity	OHL	Leisure and shopping.	Shopping, going to the movies, opera show, exercising at the gym etc.
Out-of-home other activities	OHO	Out-of-home work, and other activities	Work, extra work, or religious and civic activity participation etc.

The dependent variables in the energy consumption component of the model are the expenditures (equal to the product of the efficiency, usage and energy price) on 9 end uses including savings, fan, air-conditioner (AC), shower, clothes washer, TV, PC, microwave oven, and car in one summer week. The problem here is that we only surveyed the information of household aggregate usage per day or per week on each end use, hence, it is difficult to differentiate the individual usage and shared usage. Actually, this problem is not easy to deal with due to the technical difficulties for collecting data. In order to repair this drawback, the aggregate usage is divided in proportion based on the staying-at-home time of each member, and the energy usage corresponding to the alone time of household member is regarded as the individual energy expenditure, while others are deemed to be the shared expenditure. For the car usage, it is just denoted as independent consumption of the main user. While for the shower and clothes washer, the expenditure is set as shared consumption. The total available money for these 9 end uses is also exogenously determined which is the household weekly income.

In this study, the time allocated to individual maintenance activity (IHM) is regarded as the outside goods for time use, while the shared savings indicating the money derived from household available money deducting the energy expenditure on all end uses is regarded as the outside goods for energy consumption. Note that savings actually do not have any energy consumption, the reason to involve savings as an end use is only for the model estimation.

Table 6-3 summarizes the time use across all activities and the average energy expenditure on all end uses within one week for each type of member. As you can see that no matter for the time allocation or energy use, the percentage of non-zero consumption is far from 100%, indicating that when dealing with these two dimensions, it is necessary to consider the censored issue. Focusing on the time use statistics, the average time on joint activities is much less than the time on independent ones in one week. Householder and householder's child allocate more time on the independent in-home leisure and in-home work/study compared with other activates, while the householder's couple and parent spend longer time on independent in-home maintenance and in-home leisure. The time on household shared activities mainly concentrates in the leisure and in-home maintenance, yet the length is not so long. Concerning the energy expenditure on the end uses, the ratio of shared expenditure to independent expenditure is about 1:2 for all members. Among the end uses, the average expenditure on car is much more than in-home end uses, presumably due to the higher price of gasoline compared with the electricity and gas in Beijing. AC is the most energy-consuming end use in the residential sector. Compared with the out-of-home car expenditure, the residential expenditure is inconspicuous. This might be the reason that majority of previous literatures separately treat these two sectors and more attention has been paid to the private vehicle usage. However, Yu et al. (2012) revealed a significant complementary effect between the household energy consumption in the private transport sector and in the domestic sector in the context of Beijing. Therefore, looking towards a low carbon future, both of the residential and transport energy consumption deserves to be emphasized.

6.5 Model Estimation Results

As shown in equations (6.4) and (6.5), ρ_{nit}^{k} and $\rho_{nje}^{k}(k = ind, sha)$ are introduced to represent the heterogeneous influence of individual/household attributes, residential environment, and other observed and unobserved factors on time allocation and energy consumption. In the survey data, there is no rich information specific to each activity and end use. Therefore, several individual and household attributes are used in the model: gender, age, employment, education level, and four dummy variables used to denote the individual identity (i.e., the householder, the householder's spouse, the householder's children, the householder's parents), and accessibility (i.e., distance) to bus or subway stations. For simplification of the model estimation, two composite variables A^{t} and A^{e}, which correspond to the time use and energy expenditure, respectively, are first designated as a linear function of the above individual variables (see equations (6.18) and (6.19)). They are then further used to define activity-specific variables A_{i}^{t} and end-use-specific variables A_{j}^{e}, to explain the heterogeneous influence of these individual attributes on time use and energy consumption behavior (see equations (6.20) and (6.21)).

$$\mathrm{A}^{t} = \sum_{l} \gamma_{l}^{t} a_{nl} \tag{6.18}$$

$$\mathrm{A}^{e} = \sum_{l} \gamma_{l}^{e} a_{nl} \tag{6.19}$$

$$\mathrm{A}_{i}^{t} = \delta_{i}^{t} \mathrm{A}^{t} \tag{6.20}$$

$$\mathrm{A}^{e}_{j} = \delta^{e}_{j}\mathrm{A}^{e} \tag{6.21}$$

Here, a_{nl} indicates individual/household attribute l, and γ^{t}_{l} , γ^{e}_{l} are associated parameters. δ^{t}_{i} and δ^{e}_{j} are activity-specific and end-use-specific parameters, respectively. Note that for the purpose of estimation, δ^{t}_{i} will be set at zero for one activity and unity for another activity, δ^{e}_{j} will be set at zero for one end use and unity for another.

The model estimations are carried out by using the standard maximum likelihood method in the software GAUSS 9.0. The results are shown in Table 6-4.

6.5.1 Overall Model Performance

Focusing on the overall performance of the proposed model structure, first, the Rho-squared of 0.187 indicates an acceptable validity; second, most of the estimated interaction terms are shown to be statistically significant, supporting the feasibility of including multiple behavioral interactions in the same model structure.

6.5.2 Intra-household Interaction

The result shows that the intra-household interaction (parameter λ) is statistically significant, which means that on the time allocation and household energy consumption issues, household members do care about other members' preferences and/or needs. The negative sign signifies that such kind of interaction to some extent reduce the total household utility derived from their behavior of time use and energy consumption. The negative result derived from this model makes it easy for readers to misunderstand that forming a household has no positive gain in life. However, it is important to recognize that people's happiness and life satisfaction are determined by many life domains, like health, living environment, employment status, social activities, etc. (see Phillips, 2006 for details). The intra-household interaction parameter here is the product of only considering time use and energy consumption behaviors instead of involving all facets in life. Actually, the negative intra-household interaction on the time use and energy consumption is understandable due to altruism. Tradeoffs always occur in the household. Previous literature also provided evidence to support this phenomenon, see Golob and McNally (1997), Srinivasan and Bhat (2006) and Zhang and Fujiwara (2006).

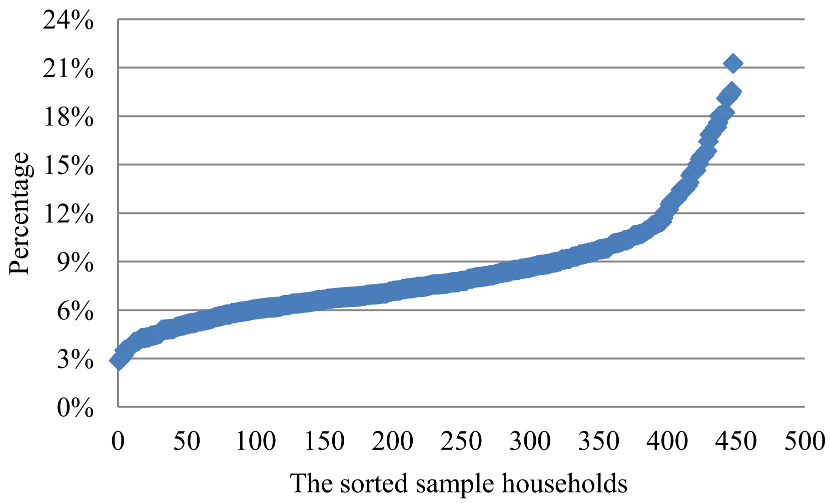

Figure 6- 2 The percentage of the interacted utility in the total household utility

Concerning the percentage of the interacted utility among members in the total household utility (see Figure 6-2), it is found to be between 5%~15% for the majority of households, suggesting a significant but not substantial proportion in the decrease of utility caused by the intra-household interaction.

6.5.3 Time-to-energy Interaction

Time-to-energy interaction is described by the parameters “IIte, IOte, OOte, OIte”. The estimation results reveal significant time-to-energy interaction, especially between residential and transport sectors. Specifically, the interaction between in-home time use and out-of-home car consumption, and the interaction between out-of-home time use and in-home end-use consumption, are found to be 95% statistically significant, while the interaction between in-home time use and in-home energy expenditure is less significant. In this sense, the covariant interrelationship is identified for temporal dimension and energy dimension. In addition, the negative sign of IOte and OIte indicated that the more time spent on in-home activities (out-of-home activities), the less money spent on out-of-home cars (in-home end uses). The positive sign of IIte implies that with more time spent staying at home, the usage of in-home end use is more. The above results are acceptable. For the out-of-home time use and out-of-home car usage, there is no significant interaction found.

6.5.4 Time-to-time Interaction

For the time-to-time interaction, significant estimated negative results of IIt and IOt suggest that time allocation among in-home activities and between in-home and out-of-home activities are competitive. This is consistent with most of the previous research (e.g., Zhang et al., 2005a, 2007). Moreover, the competition between in-home activity and out-of-home activity (IOt equals to -7.096) is more intense. In contrast, there is a synergetic relation among out-of-home activities given OOt's positive sign, indicating that more time allocated on out-of-home dining will induce more out-of-home leisure activities and/or other social activities, and vice versa. This sounds plausible since if people intend to spend much time outside to support his/her leisure or social activities, then they are more inclined to eat outside, and conversely it is also understandable.

6.5.5 Energy-to-energy Interaction

Because the car is the only out-of-home end use in the model, thereby, the interaction term for out-of-home end use usage is excluded. For the other two interaction terms (i.e., IIe and IOe), it is found that a positive relationship exists between the usage of in-home end uses.

It is very common that multiple end uses are consumed together when staying at home, in this sense, the synergetic effect is plausible. In addition, significant competition between energy expenditure of in-home end uses and out-of-home cars is verified, which supports the necessity of joint representation of the energy consumption behavior across residential and transport sectors.

6.5.6 Utility composition

After the explanation of the results of TTI, EEI, and TEI, the percentage of the additive utility and the interacted utilities in the total member's utility is calculated based on equation (2). Figure 3 is the graph after sorting the percentage of each utility from smallest to largest. It is shown that the additive utility comprised of both the time use and energy consumption behavior only accounts for 3%~30%, indicating the utility resulting from the multiple interactions occupies a large amount (i.e., 70%~97%) in the total member's utility, especially the EEI utility (10%~85%) and TEI utility (10%~70%). This finding implies that ignoring the influence of TTI, EEI, and TEI might lead to biased policy evaluation related to time use and energy consumption in the household sector. More seriously, because of its inaccurate representation of actual behavior, incorrect policies might even be derived from the additive model. From the above discussion, we can conclude that the proposed model should be adopted to analyze household energy consumption behavior for policy decisions.

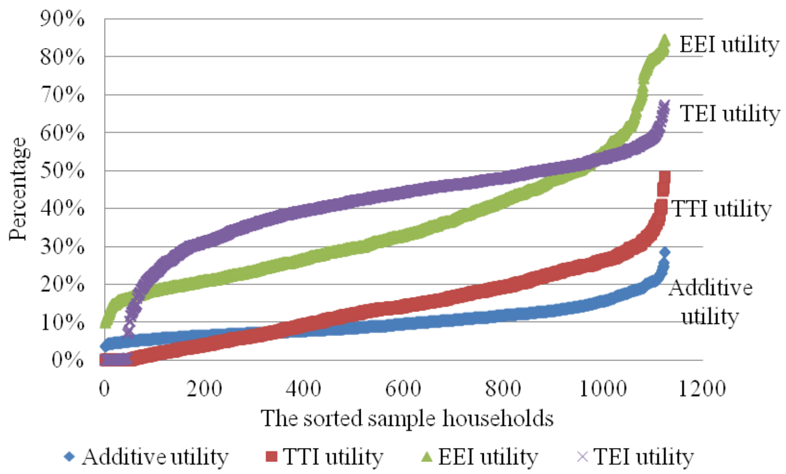

Figure 6- 3 The percentage of each utility element in the total member's utility

6.5.7 Explanatory Variables

It is found that many attributes in the composite variable is significant. By multiplying the composite variable with the corresponding coefficient, how the explanatory variables influence the time use on each activity and energy expenditure on each end use can be known. Specifically for the time use part, three out of four identity dummy variables (except the householder's parents) are found to positively affect the time use on the independent in-home work/study and in-home leisure activity, as well as the shared in-home work/study and out-of-home dining activity, while negatively influence the other activities. Regarding the energy consumption behavior, the householder and householder's children show a higher preference for consuming the car, AC, PC, and microwave oven, but lower preference for watching TV. These results indicate that household members with different identities (e.g., the householder, the householder's wife, and the children) do have diverse performances on the time use and energy consumption behavior.

Gender, education level, and accessibility to public transit play a great role on explaining both the time allocation and end-use consumption, while the age and employment status is only meaningful to either time use or end-use consumption. Taking the policy variable "accessibility to public transit" as an example, this factor shows a negative influence on independent out-of-home activities, and shared in-home leisure, out-of-home leisure, and out-of-home other activities. In other words, as the distance to public transit increases, households are less likely to allocate much time on the above activities. This might result from the inconvenient mobility which consumes more time on travel and in turn makes people have to spend their limited time on basic maintenance and independent in-home leisure activities. Concerning the end-use usage, the farther away from public transit the households reside, the more consumption on car, AC, PC and microwave oven occurs. On one side this is probably due to the substitution of car for the public travel mode, on the other side, for households without a car, heavier usage of PC and AC is to support the leisure activities at home.

6.5.8 Sensitivity Analysis of Telecommuting

The proposed model can be used to evaluate how the time use policies (e.g., telecommuting, flexible working arrangements, and work-holiday balance) affect the household energy consumption because of the incorporation of the multiple interaction terms. Here, we take the telecommuting option as an example to explain how to implement. The policy evaluation is a process of comparing the prediction results of the scenario with the intervention of the policy and the scenario without any change (i.e., reference scenario). In other words, what we need to do is to adopt the model to forecast the energy consumption under the option of telecommuting and compare it with the reference scenario.

For interpretation, only the households comprised of two persons (312 households) are targeted in this telecommuting policy analysis. It is assumed that all the householders who are still in employment alter to be the telecommuters at home. The average time use change of each member and the household energy consumption change are looked at in the policy analysis.

As for the technical implementation, we only need to deal with a constrained optimization problem. Specifically, all the estimated parameters in Table 6-4 are treated as known and put them into the model directly, and then fix householder's in-home working time, the time use for other activities and the energy expenditure on each end use are unknown and waiting for being predicted. By using the constrained optimization method to estimate the model, all the unknown elements can be obtained. Comparing the time use and end-use energy consumption with the values derived from the reference scenario, how the telecommuting policy works can be easily found. Figures 6-3, 6-4, and 6-5 clearly show the aggregate results of the policy effect.

Before explaining the results, the mechanism is briefly interpreted. Due to the incorporation of the time-to-time interaction term, how the time use on one activity changes influences other activities can be simulated; the incorporation of the energy-to-energy interaction term makes how the energy use on one end use changes influences other end uses be known; the incorporation of the time-to-energy interaction term makes how the time use (energy use) on one activity (end use) changes influences the energy consumption on end uses (activities) be known. If someone in the household alters to working at home, then his/her change on the time allocation across different activates will meanwhile change the time use on other activities and the energy consumption on the end uses due to the time-to-time interaction term and time-to-energy interaction term, respectively. And, the change of energy consumption on end uses might additionally cause the consumption transformation for other end uses due to the energy-to-energy interaction term. Consequently, a covariant relationship can be found between time use and energy consumption. Furthermore, due to the incorporation of the intra-household interaction term, one member's change not only affects his/her time use and/or energy consumption, but also affects the other household members' time use and/or energy consumption.

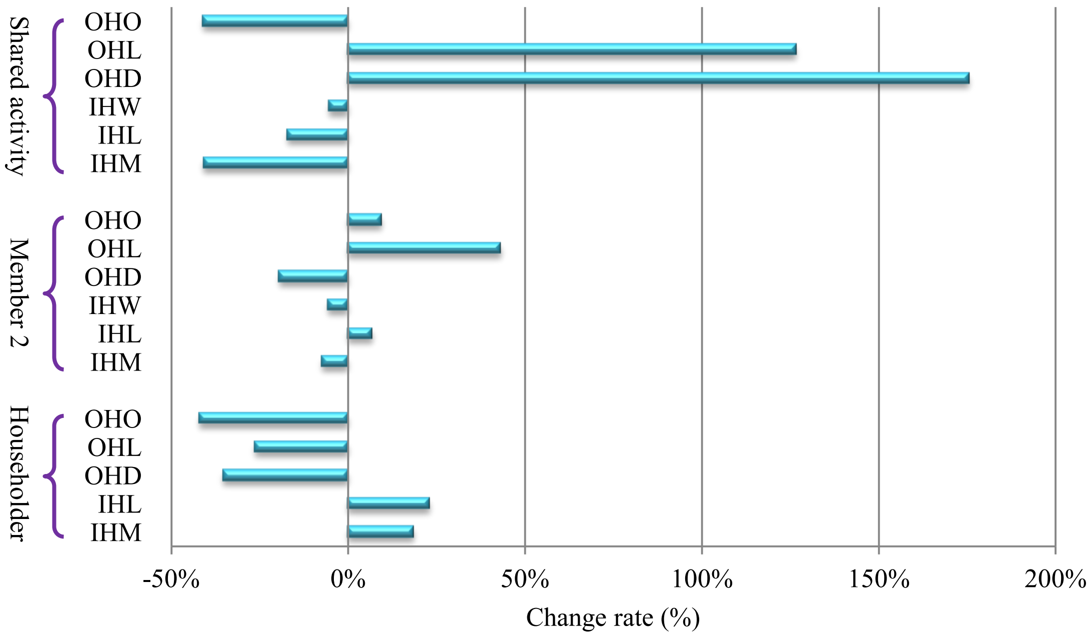

Figure 6- 4 Time use change of each member after the telecommuting policy

Figure 6-4 shows the time use change of each member after the telecommuting policy. Specifically, it is found that after the householder alters to work at home, his/her independent time allocated to out-of-home activities decreases a lot (i.e., -42% ~ -25%) and the independent time allocated to the in-home leisure and maintenance increases a little. This outcome is very easy to understand. While, for the independent time of the other member in the household, only time allocated to the out-of-home leisure activity obviously rises, probably due to the reason that the householder helps finish some in-home maintenance for member 2, which makes member 2 can spend more time on out-of-home leisure. As for the shared time, it seems all the activities are influenced by the householder's telecommuting choice, especially the out-of-home leisure and out-of-home dining.

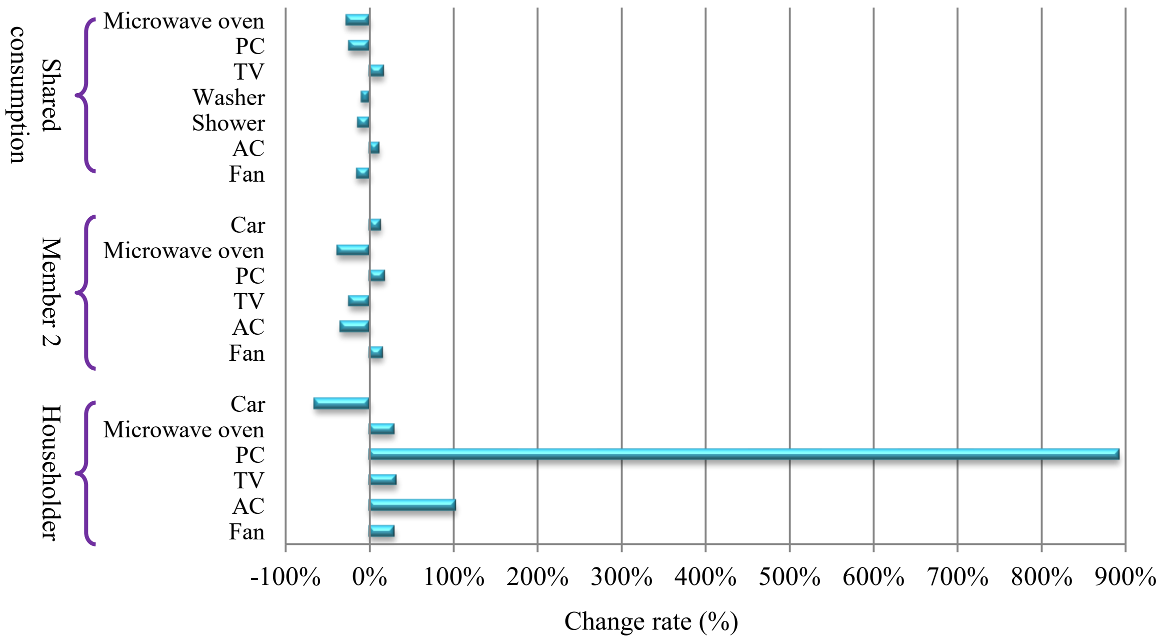

Figure 6- 5 End-use energy consumption change of each member after the telecommuting policy

Accompany with the time use change, the end-use energy consumption also significantly changed (see Figure 6-5), especially the usage of PC resulted from the dramatic increase of the in-home working time. For the householder, his/her energy consumption on the out-of-home end use (i.e., car) reduces while consumption on all the domestic end uses increases. In contrast, the change of the independent energy consumption of member 2 and the shared consumption is not as apparent as the householder. Looking at the total energy consumption change (see Figure 6-6), it is revealed that for householder, almost 50% of his/her consumption can be reduced after choosing the telecommuting option. Accordingly, the consumption of member 2 is also affected which is found 8% more than before, probably due to the contribution of the increasing car usage. The shared consumption is slightly decreased (i.e., -0.06%). Finally, the total household energy consumption is 15.66% less than before. This number verifies the substantial efficacy of telecommuting policy on the energy conservation.

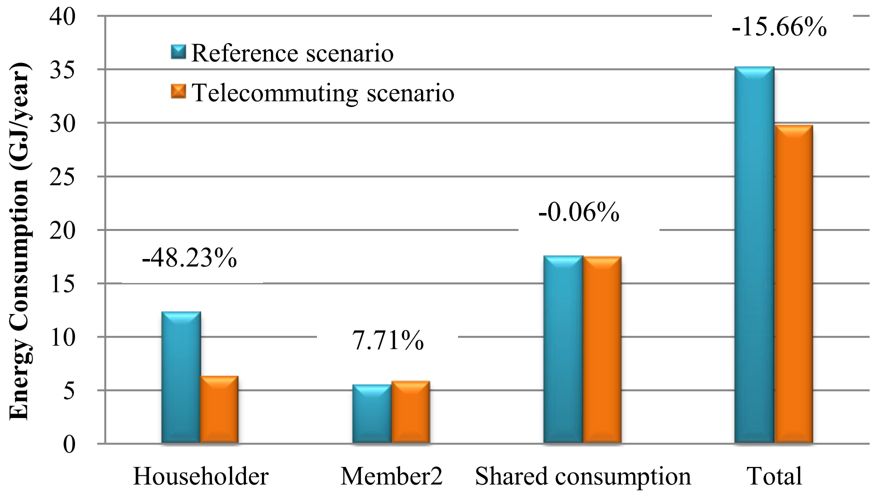

Figure 6- 6 Total energy consumption change of each member

6.6 Summary and Conclusion

To achieve an environmentally sustainable society, it is important for policy makers to properly understand household energy consumption behavior (both residential and transport consumption from various appliances and vehicles), which is in fact closely related to the household time use behavior. This chapter proposed a household time use and energy consumption model, which can simultaneously represent various behavioral interactions, including time-to-energy interaction, time-to-time interaction, energy-to-energy interaction and the intra-household interaction. In the model, the zero-consumption on time use and energy consumption is also endogenously included. The findings can be summarized below.

The model accuracy suggests that the developed model is acceptable to represent the household time use and energy consumption behavior. In addition, multiple behavioral interactions are found in the empirical analysis, which on the one hand supports the rationality for the joint representation of time use and energy consumption behavior, while on the other hand confirms the necessity for describing the energy consumption behavior of in-home end uses and out-of-home vehicles simultaneously. This proposed model has important policy implications. The existence of the various interactions suggests that different policies should be packaged so as to enhance the synergetic effects of policy interventions. Specifically, due to the existence of time-to-energy interaction, we can quantify how time use policies (e.g., telecommuting, flexible working arrangements, and work-holiday balance) affect the household energy consumption, and by carrying out the time use policy and energy control policy simultaneously, the policy benefit might be much greater than the sum of their respective contribution. The effect of telecommuting policy on household energy consumption is examined and it is found that 15% of energy use can be cut down for the two-person households. Since the energy-to-energy interaction is significantly influential to the energy consumption, the necessity of collaborated policies between domestic and private transport sectors is confirmed, such as extending the Japanese "eco-point" scheme[2] to cover both domestic appliances and vehicles (see Yu et al. (2011) for more details). Furthermore, it is true that the intra-household interaction does exist. This implies that no matter what kind of policy which might specifically aim to certain member(s) in the household is implemented, not only the individual but the whole household will be influenced. Therefore, the policy effect should be evaluated at the household level considering that the policy benefit might be transformed or re-distributed among the household members.

Following the conclusions, there are several research issues that need to be mentioned. First, we calculate the energy consumption based on respondent's self-reported end-use efficiency and usage which might include reporting biases (Vine, 1986). Such reporting biases should be corrected by further improving data collection methods and/or adopting more advanced modeling techniques. Second, it might be worth explicitly incorporating rebound effects and self-selection effects in the time use and energy consumption model. Especially

[2] http://www.japanfs.org/en/mailmagazine/newsletter/pages/029766.html (Accessed on Feb. 2, 2012).
The Japanese government is promoting the purchase of eco-friendly electric appliances through the legalized "eco-point" scheme, which allows consumers to spend the credits gained from buying one appliance on the other appliances. However, currently, such credits cannot be spent on the purchase and/or usage of vehicles.

for representing the rebound effects, panel surveys should be implemented and dynamic models are needed. Third, the effects of some omitted factors (e.g., social interaction, awareness, and taste heterogeneity) on energy consumption should be properly incorporated into the analysis. Fourth, since representing complex behavioral mechanisms usually requires advanced estimation techniques, which are difficult to implement in practice, it is necessary to develop user-friendly software packages. Finally, even though only the telecommuting policy has been evaluated in this study, our model can be further applied to examine the effects of various policies, including all the aforementioned policies, land use policy, monetary policy, energy tax, etc. This is left as a future research issue.

Table 6- 3 Descriptive statistics of the explanatory variables and dependent variables

		Householder		Householder's couple		Householder's child		Householder's parent		Total	
Sample size		614		434		186		80		1314	
Gender (Percent of male)		58.40%		37.80%		52.69%		46.25%		50.10%	
Age		39		38		15		55		33	
Education (>=bachelor)		50.20%		51.60%		22.58%		23.75%		45.13%	
Employment		79.50%		74.65%		41.83%		27.50%		69.40%	
Distance to public transit (km)		0.62		0.63		0.62		0.69		0.63	
Dependent variables		Independent portion for each household member								Shared portion	
		Householder		Householder's couple		Householder's child		Householder's parent			
Items		Non-zero %	Mean(S.d.)	Non-zero %	Mean(S.d.)	Non-zero %	Mean(S.d.)	Non-zero %	Mean(S.d.)	Non-zero %	Mean(S.d.)
Time allocation (Unit: hour)	Total	100	59.9(13.19)	100	44.75(36.97)	100	55.91(28.92)	100	56.41(52.95)	63.34	17.86(7.16)
	IHM	100	18.68(18.06)	100	29.82(15.01)	100	15.52(12.41)	100	26.79(20.21)	61.54	5.94(4.06)
	IHL	42.18	21.17(15.02)	23.73	17.90(15.04)	81.83	20.20(12.37)	56.25	25.38(11.82)	52.05	5.53(4.20)
	IHW	57.65	19.90(17.95)	42.4	16.95(19.50)	33.44	30.48(21.10)	17.5	17.64(22.08)	25.86	1.78(1.71)
	OHD	50.49	7.63(5.59)	34.33	6.91(5.76)	62.37	8.78(5.84)	20	6.13(2.64)	35.84	3.21(2.71)
	OHL	59.61	12.56(11.64)	43.78	15.79(14.16)	38.28	15.94(26.78)	70	20.77(10.66)	37.48	6.14(4.66)
	OHO (Work)	59.93	30.17(19.14)	48.85	29.46(21)	22.04	31.71(14.98)	20	13.91(14.35)	/	/
	OHO (Without work)	35.34	9.00(7.75)	26.96	8.59(8.84)	10.22	10.42(12.45)	26.25	9.27(4.78)	22.91	1.41(1.16)
Energy consumption expenditure (Unit: RMB)	Total	61.56	104.02(129.47)	74.1	87.77(156.68)	61.29	95.75(142.74)	82.25	101.62(102.42)	94.32	41.19(32.70)
	Fan	35.99	1.76(4.98)	20.51	0.58(2.05)	55.91	0.33(0.53)	58.75	3.42(0.62)	55.65	2.08(5.19)
	AC	37.95	16.75(19.67)	26.5	7.89(12.32)	55.91	6.34(7.83)	10	10.15(12.24)	66.78	24.19(20.58)
	Shower	/	/	/	/	/	/	/	/	90.18	11.23(19.24)
	Washer	/	/	/	/	/	/	/	/	94.27	0.82(1.30)
	TV	41.53	3.93(4.09)	27.42	1.31(2.17)	55.91	1.30(1.39)	80	7.31(1.15)	70.05	4.62(3.48)
	PC	40.07	2.77(4.73)	26.5	0.77(1.38)	55.91	0.50(0.69)	10	1.49(1.36)	63.34	3.27(3.95)
	Microwave oven	30.62	0.26(0.41)	21.2	0.55(0.08)	54.84	0.07(0.07)	28.75	0.81(1.03)	52.05	0.43(1.25)
	Car	28.34	192.17(132.57)	8.06	206.31(139.66)	5.38	233.26(108.63)	11.25	181.93(84.11)	/	/

Note: Mean and standard deviation are the corresponding values to the non-zero sample.

Table 6- 4 Estimation results of time use and energy consumption expenditure

	Independent		Shared	
Parameters	Estimated parameter	t-score	Estimated parameter	t-score
Interaction term				
Intra-household	-0.009	-2.824	Same values shown left	
IIt	-4.362	-1.946		
OOt	0.769	6.318		
IOt	-7.096	-10.562		
IIe	3.839	2.319		
IOe	-0.493	-10.521		
IIte	7.609	1.727		
IOte	-0.327	-12.331		
OOte	0.231	0.821		
OIte	-0.668	-2.324		
Attributes in composite variable for time allocation behavior				
Householder	-0.576	-2.447	Same values shown left	
Householder's couple	-0.149	-6.749		
Householder's child	-0.306	-5.649		
Householder's parent	0.053	0.115		
Gender(male is 1, female is 0)	-0.144	-3.479		
Age	1.411	1.398		
Education level (1 >=bachelor, 0 other)	-0.222	-3.021		
Whether is worker	-0.484	-2.421		
Accessibility to public transit	-0.254	-5.902		
Attributes in composite variable for energy consumption on end uses				
Householder	0.116	6.695	Same values shown left	
Householder's couple	-0.156	-1.323		
Householder's child	0.224	4.043		
Householder's parent	-0.049	-1.070		
Gender(male is 1, female is 0)	0.034	1.933		
Age	0.481	5.259		
Education level (1 >=bachelor, 0 other)	-0.027	-5.987		
Whether is worker	0.069	0.865		
Accessibility to public transit	0.030	2.424		
Influence of composite variable for time allocation behavior				
IHM	0.000	-	1.463	10.201
IHL	-0.657	-3.758	0.549	7.817
IHW	-0.126	-2.089	-0.504	-3.790
OHD	0.314	7.468	-0.411	-7.342
OHL	0.639	5.824	0.382	6.334
OHO	1.000	-	0.040	3.378
Influence of composite variable for energy consumption on end uses				
Fan	-0.446	-3.906	0.013	0.262
AC	0.043	0.921	0.031	6.168
Shower	-	-	-0.041	-1.277
Clothes washer	-	-	-0.114	-1.110
TV	-0.353	-2.572	-0.120	-4.970
PC	0.092	1.970	0.090	1.571
Microwave oven	1.156	3.437	0.135	5.758
Car	1.000	-	-	-
Variance of time allocation behavior				
IHM	-	-	1.329	2.119
IHL	0.916	3.391	1.261	1.951
IHW	0.826	5.666	1.146	2.346
OHD	0.940	4.030	1.521	2.010
OHL	1.151	3.940	1.718	2.094
OHO	1.017	4.271	1.350	2.049

Table 6-4 Estimation results of time use and energy consumption expenditure (continue)

	Independent		Shared	
Parameters	Estimated	t-score	Estimated	t-score
Variance of energy consumption behavior				
Fan	0.700	4.923	0.347	1.356
AC	0.116	8.301	1.858	4.404
Shower	-	-	1.194	1.779
Clothes washer	-	-	0.120	0.976
TV	0.275	4.366	0.832	1.585
PC	0.616	4.813	0.640	1.580
Microwave oven	0.156	4.675	0.068	0.927
Car	1.961	2.108	-	-
Initial log-likelihood	-46523.056			
Converged log-likelihood	-37820.218			
Rho-square	0.187			
Adjusted Rho-square	0.185			
Sample size	611			

Chapter 7

Residential Location Choice and Household Energy Consumption Behavior

7.1 Introduction

In the behavioral sciences, the importance of relationships between long-term choices, medium-term choices and short-term choices is emphasized (Eliasson and Mattsson, 2000; Waddell, 2001). In the household energy consumption domain (note that household energy consumption here is defined as direct energy used within households and for personal transport, while the indirect energy embedded in goods and services purchased by households is excluded), following the definition given by Ben-Akiva and Lerman (1991), the long-term decision is defined as the residential choice; medium-term decision as the choice of end-use ownership; and short-term decision as the end-use usage (e.g., frequency, duration, distance traveled, etc.). It is plausible that the decision of residential location not only determines the connection between the household with the rest of the urban environment, but also influences the household's activity time allocation (Pinjari et al., 2009) as well as the concomitant energy consumption behavior. Under such kind of consideration, it is reasonable to infer that residential location choice might be influential to household energy consumption behavior. Although the integrated analysis on land-use planning and travel behavior has received a great deal of interest, the land-use and energy consumption by domestic end uses does not gain the same level of attention in both academic and practical sides (Cooper, 2011). According to the CFA (Consumer Federation of America) survey result, it is surprising that in America, since 2009, the energy consumption caused by domestic end uses has taken just as large a bite out of household budgets as does expenditures for gasoline. Therefore, both of the residential and transport energy consumption deserves to be emphasized, furthermore, due to the total money and time budget constraints, it is necessary to consider these two together (see Yu et al. 2011 for an elaboration).

Essentially, the inter-relationship between residential location and household energy consumption behaviors can be very complicated. However, majority of earlier research assumed that there is a one-way causal effect from the residential environment (*RE*) characteristics to household energy consumption behavior. Specifically to say, households and individuals locate themselves in neighborhoods, and then based on neighborhood attributes, determine their energy consumption behaviors. In this context, if it is found that accessibility to bus/subway station has a negative influence on household energy consumption, the implication would be that building neighborhoods by configuring a near bus/subway stop could decrease the aggregate energy demand in the population. The problem here is that how individuals/ households make residential choice and energy consumption decisions is not comprehensively known. In reality, households and individuals who are environmentally-friendly may self select to settle down in neighborhoods with good accessibility to bus/subway station, hence, they can pursue their energy-saving lifestyles. If this were true, urban land-use policies aimed at increasing the accessibility to public transport would not get the expected result on reducing household energy consumption. Such kind of non-causal association between residential choice and energy consumption behavior derived from intervening variables (e.g., social factors, cultural factors, psychological factors, social-demographics, etc.) which are causing both is termed as “self-selection effect”. Statistically, self-selection arises in any situation in which individuals select themselves into a group. In this sense, interaction between residential choice and household energy consumption behavior should not be simply interpreted by regarding the residential environment indicators as exogenous explanatory variables. The observed inter-relationship between these two might be part causal and part self-selection. That is to say, after controlling for the spurious association due to self-selection effect based on demographics and other unobserved characteristics, we are more confident of assessing the causal impact of *RE* on household energy consumption, and then more credible and persuasive policies can be developed. Meanwhile, the self-selection effect might vary with end uses. For example, households who do not like cooking may choose to reside in the neighborhood with good catering facilities (e.g., restaurants and/or supermarkets) and use less cooking-related end uses, while households with a preference on driving may prefer to live in suburban area so as to satisfy their desire of driving. Obviously, these two effects are distinct. Thus, it's better to consider multiple self-selection effects which reflect the diverse self-selection effects for different end uses. Additionally, the above-mentioned behavioral aspects might be heterogeneous across households, caused by observed and unobserved factors. Still now, there is no analysis which considers the self-selection effect when dealing with the integrated analysis of residential location choice and household energy consumption behavior. Consequently, our study is devoted to fill this gap.

The above-mentioned behavioral mechanisms actually pose some policy issues which have not been highlighted in practice. First, whether is the land-use policy effective on controlling the household energy consumption and to what extend does it work? The "true" effect of land-use policy might be wrongly predicted if the self-selection phenomenon is ignored. Second, whether does the self-selection effect significantly exist and for what types of end uses may households have significant self-selection effects? By answering these two questions, the need for "soft policy" (e.g., enhancing the residents' environmental awareness, making the residents aware of their excessive energy consumption patterns, and promoting energy-saving behavior) and what kinds of end uses should be emphasized when implementing the "soft policy" could be identified. Third, whether is it necessary to jointly represent the energy consumption behaviors in domestic sector and private transportation sector? This issue might provide unique lens on the necessity of the development of the package policy which could reduce the energy consumption in the above two sectors simultaneously.

In order to develop a robust policy system to reduce the total household energy consumption, this chapter aims to deal with the aforesaid policy issues by accommodating all the behavioral mechanisms mentioned above in a consistent and unified framework. Specifically, we first build an integrated model, termed mixed Multinomial Logit-Multiple Discrete-Continuous Extreme Value (MNL–MDCEV) model, which covers residential location choice, end-use (including domestic appliances and out-of-home cars) ownership, and usage behavior, and then apply it to examine the sensitivity of household energy consumption to changes in land use policy by considering a comprehensive set of residential environment (*RE*) variables, socio-demographic variables as well as multiple self-selection effects.

The remaining part of this chapter is organized as follows. Section 7.2 presents the structure of the integrated model (i.e., mixed MNL–MDCEV model). Section 7.3 further explains the data used in the model. Results of model estimation are shown and the policy scenario design based on the model results is interpreted in Section 7.4. This chapter is concluded in Section 7.5 along with a discussion about future research issues.

7.2 Modeling Methodology

As discussed previously, the household energy consumption behavior referring to the ownership and usage of varied end uses might be correlated with the residential location choice behavior, and especially, the self-selection effects cannot be ignored. To accommodate such behavioral mechanisms, the mixed MNL-MDCEV model is built up to combine the aforesaid two behavioral aspects together.

Let $i\,(i=1,2,...,\mathrm{I})$ denotes the index for the households, $j\,(j=1,2,...,J)$ denotes the index for the neighborhood of residential choice, and k ($k = 1, \ldots, K$) denotes the index for the end use. Then the utility functions of the above two behavioral aspects can be defined as follows, where the influences of the self-selection effects are explicitly incorporated.

$$u_{ij}^{R} = f_{ij}(UR_{ij}, \omega_{ijk}(k=1,..,K), \pi_{ij}) \tag{7.1}$$

$$u_{ij}^{E} = g_{ij}(UE_{ijk}, \omega_{ijk}, \varepsilon_{ijk} \mid k=1,...,K) \tag{7.2}$$

Here, u_{ij}^{R} and u_{ij}^{E} indicate the utility functions of household i's residential location choice and energy consumption behavior with respect to residential neighborhood j, respectively. The terms UR_{ij} and UE_{ijk} are observed components of utility functions explained by social-demographics and residential environment attributes, and π_{ij} and ε_{ijk} are unobserved random components which represent households' unobserved heterogeneity on residential location choice and household energy consumption behavior, respectively. There is another unobserved random component ω_{ijk}, which is shared by the two behavioral aspects and used to represent the influence of self-selection effects. Specifically, ω_{ijk} includes individual or household specific unobserved factors impacting household i's sensitivity to both residential choice and the ownership and usage of end use k. Because of the factors in ω_{ijk} like attitudes and lifestyle preferences, households self select one type of neighborhood and pursue ω_{ijk}-consistent energy consumption pattern. As mentioned before, since the self-selection effect might vary with end uses, a unique ω_{ijk} is allotted to each end use, and the multiple self-selection effects are exactly represented by the group of ω_{ijk} (k=1,2,…,K).

Attributing to the above multiple self-selection effects, it is necessary to integrate household energy consumption and residential choice behaviors within a unified modeling framework, which can incorporate not only the causal impact from residential choice to household energy consumption behavior, but also the non-causal association—self-selection effects. With such modeling approach, it is expected that the relatively "cleansed and true" causal effect of *RE* measures on energy consumption behavior can be captured in a more proper way.

7.2.1 Residential Choice Behavior

Since utility functions in the utility-maximizing modeling framework are usually defined as linear functions, the utility function of residential location choice in equation (7.1) can be re-written as follows:

$$u_{ij}^{R} = UR_{ij} + \sum_{k} \omega_{ijk} + \pi_{ij}\text{, neighborhood } j \text{ chosen if } u_{ij}^{R} > \max_{j' \neq j} u_{ij'} \; (j' = 1,2,...,J) \tag{7.3}$$

It is assumed that different households have heterogeneous sensitivity on residential neighborhoods. Thus, the unobserved random component π_{ij} is further decomposed into,

$$\pi_{ij} = v_i + o_{ij}, \tag{7.4}$$

where, o_{ij} is a purely-random error term following an independently and identically distribution, and v_i contains only those ignored or omitted household-specific unobserved factors that are associated with the residential choice. For example, toward a household with members are social extroverts, they might have a preference to lively neighborhoods so as to provide a more socially vibrant setting conducive to their social outlook. Such kind of socially extroverted nature could be captured in v_i. Here, $v_i \sim \mathrm{N}(b_v, \sigma_v^2)$.

And for the observed component UR_{ij}, it is

$$UR_{ij} = \beta_i^{'} z_{ij}, \tag{7.5}$$

where, z_{ij} is a set of residential environment (*RE*) attributes associated with household *i*'s decision on residence (e.g., land-use mix and activity accessibility), and $\beta_i^{'}$ is the coefficient vector depicting household *i*'s sensitivity to *RE* attributes in z_{ij}. Here, we further divide each element *d* of $\beta_i^{'}$ into two parts as $\beta_{id}^{'} = (\theta_d^{'}\delta_{id} + c_d)$, where δ_{id} is a vector of observed household socio-demographic characteristics (e.g., household income, household size and presence of children in the household) which modifies the households' sensitivity to the *d*th *RE* characteristics in z_{ij}, and after fully extract the interacted influence of household-specific factors on *RE* attribute, c_d can be explained as the pure influential effect on the residential choice behavior solely caused by the *RE* attribute *d*. The term $\theta_d^{'}\delta_{id}$ can be further explained as the heterogeneity on residential choice caused by observed characteristics.

Assuming that o_{ij} follows a Gumbel distribution, the residential choice probability can be derived as the following well-known multinomial logit model.

$$P_{ij}^{R} = \frac{\exp(UR_{ij} + \sum_k \omega_{ijk} + v_i)}{\sum_{j'} \exp(UR_{ij'} + \sum_k \omega_{ij'k} + v_i)} \tag{7.6}$$

7.2.2 Energy Consumption Behavior

The MDCEV model proposed by Bhat (2005, 2008) is adopted here to describe the energy consumption behavior. Assume that there are *K* different end uses that a household can potentially allocate its income to. Let e_{ijk} be the expenditure consumption on end use *k* (*k* = *2,3,…K*) for household *i* living in neighborhood *j*. If an outside goods which is always consumed is present, label it as the first goods (i.e., *k* = *1*) (see Bhat, 2008). In this study, the money calculated by deducting the energy expenditure from household income is regarded as the outside goods, which is termed as savings. The utility u_{ij}^{E} that household i obtains from energy consumption is specified as the sum of the utilities derived from spending money on end uses as well as disposal money (i.e., savings) at residential neighborhood j, as shown below.

$$u_{ij}^{E} = \frac{1}{a_1}\varphi_{ij1}\, e_{ij1}^{a_1} + \sum_{k=2}^{K}\frac{\gamma_k}{a_k}\varphi_{ijk}\left\{\left(\frac{e_{ijk}}{\gamma_k}+1\right)^{a_k} - 1\right\},\ \ \alpha_k \in (-\infty,\infty), \gamma_k > 0 \tag{7.7}$$

With the above utility function, it is assumed that household i maximizes its utility subject to its budget constraint, that is $\sum_{k=1}^{K} e_{ijk} = E_{ij}$, where E_{ij} is the total budget (e.g., expenditure, disposal income, or available time). As a result, the competitive relationship among end uses is reflected in the model. Note that only one type of budget constraints can be represented. This study only deals with households' monetary budget constraints. φ_{ijk} is the baseline utility for money spent on end use k which controls the discrete choice decision (i.e., end-use ownership) and continuous choice decision (i.e., money spent on energy consumption) with respect to end use k for household i living in neighborhood j. The parameter a_k represents a satiation parameter, which expresses the characteristic of the diminishing marginal utility with increasing consumption of end use k. The parameter γ_k (γ_k >0) is a translation parameter that serves to accommodate corner solutions (zero consumption) for end use k. Besides, it also plays the role of the above satiation parameter. Note that the translation parameter γ_1 is absent for the outsides goods, because the first goods is always consumed (see Yu et al., 2011 for detail explanation).

It is generally not able to simultaneously estimate a_k and γ_k for the non-outside goods k ($k=2,3,\ldots K$). Instead, one can estimate one of the following three utility forms. In reality, one can select the most appropriate form that fits the data best based on statistical considerations.

$$a\text{-profile } (\gamma_k = 1):\ u_{ij}^E = \frac{1}{a_1}\varphi_{ij1}e_{ij1}^{a_1} + \sum_{k=2}^{K}\frac{1}{a_k}\varphi_{ijk}((e_{ijk}+1)^{a_k}-1) \tag{7.8-a}$$

$$\gamma\text{-profile } (a_k \to 0):\ u_{ij}^E = \frac{1}{a_1}\varphi_{ij1}e_{ij1}^{a_1} + \sum_{k=2}^{K}\gamma_k\varphi_{ijk}\ln(\frac{e_{ijk}}{\gamma_k}+1) \tag{7.8-b}$$

$$\text{Constant } a: u_{ij}^E = \frac{1}{a}\varphi_{ij1}e_{ij1}^{a} + \sum_{k=2}^{K}\frac{\gamma_k}{a}\varphi_{ijk}\left\{\left(\frac{e_{ijk}}{\gamma_k}+1\right)^a - 1\right\} \tag{7.8-c}$$

Specifically speaking, the baseline preference φ_{ijk} can be represented as a random utility specification as follows:

$$\varphi_{ijk} = \exp(UE_{ijk} \pm \omega_{ijk} + \varepsilon_{ijk}), \tag{7.9}$$

where UE_{ijk} is the observed component and $(\pm\omega_{ijk} + \varepsilon_{ijk})$ is unobserved component. Further, $UE_{ijk} = \mu_k^{'} s_{ij} + \Delta_k^{'} x_i$, and $\varepsilon_{ijk} = \eta_{ijk} + \tau_{ijk}$. Here, s_{ij} is a vector of residential environment attributes with the corresponding coefficient vector $\mu_k^{'}$; x_i is a set of observed household attributes and housing attributes, $\Delta_k^{'}$ is the coefficient vector. η_{ijk} depicts the heterogeneity explained by those omitted household-specific and end-use specific factors as well as unobserved components that only influence household energy consumption behavior. ω_{ijk} represents the self-selection effect for the residential choice and energy consumption behavior of end use *k*. The "±" sign in front of ω_{ijk} term in the energy consumption behavior model means that the unobserved factors relating to residential location choice has a positive (+) or negative (-) effect on the ownership and usage of end-use *k*. It is assumed that η_{ijk} and ω_{ijk} are both normally distributed with a mean b_k^{η}, b_k^{ω} and standard deviation σ_k^{η}, σ_k^{ω}, respectively. The error term τ_{ijk} is independently and identically Gumbel distributed.

For identification, the baseline utility of the outside goods is denoted as $\exp(\tau_{ij1})$ which serves as a reference for other end uses.

According to Bhat (2005, 2008), the probability that household i chooses to own and use M_i alternatives from K end uses ($M_i \leq K$) is determined by the following equation:

$$P(e_{ij1}, e_{ij2}, e_{ij3}, \cdots, e_{ijM_i}, \underbrace{0,0,\cdots,0}_{K-M_i}) = \left[\prod_{k=1}^{M_i} f_{ijk}\right]\left[\sum_{k=1}^{M_i} \frac{1}{f_{ijk}}\right]\left[\frac{\prod_{k=1}^{M_i} e^{V_{ijk}}}{(\sum_{k'=1}^{K} e^{V_{ijk'}})^{M_i}}\right](M_i - 1)! \quad (7.10)$$

where, $f_{ijk} = \left(\frac{1-a_k}{e_{ijk}+\gamma_k}\right)$, and the expressions for the term V are as follows for each of the three utility forms in equation (7.8).

$$a\text{-profile } (\gamma_k = 1): \begin{cases} k = 1: V_{ij1} = (a_1 - 1)\ln(e_{ij1}) \\ k \geq 2: V_{ijk} = \ln(\hat{\varphi}_{ijk}) + (a_k - 1)\ln(e_{ijk} + 1) \end{cases} \quad (7.11\text{-a})$$

$$\gamma\text{-profile } (a_k \to 0): \begin{cases} k = 1: V_{ij1} = (a_1 - 1)\ln(e_{ij1}) \\ k \geq 2: V_{ijk} = \ln(\hat{\varphi}_{ijk}) - \ln(\frac{e_{ijk}}{\gamma_k} + 1) \end{cases} \quad (7.11\text{-b})$$

$$\text{Constant } a: \begin{cases} k = 1: V_{ij1} = (a - 1)\ln(e_{ij1}) \\ k \geq 2: V_{ijk} = \ln(\hat{\varphi}_{ijk}) + (a - 1)\ln(\frac{e_{ijk}}{\gamma_k} + 1) \end{cases} \quad (7.11\text{-c})$$

where, $\hat{\varphi}_{ijk} = \exp(\mu_k^{'} s_{ij} + \Delta_k^{'} x_i \pm \omega_{ijk} + \eta_{ijk})$.

7.2.3 The Integrated Choice Model

Re-write the utility functions of household i's residential location and energy consumption behaviors as follow.

$$u_{ij}^{R} = (c_d + \theta_d^{'} \delta_{id}) z_{ij} + \sum_k \omega_{ijk} + \nu_i + o_{ij} \quad (7.12)$$

$$u_{ij}^{E} = \frac{1}{a_1}\exp(\tau_{ij1}) e_{ij1}^{a_1} + \sum_{k=2}^{K} \frac{\gamma_k}{a_k} \exp(\mu_k^{'} s_{ij} + \Delta_k^{'} x_i \pm \omega_{ijk} + \eta_{ijk} + \tau_{ijk})\left\{\left(\frac{e_{ijk}}{\gamma_k} + 1\right)^{a_k} - 1\right\} \quad (7.13)$$

Here, it is assumed that η_{ijk}, ω_{ijk}, and τ_{ijk} are independent with each other. The common unobserved random component $\omega_{ijk}(k=1,2,...,K)$ in the above equations (7.12) and (7.13) are used to describe the influences of multiple self-selection effects.

The integrated residential location and household energy consumption behavior choice probability can be derived by multiplying the probabilities of the two choice components. For simplifying the description, denote Γ as a vector that contains all the parameters to be estimated (i.e., $c_d, \theta_d^{'}, \mu_k^{'}, \Delta_k^{'}, a_k, \gamma_k (k=1,2,...,K)$, and the mean as well as variance of the stochastic components: v_i, η_{ijk}, and ω_{ijk}). If household *i* resides in residential neighborhood *j*, then define $y_{ij}=1$, otherwise $y_{ij}=0$. Given these notations, the likelihood function conditional on the value of Γ can be written as:

$$L_i(y_{ij}, e_{ijk}|\Gamma) = \prod_{j=1}^{J} \left(\begin{array}{l} \left\{ \dfrac{\exp\left((c_d + \theta_d^{'}\delta_{id})z_{ij} + \sum_k \omega_{ijk} + v_i\right)}{\sum_{j'} \exp\left((c_d + \theta_d^{'}\delta_{id})z_{ij'} + \sum_k \omega_{ij'k} + v_i\right)} \right\} \\ \times \left\{ \left[\prod_{k=1}^{M_i} f_{ijk} \right] \left[\sum_{k=1}^{M_i} \dfrac{1}{f_{ijk}} \right] \left[\dfrac{\prod_{k=1}^{M_i} e^{V_{ijk}}}{(\sum_{k'=1}^{K} e^{V_{ijk'}})^{M_i}} \right] (M_i - 1)! \right\} \end{array} \right)^{y_{ij}} \tag{7.14}$$

To incorporate the influences of heterogeneity in a more comprehensive way, parameter of each explanatory variable is also assumed to follow a probability distribution, in addition to those unobserved random components. Consequently, the unconditional likelihood probability is the integral of $L_i(y_{ij}, e_{ijk}|\Gamma)$ over all values of Γ weighted by the probability density of Γ:

$$L_i(y_{ij}, e_{ijk}|b,\Sigma) = \int (L_i(y_{ij}, e_{ijk}|\Gamma)) dF(\Gamma|b,\Sigma) = \int (L_i(y_{ij}, e_{ijk}|\Gamma)) f(\Gamma|b,\Sigma) d\Gamma \tag{7.15}$$

where, $F(\Gamma|b,\Sigma)$ is the multidimensional cumulative normal distribution, $f(\Gamma|b,\Sigma)$ is the probability density function, and all the elements in Γ are assumed to be normally distributed with mean (***b***) and variance Σ.

Although the model presented in the study is similar with the one proposed by Pinjari et al. (2009), richer heterogeneity and end-use specific self-selection effects are accommodated into the model. In addition, this is the first instance to apply such an integrated model into the energy domain. To achieve the goal of estimating the multifold heterogeneity, the hierarchical Bayesian procedure based on Markov Chain Monte Carlo (MCMC) method is applied in this study given its simple and feasible manipulation on generating the draws of parameters as well as the fitness on high dimension problem. Also, previous studies have confirmed that the estimation results from Bayesian procedures are asymptotically equivalent to those from the maximum simulated likelihood method (e.g., Train, 2003). Under a Bayesian framework, it is necessary to specify the prior for the parameters. The prior on $\boldsymbol{b}$ is depicted to be normal with sufficiently large variance because we do not have any prior information. Since the parameters are assumed to be independent with each other, we only need to draw the diagonal elements of Σ. In this context, the prior on each diagonal element is specified as inverted gamma (IG) distribution with one degree of freedom and scale 1. Consequently, household heterogeneity from both explanatory variables and unobserved factors in Γ can be included. Based on these priors, the joint posterior for $\Gamma_i \forall i$, $\boldsymbol{b}$ and $\sum$ is

$$\Lambda(\Gamma_i \forall i, \boldsymbol{b}, \Sigma | y_{ij}, e_{ijk}) \propto \prod_i (L_i(y_{ij}, e_{ijk} | \Gamma_i) f(\Gamma_i | \boldsymbol{b}, \Sigma) IW(\Sigma | K, KI)). \tag{7.16}$$

Gibbs sampling is used to facilitate the obtaining of draws from this posterior. Draws of each parameter are taken, conditional on the previous draw of other parameters: (1) Take a draw of mean vector $\boldsymbol{b}$ conditional on values of $\sum$ and $\Gamma_i \forall i$; (2) Take a draw of variance matrix $\sum$ conditional on values of $\boldsymbol{b}$ and $\Gamma_i \forall i$; (3) Take a draw of $\Gamma_i \forall i$ conditional on values of $\boldsymbol{b}$ and $\sum$. The calculation for the first two steps is extremely fast, while drawing $\Gamma_i \forall i$ is the only computationally intensive part. The Metropolis-Hasting (M-H) algorithm is used to help take draws for Γ_i (See Chib and Greenberg, 1995, for a general explanation of the M-H algorithm). Movement to convergence in the M-H algorithm for each household and in the whole Gibbs sampling is achieved simultaneously (Train, 2003). The detail process of MCMC is given in Appendix A.

7.3 Data

In addition to the information directly collected from the quasi panel survey, it is also expected that urban forms and functions surrounding the residential district under study (hereafter, named as residential environment) influence households' residential choice. Under the rapid urban development in Beijing, when people make a decision on where to move/live, not only the residential environment observed at the time when decisions were made, but also that in the future defined at the time of decisions might affect households' decisions on their residential locations. Especially, in cities like Beijing, residential environment in future might be more influential than that at present. Unfortunately, it is not an easy task to collect the relevant information in the past, especially considering that respondents have different residential history. Recognizing such difficulties, in this case study, we extracted 530 households who experienced residential re-location in the last ten years. In order to describe the residential location choice behavior, we assume that the current residential environment information can be known by households when they decided to move or not in the past. This is because the future land use plan in Beijing is usually clearly shown in the Beijing's Ten-Year Programme profiles and needless to say, real estate developers also explain such information clearly to their customers. Consequently, a series of residential environment (*RE*) attributes at present, which are not obtained from the survey but from the Beijing map database, are chosen to be explanatory variables in the residential location choice model, including: the numbers of the shopping malls, supermarkets, top-ranking hospitals, top ranking schools (involving primary school and high school), recreational facilities, restaurants, parks, bus lines and train lines. Note that the number of bus lines and train lines signifies how many bus/train lines serve this residential area, which is not merely the amount of bus/train lines going through the area, but also there must be at least one station for that line inside the area. When collecting these *RE* attributes, first the area with 1.2 km radius around the survey residential district is defined as a residential neighborhood, and then the *RE* attributes are measured based on the neighborhoods. In addition to the *RE* variables, the socio-demographics at the movement time are used in the residential location choice equation (considering the socio-demographics at the movement time (e.g., income level, household size, employment, etc.) are relatively easy to recall, therefore the reliability of the data is thought to be convincible), while the current socio-demographics are included in the household energy consumption behavior model.

Based on the urbanization degree and the access to train station (including MRT and LRT), the 10 residential neighborhoods are grouped into 6 clusters: CBD area with train station, CBD area without train station, urban area with train station, urban area without train station, suburban area with train station, and suburban area without train station. These 6 clusters are regarded as the alternatives in the choice set of the residential choice model, and it is worth mentioning that this choice set is exclusive and exhaustive.

Table 7- 1 Statistical relation between energy consumption and residential neighborhoods

	Pearson Chi-Square	Sig. (2-sided)
Total household energy and residential neighborhoods	41.420	.003
Residential energy and residential neighborhoods	32.330	.040
Transport energy and residential neighborhoods	40.997	.023
Car number and residential neighborhoods	24.579	.006

Here, the Chi-square test between household energy consumption and residential location is first carried out (see Table 7-1). Significant difference of the household energy consumption among varied residential neighborhoods is found not only for total household energy consumption but also for residential energy as well as out-of-home gasoline consumption. From the statistical viewpoint, the necessity of integrated analysis for residential choice and household energy consumption behavior is supported.

Table 7- 2 Summary statistics of household end-use ownership and expenditure

End use type	Ownership rate (%)	Average ownership	Household annual operating cost [a] (RMB)	Household energy consumption [a] (GJ)
Fridge	96.10%	1.01 (0.29)	201.29(192.26)	1.48(1.42)
Fan	77.50%	1.11 (0.84)	31.11(73.42)	0.23(0.54)
AC	93.00%	1.45 (0.94)	405.98(437)	2.99(3.22)
Electric stove	15.70%	0.26 (0.71)	716.97(957.15)	5.29(7.06)
Electric shower	49.70%	0.52 (0.52)	254.21(321.23)	1.87(2.37)
Gas shower	44.20%	0.46 (0.50)	886.77(1392.87)	19.45(30.55)
Clothes washer	94.70%	0.96 (0.28)	50.72(85.38)	0.37(0.63)
TV	95.50%	1.33 (0.62)	290.15(234.23)	2.14(1.73)
PC	86.70%	1.20 (0.76)	284.44(383.02)	2.1(2.82)
Microwave oven	70.10%	0.69 (0.48)	21.44(37.19)	0.16(0.27)
Car	38.10%	0.40 (0.57)	6915.46(8197.09)	35.03(41.53)

Note: the number in the parenthesis is the standard deviation.
[a] : The operating cost and energy consumption are the values only for the end-use owners.

Table 7-2 provides descriptive details of end-use ownership, total household annual expenditure (i.e., the product of the energy price, the efficiency of the end use and its usage) as well as energy consumption (i.e., the product of the conversion factor, the efficiency of the end use and its usage). Note that if there are multiple pieces for some end uses in a household, the expenditure and energy consumption of each type is calculated by summing up the quantity of all pieces for each end use. The second and third columns indicate the ownership for each type of end use, the fourth and fifth columns indicate the average annual energy expenditure and consumption caused by each type of end use, respectively. It can be seen that the penetration rates of electric stove, gas shower and car are the lowest, but their operating cost and energy consumption are much higher than those of other end uses. The cooling and recreational end uses (i.e., AC, TV, and PC) belong to the second energy intensive group which has a high ownership rate and also not low energy consumption. In spite of the different conversion factors from expenditure to energy for electricity, gas and gasoline end uses, the energy consumption and the monetary expenditure are reflecting the same trend of end uses' utilization, furthermore, energy consumption is always seem to be an accompanying product of monetary expenditure. Therefore, it is feasible to measure the energy consumption by monetary expenditure.

7.4 Model Estimation Results

Several types of variables are introduced in the integrated model based on a preliminary analysis, including: (1) residential environment attributes in the current situation (living in CBD or suburban area (dummy variable), numbers of shopping malls, supermarkets, recreational facilities, restaurants, parks, bus lines, and train lines within the neighborhood); (2) household attributes at the movement time (annual household income, household size, presence of children and senior people, number of household members in employment, the highest education level in household); (3) housing attributes at the movement time (residential duration, housing area, and whether the house is rent or not).

For the model estimation in our application, each of the above coefficients is given an independent normal distribution with mean and standard deviation that are estimated. The estimation program is coded using the Gauss language[3]. A total of 1,200,000 iterations were done for the Bayesian inference, among which 1,000,000 iterations for "burn-in" (i.e., movement to convergence) followed by 200,000 iterations after convergence, of which the draws in every 100*th* iteration were retained to conduct the inference. Specifically, the average of these 2000 draws per iteration is the simulated mean of the posterior, which is the

[3] http://elsa.berkeley.edu/~train/software.html.

estimate of the parameters from a classical speaking. The standard deviation of the draws is the simulated standard deviation of the posterior which refers to the standard error of the estimate. The Geweke diagnostic (Geweke, 1992), trace plot and autocorrelation plot for each parameter are checked and the estimated results are identified to achieve the convergence (see Appendix B).

Model estimation results are shown in Tables 7-3 and 7-4, where the estimated mean and variance (or standard deviation) are given for each variable. Concretely speaking, a significant mean reflects that the fixed effect of the factor in the whole population is obviously different from zero, while a significant variance (or standard deviation) indicates that the factor under study has an apparent random effect among the population (that is, the hypothesis of no variance in the population can be rejected). By comparing the standard deviation with its mean, the population heterogeneity can be captured.

7.4.1 Overall Model Performance

Focusing on the overall performance of the proposed model structure, first, the Rho-square of 0.1246 indicates an acceptable validity; second, the estimated means and variances of ω_{ijk} are shown to be statistically significant, supporting the integration of household energy consumption behavior and residential choice behavior; third, focusing on mixed model structure, the means and variances of unobserved component specific to both household and end uses, η_{ijk}, is also statistically meaningful, which signifies the rationality of extracting the above two separate unobserved components from the error term of household energy consumption utility; finally, concerning the mean and variance of each explanatory variable, significant results can be found as well, implying the feasibility of including the observed household and end-use heterogeneity in the model system.

7.4.2 Results of Residential Location Choice Sub-model

Table 7- 3 Estimation results of residential location choice sub-model

Variables	Mean		Variance	
Number of shopping malls in the neighborhood	-16.762	*	6.828	
Interacted with household size	-2.669	*	0.272	*
Number of supermarkets in the neighborhood	-2.185	*	0.303	*
Interacted with household size	2.264	*	0.504	*
Number of top-ranking hospitals in the neighborhood	9.355	*	3.803	
Interacted with presence of senior people	4.627	*	12.716	
Number of top ranking schools in the neighborhood	-5.255	+	10.311	*
Interacted with presence of children (age ≤ 16) in household	6.443	*	0.666	*
Number of recreational facilities in the neighborhood	-1.539	*	1.115	*
Interacted with household size	0.134		7.388	*
Number of restaurants in the neighborhood	0.673	*	0.077	*
Interacted with household annual income	3.107	*	0.18	*
Interacted with household size	3.739	*	20.16	*
Number of parks in the neighborhood	-4.108	*	6.457	*
Interacted with presence of senior people	-3.694	*	11.269	*
Number of bus lines in the neighborhood	-0.100		0.554	
Interacted with household annual income	-7.876	*	3.606	*
Interacted with number of workers	2.459	*	3.683	*
Unobserved household-specific attributes (ν_i)	-7.098	*	0.857	*

Note: * significant at the 5% level; +significant at the 10% level.

In the residential location choice sub-model, the choice set is comprised of six residential neighborhoods mentioned in section 7.3. Table 7-3 lists the estimation results, where not only the pure effect of *RE* attributes on residential location choice, but also the heterogeneous sensitivity on *RE* attributes caused by household observed social-demographics is incorporated.

Regarding the effect of residential environment attributes, it is found that the number of restaurants and top-ranking hospitals have a positive fixed effect on the residential location choice, indicating that households prefer to settle down in areas with better medical and dining conditions. On the other hand, the number of shopping malls, supermarkets, top-ranking schools, recreational facilities, and parks show a significant and negative average influence in the population. This might be because the neighborhoods in Beijing with many these facilities are always accompanied by a higher housing price. The uncoordinated ratio between the housing price and Beijing citizens' income made households less inclined to the neighborhoods mentioned above. Moreover, the hindered housing market because of the transition economies in China might be another incentive (see Zheng et al., 2006 for more details about the housing market in China). Therefore, the negative signs of these variables derived from the model are consistent with China's situation. But according to the random effect (i.e., variance), considerable population heterogeneity in the sensitivity to the number of top-ranking schools, recreational facilities and parks exists in residential location choice. On the contrary, the variances of the number of supermarkets and restaurants are smaller, meaning a less volatile sensitivity to these two variables in the population.

Households with different socio-demographics sometimes present diverse recognition on *RE* attributes which results in the different choice of residential location. This can be explained as household heterogeneity caused by observed traits, like income, household size, etc. It is revealed that households with more members are less likely to choose to live in neighborhoods with many shopping malls but more likely to reside in the place with more supermarkets. This implies that basic life related infrastructures are more attractable than recreation-related infrastructures for large families. Households with elder people prefer to locate in the neighborhood with top-ranking hospitals, similarly households with children (younger than 16 years old) are more preferable to neighborhoods with top-ranking schools, and these are understandable. Higher income households incline to select the neighborhood having more restaurants but fewer bus lines. The more workers in a household, the more possible the household will choose a neighborhood with good bus service. Whereas, concerning the heterogeneity caused by the above variables, it is found that the number of parks interacted with senior people, the number of restaurants interacted with household size, number of bus lines interacted with worker show greatly volatile effects in the population.

Due to the limitation of data, many *RE* attributes are omitted from the model, thus, a random unobserved component v_i used to supplement those omitted attributes together with other household-specific unobserved factors is added here and it is found that v_i plays a significant role in explaining the residential location choice behavior. This also suggests the existence of the unobserved heterogeneity among households. Besides, through the small variance compared with the mean value, it can be said that the heterogeneity caused by unobserved factors is relative stable across different households.

The estimation results verify that some of the residential environment attributes themselves do not generally influence the whole population's residential location choices (e.g., number of bus lines), but specifically affect certain groups' decisions (e.g., high-income households, households with many workers, etc.). Due to these particular attributes, households may show heterogeneous sensitivity to *RE* attributes. If such kind of heterogeneity caused by both observed social-demographics and unobserved factors is not accounted for in the modeling process, it might be wrongly inferred that the *RE* attributes have larger effects on the residential location choice.

7.4.3 Results of Household Energy Consumption Sub-model

In the household energy consumption sub-model, 11 expenditure categories (expenditures of refrigerator, fan, air conditioner (AC), electric stove, electric shower, gas shower, clothes washer, TV, PC, microwave over, and car) and savings are set as the alternatives in the MDCEV model. Here, savings, indicating the remaining income after deducting the energy expenditures, serves as the outside goods and also the reference alternative whose parameters in the baseline utility are set at zero. In the model, the ownership refers to whether a household owns an end use under question and the usage relates to how much the household uses in terms of monetary expenditures. For facilitation of parameter estimation, the model structure with satiation parameter a_k being zero and translation parameter γ_k being unity (a combination of a-profile and γ-profile) is adopted, which is also one member of the MDCEV family. Table 4 lists the estimated mean and standard deviation of all the variables including residential environment attributes, household attributes, residential attributes, heterogeneity and multiple self-selection effects.

7.4.3.1 Influence of Explanatory Factors

It is seen that, not only the *RE* attributes, but also other three groups of attributes play a significant role in explaining the energy consumption behavior for different end uses. Bearing in mind the policy focus of this study (i.e., the land-use policy effect on household energy consumption behavior), we merely discuss the parameters associated with residential environment attributes here.

Whether living in CBD and suburban or not: Note that the urban residents are set as the reference for households living in CBD and suburban area in the model. Households residing in CBD area spend less money on almost all the domestic end uses than urban residents, but more money on car. This might be because that households living in high density neighborhoods (here, CBD) have a better access to outside the residential area and consequently, the time staying at home decreases and the needs of owning/using domestic end uses decrease as well. While, for the cooling and heating end uses, there are great deviations for the energy consumption behavior in the population. In spite of the positive average effect of whether living in CBD area on the ownership and usage of a car, a considerable population heterogeneity is found (with mean 3.882, standard deviation 4.628), implying that part of households in CBD area are more likely to own and use cars which may be due to the busy work, while others choose to use less car or not use a car due to the good accessibility to public transit. In contrast, suburban households spend more money on AC, electric stove, TV, PC, and car, but less money on fan, electric shower, clothes washer, and microwave oven. Generally, because of amenity inconvenience and mobility problems, households living in low density neighborhoods (here, suburban areas), on the one hand are more likely to spend their leisure time at home accompanied by the increasing demand for domestic end uses with leisure functions such as AC, TV, and PC; on the other hand choose to commute by car and go far away from home to the urban area to enjoy themselves in weekends. In this line, the estimated results are understandable. In addition, the diversity of energy consumption behaviors among suburban population is not noticeable for most end uses.

Number of shopping malls: The effects of the number of shopping malls on household energy consumption are found positive for gas shower, clothes washer, microwave oven, and car, while negative for refrigerator, fan, AC, TV, and PC. The reason might be that households living in the area with more shopping malls incline to spend more time on outside shopping or other recreation activities instead of staying at home, and as a result, the in-home recreation and cooking time is reduced concomitant with the less ownership and usage for refrigerator, fan, AC, TV and PC, but the use of gas shower, washer and time-saving microwave oven increases. Although this factor has a positive influence on car ownership and usage, a great variance exists among the population living in neighborhoods with shopping malls.

Number of supermarkets: The number of supermarkets in the neighborhood is revealed to greatly increase the in-home activity time. The evidence is that the energy consumed by refrigerator, fan, AC, and PC in this group of households is more than other households. But the electric shower and clothes washer are not so popular to them. Besides, sizable population heterogeneity on the ownership and usage of fan and clothes washer are found.

Number of recreational facilities: The more recreational facilities in the neighborhood, the lower probability for households to own and spent money on cooling, in-home recreational and travel end uses (i.e., fan, AC, TV, PC, and car). These households are more possible to spend their leisure time outside but just stay nearby instead of going far away. On the contrary, due to a lot of outside trips, the use of electric shower increases. The consumption deviations for these end uses are not very large except for PC.

Number of restaurants: Number of restaurants has a negative influence on fan, electric stove, clothes washer, TV, and microwave oven, but a positive influence on ownership and usage of AC, PC and car. People might choose to reside in a neighborhood with better dining conditions because of their busy work and limited time for cooking, and what's more, such kind of households are more likely to own and use a car to save commuting time and use PC to continue working at home. Here, the population heterogeneity on the energy consumption behavior of AC is notable.

Number of parks: Number of parks increases the probability to own and use refrigerator, shower, and car, but opposite for AC, electric stove, clothes washer, TV and microwave oven. If households live in the area with a park nearby, it is more likely for them to enjoy the natural landscape, and some fitness activities like doing morning exercise and taking a walk after dinner in the park might become more possible in this group of households during their leisure time, which makes their lifestyle healthier. In this way, the in-home recreation time will be reduced accompanied by less expenditure on AC, electric stove and TV, but the maintenance time is tend to increase along with more cost on refrigerator and shower, which may be due to their regular lifestyle. The energy consumption of car is shown more in the households living near a park but with a large variance in the population.

Number of bus lines and train lines: These two variables can index the accessibility to the rest of city. It is easy to find a significant complementary effect between the bus and car but a synergetic effect between train and car. Households locating in the area with ample bus lines are more likely to commute by bus, thus the needs for the ownership and usage of car retrench. On the contrary, households residing in the neighborhood with train stations have a higher probability to own a car and spend more money on the car. This phenomenon is extremely different with developed countries. However, due to the truth that the train lines in Beijing now are always go through the regions with some important roles like economic center, education center, official center and recreation center, it is acceptable that households living in such kind of areas are more likely to own and use cars instead of train even there is one; another explanation is that though they use the train to commute, but during the vacations, they might always drive far away to outer city area to enjoy themselves, which increases the gasoline consumption a lot. In addition, the considerable variance signifies an evident diversity of the train effect on car ownership and usage among households, that is to say, in such area a portion of households prefer intensive car usage, while the other portion are inclined to train. With respect to the residential sector, end uses (i.e., fan, gas shower, TV, and microwave oven) for cooling, maintenance, and recreation show positive relation with the number of bus lines, while end use for online recreation or working (i.e., PC) together with the clothes washer shows a negative relation. The reason might be that: after the tired and long trip in the bus, households have no interest in the sumptuous dinner and concentrative recreational activities, and the limited time is just allocated to satisfy the basic maintenance or just watch TV for a while. Similarly, the number of train lines also shows a positive effect on the ownership and usage of maintenance end uses (refrigerator and washing machine). Besides, an inverse effect between TV and PC is revealed, as with the case of bus line. Concerning the population heterogeneity on the energy consumption behavior of domestic end uses caused by number of bus and train lines, it is not as great as the out-of-home end use.

7.4.3.2 Heterogeneity and Multiple Self-selection Effects

Heterogeneity from both observed variables and unobserved factors η_{ijk} are represented in the energy consumption behavior sub-model by assuming these parameters following a normal distribution in the estimation procedure. Heterogeneity is used to describe the variance among the population. After including heterogeneity in the model, it may be desirable to have an estimate of the parameters of interest for each individual in a cross-section, not just the average value in the population (Barsky et al., 1997). In contrast, the self-selection effect discussing in this paper is just derived from unobserved factors corresponding to ω_{ijk} term. Self-selection effect arises due to the non-causal association between residential choice and household energy consumption behavior caused by some intervening unobserved factors for each observation. The estimation results of heterogeneity and multiple self-selection effects are specifically explained as follows.

Heterogeneity caused by observed factors: From the mean of explanatory variables including *RE* attributes, household social-demographics and housing characteristics, it can be seen that majority of variables are significant which indicate meaningful average effects on the whole population from them. Meanwhile, plenty of these variables have statistically significant variances and moreover some of them are considerable, which provides convincing evidence for the real existence of the population heterogeneity caused by observed factors. Jointly looking at the results of residential location choice model and household energy consumption model, the self-selection effects resulting from the observed factors can also be identified. Taking into account the main purpose of this study (i.e., evaluating self-selection effect caused by unobserved factors), we do not give further explanation here.

Heterogeneity caused by unobserved factors: In the integrated model, η_{ijk} reflects the unobserved heterogeneity just relating to the household energy consumption behavior. Concerning the mean and standard deviation of unobserved factor η_{ijk}, significant average effects and variances are found for the ownership and usage of maintenance, cooling, space heating, water heating, recreational, and transportation end uses (i.e., refrigerator, AC, electric stove, electric shower, TV, and car). This type of heterogeneity only referring to household energy consumption behavior always associates to the unobserved end-use specific preference or sensitivity. For example, for refrigerator and TV, the efficiency might be varied due to household inclination for the brand, size or other attributes, which converges to a larger difference day by day; for AC, electric stove, and electric shower, people may have different sensitivity to the temperature which makes the ownership and usage of them differ; for car, due to the diversity of preference to car engine, driving or others, households are likely to self select their preferable car type and use style. Noticeable quantities of the standard deviations indicate significant variance on the energy consumption behavior among population caused by unobserved factors.

Multiple self-selection effects caused by unobserved factors: ω_{ijk} (k=1,2,…,K) depict the unobserved factors associated with both residential choice and household energy consumption behavior, which are regarded as the cause of multiple self-selection effects. Based on the mean of ω_{ijk}, it is found that there is a significant unobserved component simultaneously affect the residential location choice and the ownership and usage of all 11 end uses, indicating that the long-term residential location choice behavior and medium/short term household energy consumption behavior do correlate with each other, in addition, the self-selection effects differ across end uses, verifying the necessity for incorporating multiple self-selection effects into the integrated model. In this sense, the spurious effect of *RE* attributes does occur when explaining household energy consumption behavior due to the existence of multiple self-selection effects. Based on several trails, the estimation result with positive signs in the term $\pm\omega_{ijk}$ in equation (7.11) for all end uses gives the best model fit which indicates that the unobserved factors have a positive influence on the residential choice and meanwhile lead to a high preference to the ownership and usage of the *k*th end use. In spite of the plus signs for $\pm\omega_{ijk}$, the ω_{ijk} itself can be either positive or negative. Specifically, for domestic end uses (i.e., refrigerator, AC, electric stove, clothes machine, TV, and PC), the positive self-selection effect indicates that some unobserved factors make households self select themselves to a special neighborhood and be more likely to own and spend more money on these end uses. While for fan, gas shower, microwave oven, and car, the negative sign represents that certain unobserved factors make households select themselves to a special neighborhood and be less likely to own and spend less money on car. With regards to the standard deviations of ω_{ijk}, it is confirmed that the multiple self-selection effects on the residential choice and energy consumption behavior of refrigerator, AC, electric shower, clothes washer, TV, PC, and car significantly vary with households. Furthermore, such kind of heterogeneous self-selection effects are more obvious on the ownership and usage of electric shower and car. This also supports the rationality of accommodating multiple self-selection effects into the integrated model instead of using a common one for all end uses. The self-selection effect might come from some social factors like life-style and life stage (e.g., Lutzenhiser, 1993; Weber, 2000), cultural factors (e.g., Abrahamse et al., 2005; Lutzenhiser, 1992;), motivational factors (e.g., Seligman et al., 1979; Spangenberg, 2002) or others. Although based on the model results, we cannot clarify what the self-selection effect exactly is and how to change it, but after controlling the self-selection effect in the model, the relatively true effect from residential environment variables can be captured. Consequently, less biased evaluation of land-use policy on household energy consumption can be derived.

7.4.4 Variance Proportion

To further clarify the effects of the explanatory variables, next, we calculate the proportion of variance explained by each explanatory variable in the total variance of the baseline preference for both ownership and usage as follows.

$$
\begin{aligned}
\mathrm{var}[\ln(\varphi_{ijk})] &= \mathrm{var}(\mu_k' s_{ij}) + \mathrm{var}(\Delta_k' x_i) + \mathrm{var}(\eta_{ijk}) + \mathrm{var}(\pm\omega_{ijk}) + \mathrm{var}(\tau_{ijk}) \\
&= \mathrm{var}(\mu_k' s_{ij}) + \mathrm{var}(\Delta_k' x_i) + (\sigma_{\eta k}^2 + \sigma_{\omega k}^2 + \frac{\pi^2}{6}).
\end{aligned}
\tag{7.17}
$$

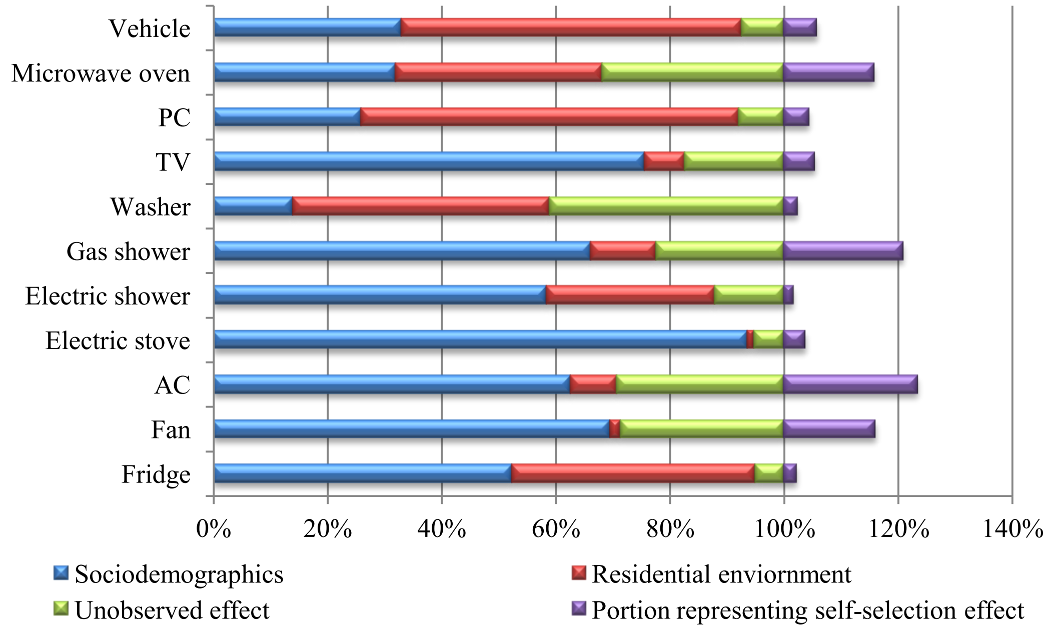

Figure 7- 1 The variance portion for end uses

To identify how much various factors influence the household energy consumption behavior, here, variance proportion explained by each factor is calculated. For the ease of interpretation, instead of listing the variance proportions for all factors, the total effects from three groups of variables: household attributes, residential environment attributes, and unobserved factors (collective impact of η_{ijk} and ω_{ijk}), together with the sole effect of ω_{ijk} which cause the self-selection effect, are presented in Figure 7-1. It can be seen that different attributes have their own leading domain. For the energy consumption behavior of refrigerator, fan, AC, electric stove, electric shower, gas shower, and TV, household and individual attributes dominate. And for clothes washer, PC, microwave oven, and car, residential environment attributes play a more important role in explaining the ownership and usage behavior. The variance proportion of unobserved factors varies a lot with end uses, ranging in 5% ~ 41%, among which the portion causing self-selection effects change from 2% to 24%, suggesting a significant existence which cannot be neglected when modeling the interaction between residential choice and household energy consumption behavior.

7.4.5 Sensitivity Analysis of Policy Interventions

The final objective of the household energy consumption sub-model is to be able to approximately evaluate the policy influence on the energy demand. A rather straight forward manner for describing the procedure is as follows:

$$Max \quad \tilde{u}_{ij}^{E} = \exp(\tau_{ij1}) \ln e_{ij1} + \sum_{k=2}^{K} \exp(\mu_k^{'} s_{ij} + \Delta_k^{'} x_i \pm \omega_{ijk} + \eta_{ijk} + \tau_{ijk}) \ln(e_{ijk} + 1) \quad (7.18)$$

subject to

$$\sum_{k=1}^{K} e_{ijk} = E_{ij}, \quad e_{ijk} \geq 0 \quad \text{for all } k \ (k = 1,2,...,K)$$

Note that household i allocates the budget to various end uses based on maximizing $\tilde{u}_{ij}^{E}$ subject to the money budget. All the aforementioned parameters are treated as known and put them into equation (7.14) directly, whereas the expenditure on each end use is unknown and waiting for being predicted. Consequently, the predicted energy expenditure on each end use (i.e., e_{ijk}) for household i would be obtained by solving the above constrained optimization problem. In this paper, software R is used to achieve the purpose. Based on the new outcomes, the policy impact can be predicted.

To examine the sensitivities of household energy consumption to policy interventions, seven policy scenarios are designed by changing the residential environment attributes, including: increase the number of shopping malls by 1; increase the number of supermarkets by 1; increase the number of recreational facilities by 10%; increase the number of restaurants by 10%; increase the number of parks by 1; increase the number of bus lines by 1; and increase the number of train lines by 1.

Sensitivity analysis is conducted by calculating the aggregate change between the predicted household energy consumption in each scenario and the consumption in the reference scenario (the scenario without any change of the variables). Table 7-5 lists both the percentage change and the exact MJ change. It can be seen that: (1) Compared with the current situation, an increase of shopping malls in the neighborhood leads to a decrease of energy consumption for fan (1.23% less), electric stove (0.12% less), TV (0.08% less), and car (0.01% less), but these savings are off-set by the incremental use of other end uses (especially the gas shower), and finally total energy use is 5.76 MJ more than before. (2) An increase of supermarket in the neighborhood can reduce the energy use of electric shower (0.12% less), TV (0.07% less), and car (-0.10%), but this effect is also compensated especially by AC and microwave oven. In the end, 13.43 MJ is increased. (3) After increasing the number of surrounding amenity facilities by 10%, the energy consumption by AC and TV declines considerably (1.07% less and 1.28% less, respectively), and finally 43MJ energy can be saved. (4) Although the energy consumed by fan, clothes washer, TV and microwave oven is a little bit decreased if the number of restaurants in the neighborhood increases by 10 percent, the car usage is 0.13% (i.e., 23.34MJ) more than before which completely cancel out the savings, and totally extra 28.4MJ energy will be consumed. (5) The energy consumption change by increasing a park in the neighborhood will increase about 9 MJ due to the main contribution of gas shower. (6) The change of bus line number causes the greatest influence on household energy consumption, especially on out-of-home gasoline use, for which 3.18% (i.e., 600 MJ) of energy consumption on car are retrenched. In addition, the significant saving on PC (1.01% less) is found in this scenario. (7) Increasing a train line serving the residential area under study plays relatively small effect on car usage (less than 0.01% change). Nevertheless, due to the energy increase by domestic end uses, a total of 11.77 MJ are added.

As a whole, we found that changing some *RE* attributes (e.g., recreational facilities and bus lines) can significantly save the energy on one hand, and the change of *RE* attributes (e.g., supermarket and restaurant) can increase the energy consumption a lot on the other. In addition, the magnitude of the percentage changes of AC, gas shower, and PC indicate a relative inelasticity to changes in *RE* attributes, while opposite for fan, microwave oven, and car. Furthermore, the necessity of joint representation for the energy consumption behavior in both residential and transport sectors is emphasized because of the significant complementary effect between them. Specifically, if we just concern how energy consumed by car response to the change of *RE* attributes, it can be revealed that increasing the number of shopping malls, supermarkets, recreational facilities, and bus lines has a negative influence. However due to the complementary effect from other domestic end uses, finally, increasing the number of shopping malls and supermarkets not only do not reduce the energy consumption, but oppositely leads to an increment. In this sense, many previous studies which exclusively focus on the relationship between land-use and transport sector or land-use and residential sector might be not comprehensive enough.

7.5 Summary and Conclusion

This chapter presents the first instance of a comprehensive analysis of the correlation between residential location choice and household energy consumption behavior (referring to the ownership and usage of both domestic appliances and out-of-home cars) by explicitly considering multiple self-selection effects. In this study, household energy consumption behavior is indirectly described by using the relevant monetary expenditure. Three main conclusions are obtained in this study:

First, the empirical analysis confirmed the effectiveness of the integrated model to describe the residential location choice and household energy consumption behavior by simultaneously incorporating the one-way causal relationship and the non-causal association (i.e., self-selection effect) between them. This provides a strong support for the accurate pre-evaluation of the policy effects.

Second, the statistically significant residential environment attributes acting on the household energy consumption behavior indicate that land-use policy do play a great role in changing Beijing residents' energy consumption pattern. Therefore, besides the technological improvement and economic control tools, land-use policy can be regarded as another instrument to influence household energy consumption. While the significant unobserved factors associated with the self-selection effects suggest that residential environment attributes are not completely exogenous in household energy consumption behavior. In other words, the effect of land-use policy on household energy use would be incorrectly estimated due to the existence of self-selection effects. In addition, the self-selection effect is found to vary with end uses (ranging from 2% to 24%). This validates the necessity of considering end-use specific self-selection effect. The above finding calls the planners' attention to that when attempting to develop the land-use policy to save energy, besides the observed factors (e.g., *RE* attributes, social-demographics, housing attributes, etc.), the unobserved factors (e.g., the social factors, cultural factors, psychological factors, etc.) which might cause the self-selection phenomenon should be introduced to understand the energy consumption behavior as well. It is also implied that introducing "soft policy" is important to conserve household energy consumption in Beijing, such as the provision of information about energy-saving behavior and an evaluation platform for households to monitor their energy consumption and emissions (as OECD countries do[4]). Moreover, the soft policies focusing on electric fan, air conditioner, gas shower, microwave oven and car in Beijing should be given a priority because of the larger variance proportion of their factors associated with self-selection effect on the energy consumption.

After controlling for the self-selection effects, the land-use policy scenario analysis shows that by changing the number of recreational facilities and bus lines in the neighborhood, households' energy-saving behavior can be significantly promoted, while increasing the number of supermarkets and restaurants in the neighborhood will increase the energy consumption a lot. It is further found that the consumption change of AC, gas shower, and PC is relatively inelastic to changes of residential environment attributes, while opposite for fan, microwave oven, and car.

Finally, the need of joint representation for residential and transport energy consumption behavior is emphasized attributing to the significant complementary effect between these two parts which is shown in the policy scenarios. In other words, if only focus on residential or transport sector, a specious energy demand change responding to the policy would be derived which may actually lead a great increase of the total energy consumption. From this viewpoint, some package policies which could reduce the energy consumption in both of these two sectors can be developed, such as extending the Japanese "eco-point" scheme[5] to cover both domestic appliances and vehicles (see Yu et al. (2011) for more detail examples).

Following the main conclusions, there are several research issues that should be identified. In this study, the energy consumption is calculated based on the end-use efficiency

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4 http://www.consumerspower.org/home_energy/billestimator.php (Accessed on Nov. 10, 2011); http://hes.lbl.gov/consumer/ (Accessed on Nov. 10, 2011).

5 http://www.japanfs.org/en/mailmagazine/newsletter/pages/029766.html (Accessed on Feb. 2, 2012). The Japanese government is promoting the purchase of eco-friendly electric appliances through the legalized "eco-point" scheme, which allows consumers to spend the credits gained from buying one appliance on the other appliances. However, currently, such credits cannot be spent on the purchase and/or usage of vehicles.

and its usage which is reported by respondents. Reporting biases could occur at both the level of dependent variables and the level of explanatory variables in any type of questionnaire survey. It is also true in this study. Such reporting biases should be corrected by improving data collection methods and/or adopting more advanced modeling techniques. Some technologies, such as GIS, GPS, and ICT, could be used to reduce respondents' answering burden and consequently reduce reporting errors. Data fusion techniques might be helpful to correct reporting errors by combining different data sources, if available. Reporting biases could be accommodated in the modeling process (e.g., utilizing the concept of measurement equation in the structural equation models with latent variables, and discretizing the continuous variables). But all the above ideas are accompanied by the increased cost of data collection and model estimation tasks. For the self-selection effects, we simply use a random term to aggregately capture the unobserved factors which cause them, but indeed this integrated model can be extended to clarify where the self-selection effect exactly comes from (see Pinjari et al., 2009). Due to the sample size limitation, the more variables included in the model, the more unreliable the results are, and consequently, we did not develop such a complex model. Another shortcoming is that describing the interaction between long-term and short-term behaviors is very complicated because of numerous influential components, here self-selection effect is deemed to be a bridge connecting these choice dimensions together. From the behavior perspective, there are still many other aspects needed to be considered during the time evolution process, like the life stage change, inter-household decision mechanism change, social interaction, and so on.

Table 7- 4 Estimation results of household energy consumption behavior sub-model

	Fridge	Fan	AC	Electric stove	Electric shower	Gas shower	Clothes washer	TV	PC	Microwave oven	Car
Residential environment attributes											
CBD area (1 yes, 0 no)	2.211 *	-0.213 *	-0.471 *	-0.160 *	-0.474 *	-0.547 *	-3.037 *	-0.537 *	-1.846 *	-1.634 *	3.882 *
	0.761	0.310 *	0.458 *	0.297 *	0.249 *	0.045	1.660 *	0.210 *	0.409 *	0.472 *	4.628 *
Suburban area (1 yes, 0 no)	0.060	-0.360 *	0.440 *	0.028 *	-5.164 *	0.530	-1.767 *	2.343 *	0.846 *	-0.943 *	2.849 *
	0.746 *	0.318 *	0.173 *	0.071 *	3.846 *	2.286	0.534 *	0.506 *	0.363 *	0.699 *	0.576 *
Number of shopping malls	-5.551 *	-0.244 *	-0.038 *	-0.059	0.561	1.158 *	4.898 *	-0.964 *	-5.447 *	2.059 *	1.255 *
	0.894 *	0.245 *	0.077 *	0.892 *	0.883	0.678 *	2.196 *	0.415 *	2.055 *	0.729 *	1.252 *
Number of supermarkets	2.780 *	0.027 *	1.436 *	0.673	-10.312 *	-2.568 *	-0.446 *	-0.468 *	3.469 *	0.035	-2.473 *
	1.266 *	0.063 *	0.470 *	1.772 *	1.523 *	3.215	0.658 *	0.427	0.609 *	0.392 *	0.636
ln (number of recreational facilities)	-1.427 *	-2.704 *	-4.606 *	0.481 *	4.637 *	-1.503 *	0.918 *	-1.029 *	-0.173 *	-0.124	-4.543 *
	0.962	0.414 *	1.153 *	0.473 *	0.675 *	0.925 *	1.085	0.373 *	0.300 *	0.484 *	0.963 *
ln (Number of restaurants)	0.147	-1.511 *	1.958 *	-1.479 *	2.561 *	0.240	-1.924 *	-0.392 *	1.834 *	-0.869 *	6.599 *
	0.541 *	0.587 *	2.191 *	0.740 *	1.424	2.254	1.830 *	0.253 *	0.342 *	0.492 *	0.455 *
Number of parks	2.151 *	0.216	-1.331 *	-1.528 *	1.275 *	1.807 *	-0.500 *	-0.818 *	0.009	-5.017 *	3.002 *
	0.640 *	2.291 *	0.586 *	0.523 *	0.636 *	1.190 *	0.265 *	0.281 *	0.405 *	0.643 *	3.521 *
Number of bus lines	0.691	1.988 *	-0.012	2.450 *	1.296 *	0.301 *	-0.170 *	1.991 *	-2.021 *	3.956 *	-26.082 *
	0.541 *	0.613 *	0.479 *	0.563	0.458	0.550 *	0.285 *	1.451 *	0.379 *	0.469 *	7.163 *
Number of train lines	8.874 *	-0.646 *	0.097	2.518 *	0.922 *	-0.987 *	1.331 *	-0.916 *	2.449 *	0.142	3.213 *
	0.851 *	0.348 *	0.709 *	2.770	0.586	0.770 *	0.378 *	0.333 *	1.458 *	0.534	4.763 *
Household socio-demographics and housing characteristics											
Household annual income (1:lowest – 6 (highest))	-8.158 *	-3.307 *	1.884 *	1.461	-3.171 *	0.785 *	-0.965 *	2.297 *	-4.284 *	1.035 *	0.409 *
	1.124	1.336	0.693 *	2.476 *	0.459 *	0.528 *	0.382 *	0.526 *	0.541 *	1.059 *	0.182 *
Household size	-0.827 *	2.179 *	0.888 *	1.296 *	3.664 *	0.115 *	0.311 *	4.606 *	-0.499 *	-0.274 *	4.250 *
	0.786	0.645 *	0.346 *	1.375 *	1.663 *	0.055 *	0.155 *	0.414 *	0.597	0.063 *	1.796 *
Presence of children (age≤ 16) (1 yes, 0 no)	2.102 *	2.376 *	-0.434 *	24.362 *	-1.175 *	-0.474 *	1.263 *	-0.056	-0.042 *	-1.610 *	-0.608 *
	0.468 *	0.311 *	0.521 *	3.865 *	2.542 *	0.483 *	0.307 *	0.255 *	0.071 *	0.925	0.756 *
Presence of senior people (1 yes, 0 no)	0.353 *	2.818 *	-4.237 *	-2.728 *	-1.935 *	-0.957 *	-0.044	-0.013	1.558 *	1.621 *	4.133 *
	0.341 *	0.635 *	0.457 *	1.044	0.645 *	0.660 *	0.226 *	0.063 *	0.840 *	0.936 *	0.810 *
Number of workers	-0.362 *	-4.818 *	0.127	1.962 *	-0.459 *	-0.034 *	-1.368 *	1.043 *	1.569 *	0.726 *	8.487 *
	0.369 *	0.539 *	0.329 *	0.552 *	0.429 *	0.134 *	0.605 *	0.981 *	0.679 *	0.362 *	0.896 *
The highest education level (1≥bachelor, 0 other)	0.276	1.780 *	-2.664 *	-0.910 *	2.216 *	0.235 *	-0.007	0.511 *	-0.532 *	3.165 *	-2.227 *
	0.540 *	0.617 *	1.104 *	0.769	0.606	1.108 *	0.063 *	0.443 *	0.632 *	1.479 *	1.034 *

Note: There are two values associated with each parameter: the upper one refers to the estimated mean and the lower one to standard deviation; * significant at the 5% level.

Table 7-4 Estimation results of household energy consumption behavior sub-model (continued)

	Fridge	Fan	AC	Electric stove	Electric shower	Gas shower	Clothes washer	TV	PC	Microwave oven	Car
Residential duration	1.415 *	0.908 *	1.677 *	4.999 *	-4.330 *	-0.060	-1.783 *	1.977 *	0.461 *	-1.842 *	-0.389 *
(years)	0.457 *	0.307 *	0.476 *	2.528	0.569 *	0.466 *	1.387 *	0.556 *	0.318 *	0.451 *	1.560 *
Housing area (m^2)	0.181 *	0.439 *	1.135 *	4.706 *	-3.864 *	-5.223 *	1.271 *	-0.667 *	-0.133 *	0.054	0.028
	0.268 *	0.358 *	0.440 *	0.391 *	2.802	3.013 *	1.508 *	0.871 *	0.326 *	0.295 *	0.182 *
Whether the house is rent	-1.085 *	4.450 *	-1.254 *	-1.965	2.774 *	-0.362 *	-0.866 *	0.438 *	-0.174 *	-0.006	2.038 *
(1 yes, 0 no)	0.355 *	0.485 *	0.362 *	1.595 *	1.324	0.462 *	0.307 *	0.315 *	0.281 *	0.089 *	0.638
Unobserved attributes											
Unobserved η_{ijk}	4.603 *	-2.572 *	-1.626 *	4.509 *	-11.229 *	0.028	-5.053	-2.169 *	0.410	0.097	-10.847 *
	2.929 *	3.310	1.408 *	2.045 *	6.231 *	0.510 *	2.572	3.027 *	2.339 *	3.675 *	1.774 *
Unobserved ω_{ijk}	6.663 *	-30.112 *	39.050 *	21.316 *	2.840 *	-2.637 *	8.764 *	8.189 *	5.608 *	-5.603 *	-9.826 *
	2.844 *	3.968	3.798 *	3.732	2.461 *	5.098	2.333 *	2.218 *	1.984 *	3.886	4.023 *

Initial log-likelihood	-41340	Converged log-likelihood	-36188
Rho-squared	0.1246	Adjusted Rho-squared	0.1188
Sample size	530		

Table 7- 5 Simulation results for the assumed policy scenarios defined by changing the residential environment attributes

	Aggregate change in the household energy consumption of each end use (number in parentheses is the exact MJ change)							
	Shopping mall increase by 1	Supermarket increase by 1	Recreational facilities increase by 10%	Restaurant increase by 10%	Park increase by 1	Bus line increase by 1	Train line increase by 1	Total (percentage)
Fridge	0.01% (0.21)	0.02%(0.34)	-0.16% (-2.27)	0.01% (0.12)	0.01% (0.09)	1.97% (27.62)	0.01% (0.19)	1.87%
Fan	-1.23% (-2.07)	2.42% (4.06)	1.26% (2.12)	-1.68% (-2.82)	1.37% (2.31)	2.28% (3.83)	1.22% (2.05)	5.64%
AC	0.05% (1.26)	0.38% (9.52)	-1.07% (-26.94)	0.06% (1.59)	-0.05% (-1.26)	-0.48% (-12.03)	0.05% (1.26)	-1.05%
Electric stove	-0.12% (-1.05)	0.07% (0.57)	1.47% (12.38)	0.03% (0.23)	0.01% (0.11)	2.10% (17.69)	0.04% (0.37)	3.59%
Electric shower	0.14% (1.28)	-0.12% (-1.15)	0.08% (0.74)	0.27% (2.51)	0.13% (1.27)	1.17% (10.96)	0.13% (1.25)	1.79%
Gas shower	0.07% (5.82)	0.04% (3.63)	-0.01% (-0.57)	0.09% (7.73)	0.07% (5.90)	-0.09% (-7.95)	0.07% (5.85)	0.24%
Clothes washer	0.62% (1.99)	0.26% (0.81)	0.11% (0.34)	-0.62% (-1.97)	0.66% (2.10)	1.37% (4.38)	0.62% (1.96)	3.01%
TV	-0.08% (-1.55)	-0.07% (-1.43)	-1.28% (-25.32)	-0.14% (-2.87)	-0.09% (-1.87)	-0.47% (-9.30)	-0.08% (-1.55)	-2.21%
PC	0.01% (0.25)	0.01% (0.26)	-0.01% (-0.14)	0.03% (0.62)	0.01% (0.27)	-1.01% (-18.64)	0.01% (0.25)	-0.93%
Microwave oven	0.06% (0.06)	15.08% (15.22)	0.73% (0.74)	-0.07% (-0.07)	-0.15% (-0.15)	5.02% (5.07)	0.05% (0.05)	20.72%
Car	-0.01% (-0.44)	-0.10% (-18.40)	-0.02% (-4.07)	0.13% (23.34)	0.00% (0.43)	-3.18% (-591.85)	0.00% (0.08)	-3.18%
Total (MJ)	5.76	13.43	-43.01	28.40	9.19	-570.22	11.77	

Chapter 8

Evaluating the Direct and Indirect Rebound Effects in Household Energy Consumption Behavior

8.1 Introduction

Improving technology efficiency is among the favorite strategies to achieve the goal of conserving energy. However, it is widely argued that efficiency improvements do not actually produce the expected savings, given that an efficiency improvement of a specific end use always leads to a decline in the cost of per-unit service, which in turn causes a feedback to incremental usage of that end use and/or the demand for other end uses. This so-called rebound effect partially or fully offsets the initial reduction of energy consumption, posing a series of concerns about the real effectiveness of technology-oriented policies. Both economists and scholars have reached a consensus on the existence of the rebound effect. The only lack of consensus is about the sources and magnitude of the rebound effect (Greening et al., 2000), probably because of the diverse empirical contexts, target end use, definition, collected data, determinants involved, and so on.

Three types of rebound effects have been identified, including a direct rebound effect, an indirect rebound effect and an economy-wide effect (Greening et al., 2000). The direct rebound effect corresponds to the case in which the increase in real income achieved by the energy efficiency improvement of a specific end use allows an increase of demand for the service provided by this end use, which in turn reduces the expected energy savings. The indirect rebound effect refers to the fact that the lower cost allows households to spend the income saved on demand for other goods, services and production that also need energy for their provision. The economy-wide effect is analogous to a general equilibrium effect that always exists in the macroeconomic context, meaning that a fall in the real price of per-unit service may lead to a series of price and quantity adjustments because the cost of intermediate and final goods within the economy may be reduced. This chapter focuses only on the direct rebound effect and part of the indirect rebound effect (i.e., the so-called “secondary effects” (Sorrell, 2007) referring to the trade-offs between the energy savings and the additional demand for services provided by other existing household end uses, while the trade-offs related to the demand triggered for the purchase of additional end uses and the embodied energy during production is excluded) in the household sector from a short-term perspective.

To provide insights into both direct and indirect rebound effects in the household sector, this chapter first develops an integrated model that represents the choice of end-use ownership and the usage decision for varied end uses under the constraint of total money budget. Ownership is described by a Logit model and the usage decision is depicted by building a resource allocation model with a multilinear function. The integrated model is then applied to identify the own-elasticity (index for calculating the direct rebound effect) of end-use energy consumption to changes of its own efficiency, and the cross-elasticity (index representing the indirect rebound effect) of end-use energy consumption to changes of the efficiency of other end uses, as well as the total rebound effect. Nine main end uses including both domestic appliances (including refrigerator, electric fan, air conditioner, gas shower, clothes washer, TV, PC and microwave oven) and out-of-home vehicles (i.e., car) are targeted in this study. Note that although the rebound effects caused by the improvement of energy efficiency can be embodied in various forms, such as an increase in the number of end uses, the average size, average usage, average performance (e.g., degrees of temperature) and/or the average load factor, we concentrate only on the rebound effects associated with the usage of end uses considering that the energy consumption in the use phase is often the greatest part of the environmental impact of a product (Chalkley et al., 2001).

The remaining part is structured as follows. The next section presents the methodology developed in this chapter. Section 8.3 illustrates the survey data. Results of model estimation are shown and the rebound effects are examined in Section 8.4. This chapter ends with conclusions and future research issues in Section 8.5.

8.2 Modeling Methodology

8.2.1 Definition

The most intuitive definition of the rebound effect is the elasticity of service demand with respect to the energy efficiency of the end use (Greening et al., 2000). Specifically, the direct rebound effect corresponds to the own-elasticity which can be denoted as

$$\eta_{\mu_j}(s_j) = \frac{\partial s_j}{\partial \mu_j} \cdot \frac{\mu_j}{s_j}, \tag{8.1}$$

indicating the relative change of service demand s produced by end use j (e.g., usage hours, temperature degree, vehicle miles traveled (VMT), etc.) due to a percentage increase of its efficiency μ_j. Having $\eta_{\mu_j}(s_j)$ in hand, the corresponding reduction of energy consumption can be specified as:

$$\eta_{\mu_j}(energy_j) = \eta_{\mu_j}(s_j) - 1 \tag{8.2}$$

Only when $\eta_{\mu_j}(s_j)$ equals to zero, $\eta_{\mu_j}(energy_j)$ amounts to -1, meaning that 100% of the potential energy savings due to an efficiency improvement are actually realized.

The indirect rebound effect studied in this paper can be represented by the cross-elasticity which is denoted as

$$\eta_{\mu_{j'}}(s_j) = \frac{\partial s_j}{\partial \mu_{j'}} \cdot \frac{\mu_{j'}}{s_j}, \tag{8.3}$$

suggesting the relative growth of service demand s provided by end use j due to a percentage increase of another end use j''s efficiency. If $\eta_{\mu_{j'}}(s_j) = 0$, then the energy consumption change of end use j following the efficiency increase of end use j' is zero.

8.2.2 Integrated Model

Given the existence of direct and indirect rebound effects, any behavioral change due to efficiency improvement might lead to the alteration of the whole household energy consumption pattern. To represent such intra-household trade-offs between end uses, a utility-maximizing modeling approach is adopted, in which a household i attempts to allocate its available money E_i to various end uses (j) so as to maximize total utility U_i. Here, the utility U_i is specified by a multilinear function with a nonadditive structure (Zhang et al., 2002, 2005), which is similar to the translog utility functions introduced by Christensen et al. (1975). Compared with the additive-type utility function (in which buying or disposing any end uses in the household will not influence the money spent on other end uses), the multilinear utility function can easily represent the interaction between end uses by using a multiplicative form (the second term on the right hand side of equation (8.4)). Note that to simplify the discussion here only the binary interactions are modeled, but it is straightforward to extend the binary form to a multinomial form.

$$\textit{Maximize} \qquad U_i = \sum_j w_{ij} u_{ij} + \sum_j \sum_{j'>j} \delta_i w_{ij} w_{ij'} u_{ij} u_{ij'} \tag{8.4}$$

$$\textit{Subject to} \qquad \sum_j e_{ij} = E_i, e_{ij} \geq 0 \tag{8.5}$$

where,

$$\sum_j w_{ij} = \text{Constant}, w_{ij} \geq 0 \tag{8.6}$$

$$u_{ij} = \rho_{ij} \ln(e_{ij}) \tag{8.7}$$

$$\rho_{ij} = \exp\left(\sum_k \beta_k x_{ijk} + \xi_{ij}\right) \tag{8.8}$$

u_{ij}: utility obtained from the service produced by end use *j* (in order to reflect the diminishing marginal utility as the level of the consumption of any particular end use increases, the utility elements are specified as logarithmic functions),

w_{ij} : a weight parameter of end use *j* to indicate the relative interest (or importance) of the service produced by the end use *j*, for understanding, it is generally assumed that the sum of w_{ij} equals to 1,

δ_i: an inter-end-use interaction parameter, if $\delta_i = 0$, the non-additive model will turn to the additive-type model.

e_{ij} : energy expenditure (money) of end use *j*.

ρ_{ij} : baseline preference (or demand) for the service produced by end use *j* which is associated with household specific attributes (e.g., income, household size, living environment, environmental awareness, etc.) and end-use specific characteristics (e.g., efficiency, size, type, etc.),

x_{ijk} : the *k*th explanatory variable to describe the preference ρ_{ij} for end use *j*,

β_k : the parameter of x_{ijk}, and

ξ_{ij} : an unobserved factor (error term) affecting the ρ_{ij}.

The following function derived from maximizing equation (8.4) subject to equation (8.5) is utilized to depict the energy expenditure on end use *j*. As it can be seen that if we include the efficiency attribute into ρ_{ij}, then the energy expenditure of end use *j* would not only be related to its own efficiency, but also the efficiency of other end uses. In this way, the trade-offs among different end uses can be embodied, in other words, the indirect rebound effect referring to the usage of end uses can be explicitly incorporated in this model.

$$e_{ij} = \frac{w_{ij}\rho_{ij}(1+\Sigma_{j'\neq j}\delta_i w_{ij'}\rho_{ij'}\ln(e_{ij'}))}{\Sigma_{j'}(w_{ij'}\rho_{ij'}(1+\Sigma_{j''\neq j'}\delta_i w_{ij''}\rho_{ij''}\ln(e_{ij''})))} E_i = \kappa_{ij} E_i \tag{8.9}$$

For ease of model estimation, equation (8.9) is transformed to the form of equation (8.10), where $\widetilde{\kappa}_{ij}$ is a new term excluding the influence of the original error terms (ξ_{ij} and $\xi_{ij'}$) in ρ_{ij} and $\rho_{ij'}$, and η_{ij} is a new composite error term which have merged all of the error terms in the utility components together. Although in this way, η_{ij} might become very complicated and are not easy to explain, it is always operable from a mathematical viewpoint. In addition, the interaction comes from the unobserved factors are not the interest in this analysis. How to clarify the error terms is left as a future research issue. η_{ij} is assumed to follow a normal distribution: $\eta_{ij} \sim N(0, \sigma_{ij}^2)$.

$$e_{ij} = \widetilde{\kappa}_{ij} E_i + \eta_{ij} \tag{8.10}$$

As shown in equation (8.5), energy expenditure e_{ij} could be zero or positive. This means that end-use ownership should be properly represented. Since choice of having an end use is a binary phenomenon, the utility of owning end use *j* (i.e., U_{ij}^o) can be described as follows:

$$U_{ij}^o = V_{ij} - \varepsilon_{ij} = \sum\nolimits_s \gamma_{js} Z_{ijs} - \varepsilon_{ij} \tag{8.11}$$

$$Y_{ij} = \begin{cases} 1 & U_{ij}^o \geq 0 \\ 0 & otherwise \end{cases} \tag{8.12}$$

where, Y_{ij} is the outcome of ownership decision (1: own; 0: non-own), V_{ij} is the deterministic term, Z_{ijs} is the *s*th explanatory variable, γ_{js} is corresponding parameter of Z_{ijs}, and ε_{ij} is an error term (note that "- ε_{ij}" is introduced for the sake of model specification).

As seen above, energy expenditure e_{ij} is not observed unless $U_{ij}^{o} \geq 0$, indicating that the observed expenditure e_{ij} is censored.

$$e_{ij} = \widetilde{\kappa}_{ij} E_i + \eta_{ij} \text{ if and only if } V_{ij} > \varepsilon_{ij} \tag{8.13}$$

$$P_{ij}(Y_{ij} = 1) = \Pr(V_{ij} > \varepsilon_{ij}) = F(V_{ij}) \tag{8.14}$$

Here, F indicates the distribution function of error term ε_{ij}. The logit model is utilized in this study to represent the end-use ownership choice, suggesting that the error term ε_{ij} follows a Gumbel distribution and the function of F is shown below.

$$F(\varepsilon_{ij}) = \frac{1}{1 + \exp(-\varepsilon_{ij})} \tag{8.15}$$

$$P_{ij}(Y_{ij} = 1) = F(V_{ij}) = \frac{1}{1 + \exp(-V_{ij})} \tag{8.16}$$

$$P_{ij}(Y_{ij} = 0) = 1 - \frac{1}{1 + \exp(-V_{ij})} \tag{8.17}$$

Since the error terms ε_i and η_{ij} might be interrelated with each other, the models for end-use ownership and usage should be estimated simultaneously. In this sense, Lee's (1983) transformation method is applied to first transform the equations (8.10) and (8.11) into a standard normal distribution, respectively.

$$\varepsilon_{ij}{*} = J_1(\varepsilon_{ij}) = \varphi^{-1}(F(\varepsilon_{ij})) \tag{8.18}$$

$$\eta_{ij}{*} = J_1(\eta_{ij}) = \varphi^{-1}(G(\eta_{ij})) \tag{8.19}$$

Here φ^{-1} denotes the inverse of the standard normal cumulative distribution function. Then, a bivariate distribution which has the marginal distribution $F(\varepsilon_{ij})$ and $G(\eta_{ij})$ can be specified as below, where o_{ij} indicates the correlation of the above two error terms.

$$C(\varepsilon_{ij},\eta_{ij};o_{ij}) = B(J_1(\varepsilon_{ij}),J_2(\eta_{ij});o_{ij}) = N(0,0,1,1;o_{ij}) \tag{8.20}$$

$$J_1(\varepsilon_{ij}) = \varphi^{-1}(F(\varepsilon_{ij})) = \varphi^{-1}(P_{ij}(Y_{ij})) \tag{8.21}$$

$$J_2(\eta_{ij}) = (e_{ij} - \widetilde{\kappa}_{ij}E_i)/\sigma_{ij} \tag{8.22}$$

After the above transformation, the joint likelihood of end-use ownership and the corresponding energy expenditure can be expressed as follows:

$$\Pr((Y_{ij}=1)\cap e_{ij}) = \Pr((\varepsilon_{ij} \le J_1(V_{ij})\cap e_{ij}) = \frac{1}{\sigma_{ij}}\phi(\frac{e_{ij}-\kappa_{ij}E_i}{\sigma_{ij}})\varphi(\frac{J_1(V_{ij}) - o_{ij}\dfrac{e_{ij}-\kappa_{ij}E_i}{\sigma_{ij}}}{\sqrt{1-o_{ij}^2}}) \tag{8.23}$$

where, ϕ denotes the standard normal probability density distribution function.

While, the probability of not holding the end use j in household i is given below.

$$\Pr((Y_{ij}=0)\cap(e_{ij}=0)) = 1 - P_{ij}(Y_{ij}=1) \tag{8.24}$$

Consequently, the log likelihood function of the joint end-use ownership and usage choice model is as follows.

$$LogL_i = \sum_j \left\{ \begin{array}{l} D_{ij}\left[\ln(\varphi(\dfrac{J_1(V_{ij}) - o_{ij}\dfrac{e_{ij}-\kappa_{ij}E_i}{\sigma_{ij}}}{\sqrt{1-o_{ij}^2}})) + \ln(\phi(\dfrac{e_{ij}-\kappa_{ij}E_i}{\sigma_{ij}})) - \ln(\sigma_{ij}) \right] \\ + (1-D_{ij})\ln(1-F(V_{ij})) \end{array} \right\} \tag{8.25}$$

Here, D_{ij} is a dummy variable that indicates the ownership of end use j, specifically, "1" means that end use j is owned and "0" means that end use j is not owned. Maximum likelihood estimation method is adopted to estimate the afore-described model.

As mentioned previously, the direct and indirect rebound effects are represented by the elasticity of service demand with respect to the energy efficiency; however, this model is unable to obtain directly the own- and cross-elasticity expressions given the intertwined relationship between expenditure on different end uses. Instead, we can calculate the elasticities based on the model's simulation results.

8.3 Data

Recently, concerns about emissions and energy issues in China have become particularly pressing. To reduce energy consumption and total emissions in the household sector (including the domestic and private transport sectors), a program of "Rebate for Automobiles & Home Appliances" was gradually launched across the whole country from 2009 to 2011. Under this program, consumers receive rebates funded by the Chinese government to purchase new energy-efficient end uses when they replace old ones. It is predicted that energy savings from these rebates may reach 20%~30%[6]. However, it is necessary to mention that this figure is estimated purely from the technical savings rather than from actual consumers' behavior. In other words, the expected energy savings might be overestimated because of the neglect of people's behavioral response to efficiency improvement.

To understand the household energy consumption pattern in China, we selected the capital city Beijing as a case study area and a quasi pannel survey was conducted there in 2010. Table 8-1 shows the basic statistics for energy intensity and utilization of household end uses (including refrigerator, electric fan, air conditioner (AC), gas shower, clothes washer, TV, PC, microwave oven and car). Note that if there are multiple items for certain end uses in a household, the energy intensity of each type is the average value weighted by usage, while the total service demand is the sum of the usage quantity of all items. Because

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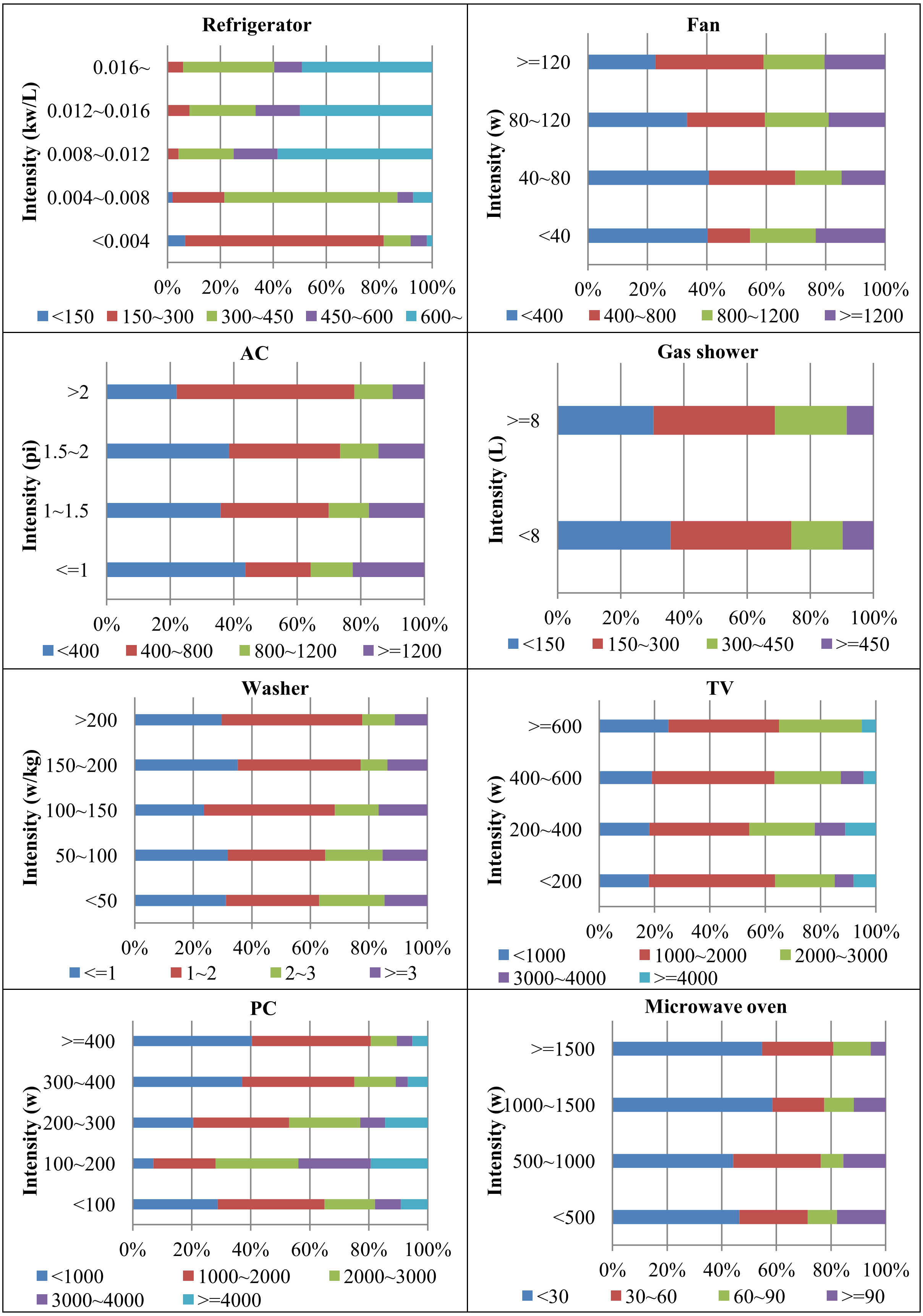
[6] http://news.xinhuanet.com/fortune/2010-11/04/c_12739667.htm (Accessed on Nov. 10, 2011).

there might be a substitution effect between the choice of energy intensity and the capacity of end uses, the intensity index of refrigerator and clothes washer is the division of power and capacity (i.e., power per liter and power per kg, respectively). By multiplying together the original energy intensity, usage of the end use and energy price, we obtain the monetary energy expenditure of each end use, which corresponds to the dependent variables in the integrated model.

Table 8- 1 Descriptive statistics of the energy intensity and service demand of end-uses

End-use	Ownership rate	Energy intensity (*1/u*)			Service demand (*s*)		
		Unit	Mean	S.D.	Unit	Mean	S.D.
Refrigerator	96.25%	kw/L	0.02	0.11	day	365	108.92
Fan	75.32%	w	78.53	126.89	hour	531.75	387.97
AC	82.82%	kw	1.15	0.57	hour	462.99	376.22
Gas shower	44.83%	L	8.06	2.66	hour	257.83	355.72
Clothes washer	93.15%	w/ kg	123.04	136.83	times	132.11	105.87
TV	91.47%	w	290.45	125.13	hour	1558.06	921.10
PC	85.27%	w	221.90	134.71	hour	1481.07	1102.10
Microwave	66.54%	w	986.84	645.55	hour	48.21	84.12
Car	36.43%	L/100km	8.17	1.77	km	10285.00	5600.24

Aggregation analysis is first conducted to see how the fuel intensity relates to the end-use usage (see Figure 1). It is found that among these nine end uses, only the air conditioner, clothes washer, microwave oven and car show a relatively apparent correlation between the intensity and end-use usage. Specifically, a negative correlation is found, in other words, more efficient AC, clothes washer, microwave oven and car (smaller intensity) will lead to heavier usage. In this case, the improvement of the efficiency for these four end uses will cause an increase of the usage, which will to some extent reduce the expected energy saving. This implies that the rebound occurs. However, whether the rebound effect is less than 100% or greater is unknown based on the aggregate results. More advanced model analysis is needed.


Refrigerator
Intensity (kw/L)
0.016~
0.012~0.016
0.008~0.012
0.004~0.008
<0.004
0% 20% 40% 60% 80% 100%
<150 150~300 300~450 450~600 600~
Fan
Intensity (w)
>=120
80~120
40~80
<40
0% 20% 40% 60% 80% 100%
<400 400~800 800~1200 >=1200
AC
Intensity (pi)
>2
1.5~2
1~1.5
<=1
0% 20% 40% 60% 80% 100%
<400 400~800 800~1200 >=1200
Gas shower
Intensity (L)
>=8
<8
0% 20% 40% 60% 80% 100%
<150 150~300 300~450 >=450
Washer
Intensity (w/kg)
>200
150~200
100~150
50~100
<50
0% 20% 40% 60% 80% 100%
<=1 1~2 2~3 >=3
TV
Intensity (w)
>=600
400~600
200~400
<200
0% 20% 40% 60% 80% 100%
<1000 1000~2000 2000~3000 3000~4000 >=4000
PC
Intensity (w)
>=400
300~400
200~300
100~200
<100
0% 20% 40% 60% 80% 100%
<1000 1000~2000 2000~3000 3000~4000 >=4000
Microwave oven
Intensity (w)
>=1500
1000~1500
500~1000
<500
0% 20% 40% 60% 80% 100%
<30 30~60 60~90 >=90

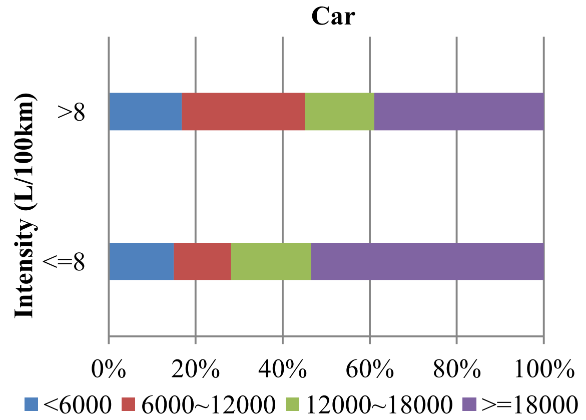


Figure 8- 1 Aggregation result of fuel intensity and end-use usage

8.4 Model Estimation Results and Rebound Effects Analysis

8.4.1 Model Estimation Results

As shown in equation (8.8), ρ_{ij} are introduced to represent the heterogeneous baseline preference on the service produced by end use j from individual/household attributes, residential environment, end-use-specific characteristics and other observed/unobserved factors. Based on the results of correlation analysis, six explanatory variables are introduced into ρ_{ij} : energy efficiency of the corresponding end use, distance to the nearest MRT/LRT station or bus stop (abbreviated as accessibility in Table 4), number of household members in employment, household annual income (1 = lowest level, 6 = highest level), household size, and presence of children younger than 12 years old (1 = yes, 0 = no).

When the efficiency of an end use increases, the savings obtained can either be respent on other end uses and/or be saved. Therefore, when explaining household energy consumption behavior, the residual, after deducting energy expenditures on the aforementioned targeted end uses from the total budget, should be regarded as a choice alternative together with the other nine end uses. This disposable money also serves as the reference alternative (always with nonzero consumption), for which the parameters in the baseline preference function are set at zero and ownership choice is excluded from equation (8.25).

To confirm the effectiveness of the proposed (nonadditive) model, apart from the model introduced in Section 8.2, the additive-type model (in which the interaction term δ_i is set as zero) is also estimated. The estimation results are listed in Tables 8-2 and 8-3.

8.4.1.1 The Effectiveness of the Proposed Model

Table 8- 2 Estimation results of the model performance

Decision-making variables	**Non-additive model** Estimate Parameter		Estimate Parameter		**Additive model** Estimate Parameter		Estimate Parameter	
Interaction term (δ_i)	-0.199	**						
	Variance of error		Correlation coefficient (ρ_{ij})		Variance of error		Correlation coefficient (ρ_{ij})	
Saving	15.202	**			6.505	**		
Refrigerator	14.326	**	-0.839		14.261	**	-0.839	
Fan	8.045	**	-0.839		7.889	**	-0.839	
AC	22.912	**	-0.839		22.766	**	-0.839	
Gas shower	56.207	**	0.227		37.142	**	0.227	
Clothes washer	9.393	**	-0.839		9.356	**	-0.839	
TV	17.775	**	-0.839		17.597	**	-0.750	**
PC	17.323	**	-0.839		16.907	**	-0.839	
Microwave oven	7.610	**	-0.839		7.574	**	-0.839	
Car	69.069	**	-0.741	**	48.395	**	-0.750	**
Initial log-likelihood	-70,381.31				-70,381.31			
Converged log-likelihood	-42,001.42				-43,855.38			
McFadden's Rho-squared	0.403				0.377			
Adjusted Rho-squared	0.401				0.375			
Number of parameters	128				127			
Sample size	774				774			
Chi-square	3,708 (△degrees of freedom: 1) (larger than the critical value 3.841 at the 95% confidence level)							

Regarding the model accuracy, the index of McFadden's Rho-squared indicates that both the nonadditive and additive models are acceptable, but the accuracy of the nonadditive model is about 7% higher than that of the additive model. The index of Chi-square also shows that the nonadditive model is better than the additive model, because the Chi-square value of 3,708 is much larger than the critical value 3.841 at the 95% confidence level. The statistical significance of the interaction term (–0.199) further supports the effectiveness of the proposed nonadditive (i.e., multilinear) model. All these results suggest that the proposed model is superior to the additive model. It is implied that ignoring the influence of interactions between end uses might lead to biased policy evaluation related to energy consumption in the household sector. More seriously, because of its inaccurate representation of actual behavior, incorrect policies might even be derived from the additive model. From the above discussion, we can conclude that the proposed model should be adopted to analyze household energy consumption behavior for policy decisions.

8.4.1.2 Significance of Behavioral Interaction and Statistical Correlations

First, as mentioned above, the interaction between the usage of end uses is confirmed as significant. This suggests that, at least for rational decision makers, it is necessary to incorporate behavioral interactions to reflect properly their decision-making mechanisms. The above model's accuracy also suggests that the assumption of such rationality is appropriate. In other words, most households, at least in this case study, behave rationally by trading off the usage of various end uses to maximize their utilities. The negative parameter sign of the inter-end-use interaction suggests a competitive relationship existing between end uses. This is mainly associated with the available energy expenditure for each household. Note that in this empirical analysis, all the end uses are treated equally by assuming their weight parameter (w_{ij}) to be unity.

The correlation between the choice of end-use ownership and the decision on its usage is revealed as significant only for car in the nonadditive model, while for the domestic end uses, this interaction is not significant. Note that the error term ε_{ij} enters the utility function with a negative sign in equation (8.11). Therefore a negative correlation (i.e., o_{ij}) between this error term and the error term η_{ij} in equation (8.10) implies that household *i*'s unobserved factors and/or omitted factors that increase (decrease) the propensity to purchase end use *j* also increase (decrease) the energy expenditure (i.e., usage) of that end use. On the contrary, a positive o_{ij} suggests negative dependency. Since the sign of the correlation for car in the nonadditive model (see Table 8-3) is negative, it is suggested that the dependency between the choice of car ownership and the decision of usage is positive, which is consistent with our expectation. Such positive dependency should be carefully considered in policy design. For example, unobserved factors encouraging the ownership of low emission vehicles might cause an increase in use of these vehicles and consequently result in an increase of energy consumption, which might offset the benefit of introducing low emission vehicles. For domestic end uses, the insignificant correlation between ownership and usage (see Table 8-3) indicates quite a large variance of the influence of unobserved factors. Because a majority of the targeted domestic end uses are durable appliances to support basic daily life, people might have to buy them; consequently, the choice of purchase or not might be independent of their usage, suggesting that ownership and usage of domestic end uses might have different decision-making mechanisms. Such an insignificant correlation should also be carefully reflected in policy design. For example, some unobserved factors affecting the ownership of energy-saving domestic end uses might contribute to the energy-saving behavior of using them; however, at the same time other factors might play an opposite role. Our results indicate that it might be worth exploring the influences of various psychological, social, and cultural factors, which are difficult to measure in practice and often ignored in policy design. Further disaggregation of ownership and usage dimensions might also be helpful. For example, it might be better to adopt a more detailed classification for each type of domestic end use, such as efficient types, aesthetic types and compact types. To examine the above unresolved issues, additional surveys are required, which are beyond the scope of this study.

8.4.1.3 Influence of Explanatory Factors

Table 8-3 lists the estimation results of the introduced explanatory variables. It is seen that, apart from the efficiency factor, the other five factors, including the built environment attribute, and socioeconomic and demographic attributes, also play a significant role in explaining the energy consumption behavior for different end uses. Bearing in mind the focus of this study (i.e., rebound effects), we merely discuss the parameters associated with end-use efficiency here. It is necessary to point out that only the end use whose energy efficiency significantly influences the baseline preference for the service produced by that end use might suffer from the phenomenon of rebound and also the trade-offs with other end uses when its efficiency improvement occurs.

It can be seen that the rebound effects (both direct and indirect effects) might exist for AC, clothes washer, microwave oven, and car because the relevant parameters of energy efficiency are statistically significant. Specifically, the positive sign of the efficiency of the microwave oven and clothes washer indicates that increasing their efficiency will make the household more likely to spend more money (i.e., more energy when the energy price is constant) on them. In other words, because of the household's behavioral change, the technological improvement not only fails to reduce the energy consumption of microwave oven and clothes washer, but instead leads to a rise of energy use. In this circumstance, the direct rebound effect is larger than 100%. This outcome has been called "backfire" (Greening et al., 2000). The negative sign of the efficiency of the AC and car suggests that more efficient ACs and cars result in less money (i.e., less energy when the energy price is constant) spent on them. In this case, the efficiency improvement plays an effective role in energy conservation. However, whether the expected energy saving can be fully achieved is still unknown. If not, then the direct rebound effects associated with AC and car will be present. Because microwave oven and clothes washer are daily necessities and cheaper, while car and AC belong to luxury items and are expensive, the above results might suggest that improving the energy efficiency of luxury items is effective in reducing their energy consumption and consequently contributes to a lower-carbon life, which cannot be realized by improving the energy efficiency of daily necessities.

Table 8- 3 Estimation results of the explanatory variables in the model

End-use	Explanatory variables	Non-additive model		Additive model	
		End-use ownership	End-use usage	End-use ownership	End-use usage
		Estimated Parameter	Estimated Parameter	Estimated Parameter	Estimated Parameter
Refrige-rator	Constant	-1.359 *		-0.906	
	Log-efficiency		-0.451		-0.255
	Accessibility	0.262	0.020	0.164	-0.085
	Employment	-0.061	0.148 **	-0.015	0.043
	Household income	0.336 *	-0.231 **	0.356 **	-0.218 **
	Household size	0.806 **	0.181 **	0.735 **	0.061
	Children presence	-0.259	-0.246 *	-0.076	0.025
Fan	Constant	0.977 **		0.960 **	
	Log- efficiency		-5.750		-2.268
	Accessibility	-0.033	-4.663 **	-0.046	-14.227
	Employment	0.041	3.862 **	0.041	2.282 *
	Household income	0.001	-4.644 **	0.007	0.099
	Household size	-0.073	-14.657 **	-0.073	-2.781
	Children presence	0.021	1.577	0.067	0.268
AC	Constant	0.928 **		0.748	
	Log- efficiency		-0.293 **		0.368 **
	Accessibility	-0.134	-0.082	-0.197 *	-0.248 **
	Employment	0.111	-0.108	0.124	-0.093
	Household income	0.142	-0.157 **	0.216 **	-0.063
	Household size	0.067	-0.183 **	0.129	-0.048
	Children presence	0.976	0.427 **	0.607	0.186
Gas shower	Constant	-0.801 **		-0.830 **	
	Log-power		-0.427		-0.249
	Accessibility	0.088	0.066 **	0.098	0.068 **
	Employment	-0.074	-0.001 *	-0.086	-0.062 **
	Household income	0.057	0.001	0.066	-0.076 **
	Household size	0.097	0.028	0.103	-0.026
	Children presence	0.296	-0.011	0.283	0.221 **
Clothes washer	Constant	0.981 *		0.391 *	
	Log- efficiency		0.140 **		0.333 **
	Accessibility	0.150	-0.171 **	0.149	-0.222
	Employment	-0.134	-0.584 **	0.026	-0.235
	Household income	0.181	-0.414 **	0.202	-0.434 **
	Household size	0.093	-0.252 **	0.214	-0.034
	Children presence	0.062	0.484	-0.017	0.579
TV	Constant	1.071		2.373 **	
	Log- efficiency		0.186		-0.080
	Accessibility	-0.401 **	-0.142 **	-0.539 **	-0.268 **
	Employment	0.589 **	-0.040	0.627 **	-0.082
	Household income	-0.084	-0.109 **	-0.219	-0.232 **
	Household size	0.461 **	-0.010	0.348 *	-0.159 **
	Children presence	-0.064	-0.498 **	1.097	0.267

Table 8-3 Estimation results of the explanatory variables in the model (continue)

End-use	Explanatory variables	Non-additive model End-use ownership Estimated Parameter		Non-additive model End-use usage Estimated Parameter		Additive model End-use ownership Estimated Parameter		Additive model End-use usage Estimated Parameter	
PC	Constant	-0.500				0.567			
	Log- efficiency			0.387				-0.021	
	Accessibility	-0.064		0.127	**	-0.246	**	-0.226	**
	Employment	0.100		-0.329	**	0.126		-0.250	*
	Household income	0.533	**	0.189	**	0.435	**	-0.065	
	Household size	0.099		-0.255	**	-0.026		-0.339	**
	Children presence	0.221		0.061		0.318		0.193	
Microwave oven	Constant	-0.466	**			-0.443	*		
	Log- efficiency			0.294	*			0.435	
	Accessibility	0.073		0.953		0.046		-0.804	
	Employment	0.052		-0.442		0.053		-0.288	
	Household income	0.132	**	0.425		0.131	*	0.005	
	Household size	0.148		-5.574	*	0.167		-0.521	*
	Children presence	0.070		0.209		0.057		0.085	
Car	Log- efficiency			-0.436	**			-0.226	**
	Accessibility	0.166	*	0.133	**	0.249	**	0.050	**
	Employment	0.057		-0.044		0.112		0.038	**
	Household income	0.294	**	0.152	**	0.389	**	0.067	**
	Household size	0.153		-0.055		0.249	**	0.043	**
	Children presence	0.250		-0.180		0.202		-0.102	**

Note: **: significant at the 95% confidence level; *: significant at the 90% level.

The results in Table 8-3 for the indirect rebound effect are not intuitive. To quantify the direct and indirect rebound effects, further elasticity analysis based on the prediction needs to be conducted.

8.4.2 Analysis of Rebound Effects

The elasticity analysis is carried out to evaluate approximately the influence of technology improvement on changes in household energy consumption. It is assumed that after households replace an old end use with a new efficient one, they will reallocate their available budget for the usage of end uses so as to maximize their total utility. A straightforward way to describe the procedure is as follows.

$$\textit{Maximize} \qquad \widetilde{U}_i = \sum_j w_{ij}\widetilde{u}_{ij} + \sum_j \sum_{j'>j} \delta_i w_{ij} w_{ij'} \widetilde{u}_{ij} \widetilde{u}_{ij'} \tag{8.26}$$

$$\textit{Subject to} \qquad \sum_j \widetilde{e}_{ij} = E_i, \widetilde{e}_{ij} \geq 0 \tag{8.27}$$

All the estimated parameters in the previous section are treated as known and are put into equation (8.25) directly, whereas the expenditure on each end use is unknown and waiting to be predicted. Consequently, the predicted energy expenditure on each end use (i.e., $\widetilde{e}_{ij}$) in household *i* would be obtained by solving the above optimization problem. In this paper, the constrained optimization module in GAUSS is used for the prediction.

Table 8- 4 Prediction accuracy indexes of the model

	Refrige-rator	Fan	AC	Gas shower	Clothes washer	TV	PC	Microwave oven	Car
Observed Mean (RMB)	199.1	29.7	386.8	842.6	43.9	284.8	200.9	22.4	6345.1
Performance of the non-additive model									
Predicted Mean (RMB)	144.1	23.0	458.0	1295.5	28.5	261.4	196.9	20.8	5881.8
RMSE (RMB)	60.5	4.5	65.9	170.9	6.0	63.3	31.7	4.8	184.3
Correlation coefficient	0.792	0.732	0.685	0.581	0.591	0.644	0.657	0.556	0.956
Performance of the additive model									
Predicted Mean (RMB)	133.4	22.8	467.9	1717.8	28.3	211.7	189.8	20.3	5678.6
RMSE (RMB)	80.4	4.7	76.4	193.3	6.0	73.2	272.0	4.8	207.3
Correlation coefficient	0.547	0.444	0.443	0.312	0.408	0.516	0.546	0.435	0.912

Note: The indexes for each end-use in the table are the results only for households who own that type of end-use.

To check the accuracy of prediction, the predicted expenditure in the reference scenario (i.e., business as usual) is compared with the observed expenditure by using the indices of Root of Mean Square (RMSE) and the correlation coefficient for both the nonadditive and additive models (see Table 8-4). Except for clothes washer and microwave oven, the RMSE of the nonadditive model is 4% lower for the minimum case (i.e., electric fan) and 88% lower for the maximum case (i.e., PC) than that of the additive model. Furthermore, the correlation coefficient of the nonadditive model is 5% higher for the minimum case (i.e., car) and 86% higher for the maximum case (i.e., gas shower). Again, these indexes support the effectiveness of the proposed model to represent the household energy consumption behavior.

Next, we use a scenario analysis to explore the rebound effects. Here, only the results of the nonadditive model are discussed. As mentioned above, AC, clothes washer, microwave oven and car suffer from the rebound phenomenon. Accordingly, five scenarios in which the energy efficiency is increased by 20%, 40%, 60%, 80% and 100%, respectively, are designed for each of them. Although the predicted outputs are the energy expenditure of each end use in the household, this expenditure can be the proxy for energy consumption given constant energy prices. The elasticities of energy consumption with respect to efficiency improvement in each household are straightforwardly derived from the quotient of the percentage change between the predicted energy consumption of end uses in each scenario and energy consumption in the reference scenario (business as usual: the scenario without any change of efficiency), divided by the percentage increase of efficiency. Subsequently, the direct rebound effects can be obtained from equation (8.2) and the indirect rebound effects are directly equal to the corresponding cross-elasticities, which are greater than zero. Based on the results of scenario analysis and equation (8.28), the total rebound effect, including direct and indirect effects, in the household sector from an efficiency improvement in a specific end use can also be calculated.

$$\text{Total rebound effect [\%]} = \frac{\text{Calculated savings (GJ) - Real savings(GJ)}}{\text{Calculated savings(GJ)}} \qquad (8.28)$$

To simplify the discussion, the average rebound effects for the whole sample in each scenario and the mean effects of the five scenarios are given in Table 8-5. It is evident that with efficiency improvement in any of the aforementioned four end uses, energy consumption changes in different ways, not only of each end use but also of other end uses.

Before exploring the rebound effects for each end use, it is worth explaining the results for the refrigerator first. At a glance, the indirect rebound effect for the refrigerator resulting from the efficiency increase of AC, clothes washer, microwave oven and car is not negligible, suggesting that refrigerator usage is also influenced by other end uses. Although for the refrigerator, usage is always fixed (e.g., 365 days for each piece), considering that households can adopt different usage styles, it is still possible for energy consumption to be different despite the efficiency of the refrigerator being the same. For example, some households do not change the temperature inside the refrigerator in different seasons; some often store many items that need more energy; some people may not wait until the food is cold before putting it into the refrigerator, etc. Therefore, a significant indirect rebound effect for the refrigerator is plausible.

Table 8- 5 Rebound effects due to the energy efficiency improvement

End-use	Scenarios with different improvement rates of efficiency					Average
	20%	40%	60%	80%	100%	
End-use with efficiency change : AC						
Refrigerator	1.59%	1.46%	1.35%	1.26%	1.18%	1.37%
Fan	-6.66%	-6.64%	-6.60%	-6.56%	-6.52%	-6.60%
AC (Direct effect)	59.16%	60.12%	60.90%	61.55%	62.09%	60.76%
Gas shower	1.49%	1.35%	1.24%	1.15%	1.07%	1.26%
Clothes washer	1.95%	1.78%	1.65%	1.54%	1.45%	1.67%
TV	2.52%	2.42%	2.31%	2.20%	2.12%	2.31%
PC	1.10%	0.94%	0.88%	0.66%	0.63%	0.84%
Microwave oven	0.01%	0.01%	0.00%	0.00%	-0.01%	0.00%
Car	0.73%	0.66%	0.61%	0.56%	0.53%	0.62%
Total rebound effect	84.61%	87.13%	89.29%	91.02%	92.71%	88.95%
End-use with efficiency change : Clothes washer						
Refrigerator	-0.02%	-0.02%	-0.02%	-0.02%	-0.02%	-0.02%
Fan	0.00%	0.01%	0.00%	0.00%	0.00%	0.00%
AC	-0.02%	-0.02%	-0.02%	-0.02%	-0.02%	-0.02%
Gas shower	-0.02%	-0.02%	-0.02%	-0.02%	-0.02%	-0.02%
Clothes washer (Direct effect)	107.68%	107.16%	106.79%	106.36%	106.05%	106.81%
TV	-0.02%	-0.02%	-0.02%	-0.02%	-0.01%	-0.02%
PC	-0.02%	0.10%	-0.02%	-0.01%	-0.02%	0.01%
Microwave oven	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Car	-0.01%	-0.01%	-0.01%	-0.01%	-0.01%	-0.01%
Total rebound effect	101.95%	102.18%	100.01%	99.18%	98.47%	100.36%
End-use with efficiency change : Microwave oven						
Refrigerator	2.00%	1.99%	1.99%	2.00%	1.97%	1.99%
Fan	-0.02%	0.00%	-0.01%	0.00%	-0.01%	-0.01%
AC	0.02%	0.02%	0.01%	0.02%	0.02%	0.02%
Gas shower	0.00%	0.00%	0.00%	-0.01%	0.00%	0.00%
Clothes washer	-0.02%	-0.01%	-0.02%	0.13%	-0.01%	0.02%
TV	3.00%	2.99%	3.00%	2.99%	3.00%	3.00%
PC	1.97%	1.99%	2.21%	1.98%	1.99%	2.03%
Microwave oven (Direct effect)	100.87%	100.82%	100.78%	100.75%	100.72%	100.79%
Car	1.37%	1.34%	1.29%	1.26%	1.21%	1.29%
Total rebound effect	515.88%	576.39%	632.38%	680.48%	727.78%	626.58%
End-use with efficiency change : Car						
Refrigerator	5.65%	5.42%	5.10%	4.83%	4.57%	5.11%
Fan	0.96%	0.83%	0.77%	0.72%	0.66%	0.79%
AC	3.31%	3.11%	2.92%	2.78%	2.66%	2.96%
Gas shower	-3.00%	-2.68%	-2.41%	-2.19%	-1.99%	-2.46%
Clothes washer	6.23%	5.82%	5.47%	5.17%	4.90%	5.52%
TV	4.31%	4.04%	3.82%	3.59%	3.43%	3.84%
PC	2.53%	2.97%	2.85%	2.75%	2.49%	2.72%
Microwave oven	5.10%	5.09%	5.09%	5.09%	5.08%	5.09%
Car (Direct effect)	33.46%	33.55%	33.62%	33.68%	33.73%	33.61%
Total rebound effect	31.42%	31.53%	31.61%	31.71%	31.80%	31.61%

8.4.2.1 Rebound Effects Caused by the Efficiency Improvement of Air Conditioners

When the efficiency of AC increases, the average direct rebound effect is 60.76%, indicating a total 60.76% take-back for a 100% increase in the energy efficiency. Compared with the existing evidence, this value is higher than the effects for OECD countries (1%~26% for the US, and 38% for Canada) (Dubin et al., 1986; Guertin et al., 2003; Hausman, 1979), but similar to the case of South Korea (57~70%) (Jin, 2007). Regarding indirect effects, except for the electric fan and microwave oven, the demand for the services provided by other end uses shows an apparent rebound accompanying the efficiency improvement of AC. The greater energy consumption of domestic appliances might be related to the increasing time spend at home, whereas the greater consumption on cars is probably because households have the illusion that they can save some money/energy from the new AC. However, such indirect rebound effects are relatively small (lower than 3%), which is consistent with the claim of previous scholars (e.g., Greening and Greene, 1998; Schipper and Grubb, 2000). The total rebound effect is found to be 88.95% on average. Obviously, the total effect is larger than the direct effect but less than 1, indicating that the efficiency increase of AC leads to additional energy consumption on other end uses, but is still able to save on total energy consumption. Comparing the rebound effects in the five scenarios, it can be seen that with the improvement rate of efficiency increasing (change from 20% to 100%), the direct rebound effect and the total rebound effect behave as a rising trend while the indirect rebound effects present a slight decline. This is understandable because the trade-offs between different end uses under the constraint of total budget are incorporated in the model.

8.4.2.2 Rebound Effects Caused by the Efficiency Improvement of Microwave Ovens

On the one hand, the technology improvement of a microwave oven in the household causes a backfire on its own usage, and on the other hand increases the usage of refrigerator, TV, PC, and car by 1% to 3%. Because a microwave oven is more convenient and faster than traditional cooking appliances (e.g., a gas stove), it is conceivable that households might be more willing to use it to cook than traditional means when its efficiency increases. And it is further speculated that the saved time might be reallocated to in-home recreation/working and out-of-home travel given the increasing consumption on TV, PC, and car. The rise in consumption for refrigerator is a phenomenon that occurs in parallel with the rebound of the demand for microwave oven. The total rebound effect is as high as 626.58%, signifying that there is around five times the extra energy consumption when the efficiency of the microwave oven improves. In the five scenarios, the backfire effect declines slightly with an increase of the rate of efficiency change.

8.4.2.3 Rebound Effects Caused by the Efficiency Improvement of Clothes Washers

As with microwave oven, clothes washer also suffers from the phenomenon of backfire when its technology efficiency increases. Households may replace hand washing by using the efficient clothes washer or use the clothes washer more frequently than before. Although this result (i.e., 106.81%) is much larger than the case of the US (<5% given by Davis (2007)), for developing countries, this very different situation is also acceptable given the unsaturated demand for the service. In the light of the tiny indirect rebound effects, it can be said that the efficiency change of clothes washer does not significantly act on other end uses. The direct rebound effect in the five scenarios presents the same variance as with the case of microwave oven.

8.4.2.4 Rebound Effects Caused by the Efficiency Improvement of Cars

The average direct rebound effect for car is calculated to be 33.61%, which is slightly higher than the suggested upper bound of the short-run direct rebound effect for OECD countries (i.e., 20%~25%) (Sorrell et al., 2007, 2009). As pointed out in many studies, rebound effects may be expected to be larger in developing countries, but the empirical evidence is very limited. Our results provide strong support for this argument. Trade-offs between the savings from a more efficient car and the demand for services of domestic end uses are evident. Specifically, the indirect rebound effects resulting from the efficiency improvement of car range from 0.66% to 6.23%, with the majority greater than 3%. Given that expenditure on the car always accounts for the largest proportion of total energy expenditure in the household, households with a more efficient car may think they have already saved a large amount of money; as a result, they spend these savings to pursue higher quality of in-home life, which increases the usage of many domestic end uses. However, the reality is that the total rebound effect is 31.61% on average, which is lower than the direct effect, meaning that the efficiency increase of car reduces total energy consumption on the other eight end uses. This is because the increased energy consumption of refrigerator, electric fan, AC, clothes washer, TV, PC and microwave oven is less than the decreased energy consumption of gas shower. Because of the higher energy conversion factor of gas compared with electricity, the above result is understandable. The reduction of gas shower usage might be related to the decreasing in-home time. The same is the case with AC: when the rate of efficiency improvement increases, the direct rebound effect and the total rebound effect rise slightly while the indirect rebound effects decline slightly.

Interestingly, as a general trend, the rebound effects do not change remarkably with increased efficiency (from 20% to 100%). This implies that an increase of energy consumption can be expected from the increased energy efficiency, but it is not unlimited. This result might suggest the existence of a specific budget constraint for each end use. In other words, households might prefer to not spend more and more money on each end use even when more disposable household income becomes available. Because the end-use-specific budget is not observed in this case study, it might be worth examining this issue in future research.

Traditionally, residential and transport energy consumption behaviors have been separately treated. This might be influenced by the sector-oriented policy decision scheme that is widely adopted currently. However, based on our results, diverse interactions are identified between domestic appliances and out-of-home vehicles, suggesting that the residential sector and private transport sector should be studied together.

Table 8-6 shows the energy consumption change (unit: GJ) corresponding to the five scenarios. In general, improving the efficiency of AC and car can reduce total energy consumption, especially the efficiency of car. If the car is twice as efficient as before, energy saving could be up to 15.6% in total. For AC, a U-shaped relationship is present between improvement in efficiency and change of energy consumption. Specifically, the total energy consumption saved as a result of the efficiency increase of AC may attain its maximum when the improvement rate is 60%~80%. In contrast, the introduction of a more efficient microwave oven will increase total household energy consumption. The change in efficiency of clothes washer has almost no impact on energy consumption.

Table 8- 6 Energy consumption change caused by the end-use efficiency improvement

End-use	Improvement rate of energy efficiency				
	20%	40%	60%	80%	100%
AC	-0.13%	-0.19%	-0.20%	-0.20%	-0.18%
Clothes washer	0.00%	0.00%	0.00%	0.00%	0.00%
Microwave oven	0.16%	0.31%	0.46%	0.59%	0.72%
Car	-5.24%	-8.98%	-11.77%	-13.93%	-15.64%

8.5 Summary and Conclusion

Due to the existence of rebound effects, the expected energy savings from technological efficiency improvements might not ultimately be attained. Given this concern, this paper provides a methodological approach that represents the choice of end-use ownership and usage decision for a number of end uses under the constraint of total money budget, to estimate the direct and indirect rebound effects associated with household energy consumption behavior in the context of a developing city, Beijing, from a short-run perspective. By combining the logit model and a multilinear utility function in the modeling framework, the interaction between end-use ownership and usage, together with the interaction between change of energy consumption of end uses when energy efficiency rises is explicitly stated. Eight types of energy-consuming household appliances and the household car are targeted in our empirical analysis.

The effectiveness of adopting the integrated model described in this study to evaluate household energy consumption by different end uses is confirmed on the one hand by the relatively good model performance and on the other hand by the rational behavioral mechanism implied by the statistical significance of many interaction terms introduced into the model. This provides a solid foundation for subsequent policy development. Based on the empirical results obtained from the model estimation, we have shown that not all the targeted end uses suffer from the rebound phenomenon. Among the nine objective end uses, the rebound effects occur only when the efficiency of air conditioner, clothes washer, microwave oven and car increases. Further, backfire is observed for clothes washer and microwave oven, but this is not remarkable. Specifically, the average direct rebound effects associated with air conditioner, clothes washer, microwave oven, and car are found to be 60.76%, 106.81%, 100.79%, and 33.61%, respectively. The total rebound effects including direct plus indirect effects for these four end uses are 88.95%, 100.36%, 626.58%, and 31.61%, respectively. Rebound effects are not always proportional to the efficiency improvements, nor are they very sensitive to the improvement. After controlling for rebound effects, the efficacy of technological improvement for the above four end uses in saving total energy consumption is detected: improving the efficiency of only air conditioner and car will reduce total energy consumption. Moreover, increasing the efficiency of air conditioner by 60%~80% might maximize energy saving compared with other improvement rates (between 0%~100%).

These results may have important policy implications. It indicates that improving the technological efficiency of end uses, especially that of air conditioner and car, remains an effective measure for energy conservation in Beijing. Therefore, on the one hand, the government could raise the efficiency standard for the end uses entering the market so as to force manufacturers to continue technical innovations (such as the top-runner program in Japan[7]); on the other hand, the government could develop policies (e.g., rebates) to encourage consumers to purchase more efficient products. However, because of the existence of substantial rebound effects, policies are required that are able to lead households to use end uses as little as possible, such as an energy tax, the provision of information about energy-saving behavior and an evaluation platform for households to monitor their energy consumption and emissions (as OECD countries do[8]), etc. Only if the above policies are executed together will the desired policy goals be achieved on schedule.

Future research on this topic could investigate the following aspects. In this paper, only a part of the indirect rebound effect is studied while the effects associated with the demand for purchasing extra end uses triggered by efficiency improvements is excluded, as is the embodied energy during production. To address these issues, more detailed information is required and the method used to deal with the supply–demand issues can be combined with our research. Here, we only focus on the short-run rebound effects; to

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7 http://www.enecho.meti.go.jp/policy/saveenergy/save03.htm (Accessed on Jan. 10, 2012).

8 http://www.consumerspower.org/home_energy/billestimator.php (Accessed on Nov. 10, 2011); http://hes.lbl.gov/consumer/ (Accessed on Nov. 10, 2011).

represent long-run rebound effects, panel surveys are needed, as are dynamic models.

Chapter 9

Policy Application Based on Dynamic Simulation

Based on the previous chapters, it is not difficult to conclude that single policy is always not enough to achieve the goal of energy conservation. In other words, to obtain an environmentally sustainable society, it might be better to implement multiple types of policies jointly, that is to say, the package policy is needed. Moreover, household energy consumption process is not static considering that the continuously changing market and the social context might significantly affect the household energy use behavior. Therefore, to develop a robust policy system to reduce the total household energy consumption, a simulation is carried out to evaluate the collaborative effects of the land-use policy, soft policy, and technology improvement/rebate program by dynamically representing the change of the market end-use diffusion rate and the neighborhood social interaction. This simulation can also overcome several aforementioned shortcomings in each chapter.

Section 9.1 gives an introduction about the referring aspects in the simulation as well as the limitations which need to be further dealt with in the future. Then the model structure and results which will be used in the dynamic simulation are shown in Section 9.2. The static sensitivity of household energy consumption to different policies is calculated so as to draw a general picture about the effects of the policies. In the dynamic simulation, there are six modules which respectively correspond to different policies or influential aspects. The details about the simulation and the results are elaborated in Section 9.3 and Section 9.4, respectively. The last section concludes this chapter and provides some potential applications of this program.

9.1 Introduction to the Simulation

9.1.1 Referring Aspects in the Simulation

In the dynamic simulation program, the year 2010~2015 are targeted. We will deal with the following issues:

- the nature change of the social-demographic and social-economic characteristics (e.g., income, retirement with the age increase, and the presence of children younger than 12 years old) in the future year;
- the influence of the technology improvement or the policy of rebate which makes the end-use efficiency changes;
- the influence of the soft policy (e.g., the environment education);
- the influence of land-use policy;
- the influence of social interaction coming from the average energy consumption of households living in the same neighborhood;
- the change of the market penetration rate of each type of end use;
- the inefficiency level of the end uses which decides the lower bound of the energy consumption on each end use.

According to the previous studies, it is found that one or several aforementioned issues can be easily represented by using a utility-based framework, however, if we want to incorporate all of them within one econometric model, it is difficult to organize and manipulate. Consequently, we conduct a dynamic simulation to incorporate all this aspects into a unified framework.

9.1.2 Limitations in the Simulation

However, in the simulation, there are some limitations which need to be posed first.

- Due to the limitation of our survey data, we have some assumptions about the respondents' energy consumption behavior. For the accurate analysis, further information is needed:

① Whether is household willing to participate in the rebate program? If yes, how much they want to improve the end-use efficiency (which type to buy).

② Whether will household change to more efficient lifestyle if some soft policies are conducted. If yes, how will they do?

③ Whether will households (non-owners) buy that end use in the future, and when they plan to? If they want to buy, which type they will choose.

④ If the average usage or some context for the energy consumption is given, how households will response to it.

- Because of our small sample survey, we cannot say that our model result can represent the whole city. To overcome this issue, one possible way is to enhance the sample scale, while another way might be that focusing our simulation program on a specific space scale.
- Backcasting approach might be more appropriate for the energy consumption analysis, it's better to compare the respective results from forecasting and backcasting approaches.

9.2 Model Structure and Results

9.2.1 Model Structure

In the dynamic simulation program, the model used for predicting the end-use energy consumption is derived from the combination of Chapter 7 and Chapter 8. As shown in Figure 9-1, based on the result of mixed MNL-MDECV model in Chapter 7, the factors for representing the self-selection effects can be obtained. By putting these factors into the logit model and adopt it to describe households' residential location choice, household residential environment (*RE*) attributes are predicted. Then by putting the derived *RE* attributes and the factors associated with self-selection effect into the Logit & Resource allocation model in Chapter 8, the model used for dynamic simulation is finally obtained. In this way, we can describe how the land-use policy, soft policy, and the technology improvement affect the household energy consumption behavior in the same model structure.

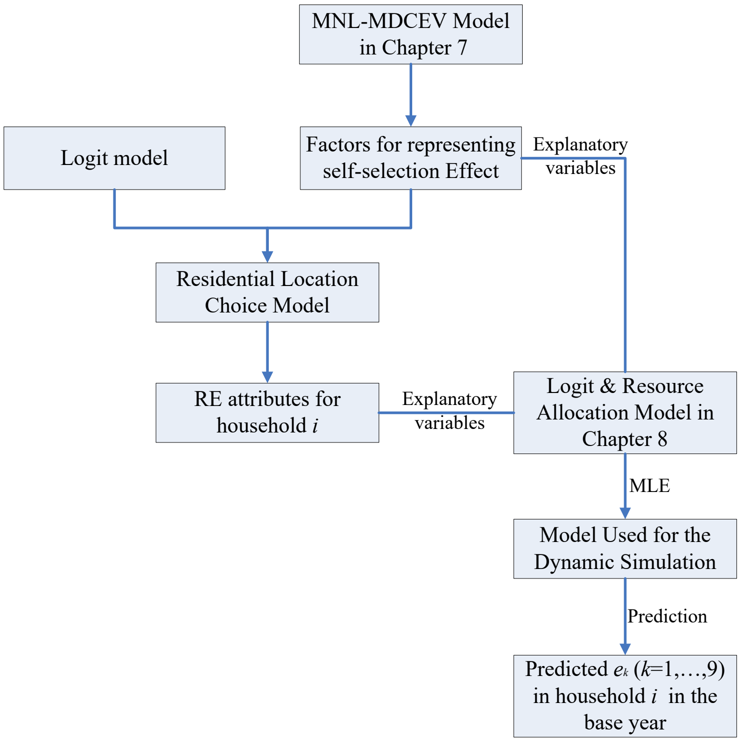


Figure 9- 1 Model derivation

9.2.2 Model Results

After accommodating the *RE* attributes and factors representing the self-selection effect, the model is re-estimated and the results are given in Table 9-1. Given the significance of the variables for end-use usage, it can be seen that the land-use policy is influential to the demand for the service provided by all of these nine end uses (i.e., ownership and usage), while the technology improvement will change the service demand for AC, washer, microwave oven, and car, moreover, the efficiency increase can only reduce the energy use for AC and car, for washer and microwave oven, a “back-fire” will occur. Negative interaction between end uses is found. These results are consistent with the ones in Chapter 7 and Chapter 8.

Table 9- 1 Model estimation results

	Estimate End-use ownership	Estimate End-use usage	Estimate End-use ownership	Estimate End-use usage
	Refrigerator		**Fan**	
Constant	-0.077 *		8.860 *	
Log-efficiency		-0.608		-1.985
Number of shopping malls	-0.217	0.105	0.161	-0.317
Number of recreational facilities	0.158	1.736	-1.436	-7.138 *
Number of restaurants	0.687	-2.116 *	0.676	0.824
Number of parks	0.913	-0.359	0.087	0.723 *
Number of bus lines	-2.357	0.707 *	-0.201	3.794 *
Number of train lines	0.459	-0.153	-0.350	1.449 *
Highest education level	0.107	-0.110	-0.062	-0.620
Employment	-0.205	-0.328 *	0.027	0.501 *
Household income	0.351 *	0.056 *	0.099	-0.365 *
Household size	0.302 *	0.062 *	-0.103	-0.176
Children presence	1.246	0.486 *	-0.015	-0.001
	AC		**Shower**	
Constant	-6.885		-1.402 *	
Log-efficiency		-0.241 *		-5.425
Number of shopping malls	-0.017	-5.918 *	-0.034	-3.710
Number of recreational facilities	0.985	-3.434 *	2.305 *	-6.564
Number of restaurants	-1.110	-0.973	-2.838 *	6.646
Number of parks	0.312	0.431	0.690 *	10.429 *
Number of bus lines	-0.599	2.443 *	1.618 *	-10.688
Number of train lines	0.066	0.887 *	1.279 *	5.859 *
Highest education level	0.092 *	-0.456	0.364	0.875
Employment	0.032 *	0.290 *	-0.034	-8.327
Household income	0.058 *	-0.192	-0.032	-1.633
Household size	0.201 *	-0.171	0.147	0.792 *
Children presence	1.048 *	0.835 *	0.481	11.943
	Washer		**TV**	
Constant	-1.266		-1.656	
Log-efficiency		1.823 *		0.147
Number of shopping malls	0.235	4.662 *	-0.076	0.148
Number of recreational facilities	0.551	-5.395	1.353	-1.801 *
Number of restaurants	-0.962	-6.112	-1.104	0.404
Number of parks	-0.558	-10.982	0.613	0.047
Number of bus lines	0.303 *	3.251 *	0.027	0.062 *
Number of train lines	-0.349	-0.700	0.673	-0.765
Highest education level	0.265	-1.589	-0.256	-0.352
Employment	0.022	0.197 *	0.471 *	0.038
Household income	0.333	-0.251	-0.215	-0.157
Household size	0.318 *	1.256 *	0.394	0.034 *
Children presence	-0.385	-2.147	0.648 *	0.022
	PC		**Microwave oven**	
Constant	0.273 *		0.373	
Log-efficiency		-1.380		0.857 *
Number of shopping malls	0.106	0.885	0.168 *	0.491 *
Number of recreational facilities	0.134	-2.242	1.084	0.493
Number of restaurants	-1.221	1.699 *	-1.191	-1.013 *
Number of parks	-0.200	-1.579	-0.434	-0.795
Number of bus lines	0.880	-1.109 *	0.555	0.186 *
Number of train lines	0.164	-1.960 *	-0.405	-0.969
Highest education level	-0.260	-1.171	0.481 *	1.550
Employment	0.113	-1.507	-0.086	0.239 *
Household income	0.394 *	0.452 *	0.237 *	0.070
Household size	0.005	-0.337	0.232 *	-0.008
Children presence	0.052	-3.337	0.397	-0.960

Table 9-1 Model estimation results (continue)

	Estimate End-use ownership		Estimate End-use usage		Estimate End-use ownership		Estimate End-use usage
	Car						
Constant	-2.997	*			(None)		
Log-efficiency			-1.652	*			
Number of shopping malls	0.128		-0.117	*			
Number of recreational facilities	1.587		-2.104	*			
Number of restaurants	-0.347		2.541	*			
Number of parks	-0.386		0.623	*			
Number of bus lines	-0.212		-1.304	*			
Number of train lines	-0.243		0.124				
Highest education level	0.385		0.272				
Employment	0.167		0.751	*			
Household income	0.391	*	0.140	*			
Household size	0.255		-0.132	*			
Children presence	0.185		-0.998	*			
Interaction term	-0.025	*					
	Standard error of error				Correlation coefficient		
Saving	16.218	*					
Fridge	14.929	*			-0.839		
Fan	5.823	*			-0.839		
AC	23.055	*			-0.839		
Shower	29.471	*			-0.618	*	
Washer	8.280	*			-0.839		
TV	17.781	*			-0.839		
PC	16.587	*			-0.839		
Microwave oven	6.258	*			-0.839		
Car	37.031	*			-0.583	*	
Initial log-likelihood	-52968.778						
Converged log-likelihood	-31853.106						
McFadden's Rho-squared	0.399						
Adjusted Rho-squared	0.394						
Sample size	530						

9.2.3 Policy Sensitivity Analysis

Sensitivity analysis is carried out to evaluate the static policy effect based on the model result (see Figures 9- 2 and 9-3). When the soft policy is conducted (i.e., improving the factors representing the self-selection effect by 10%), it is found that the energy intensive end uses including the air conditioner, gas shower, and car are consumed more efficiently, while for others, maybe due to the reallocation of the saving money, the energy use is revealed a little bit more than before. Totally, the soft policy still has a positive effect on the energy saving (i.e., 0.166% less than before). Regarding the land-use policy, similar findings with Chapter 7 can be obtained that not all the land-use policies help reducing the household energy consumption. Only increasing the number of recreational facilities, train lines, and bus lines in the neighborhood will save the energy use. Furthermore, the influence of increasing the bus lines is the most substantial. Though the percentage change resulted from the implementation of soft policy and land-use policy varies a lot and the soft policy seems more inelasticity, the actual total energy saving shows that the effect of soft policy is also as significant as the land-use policy.

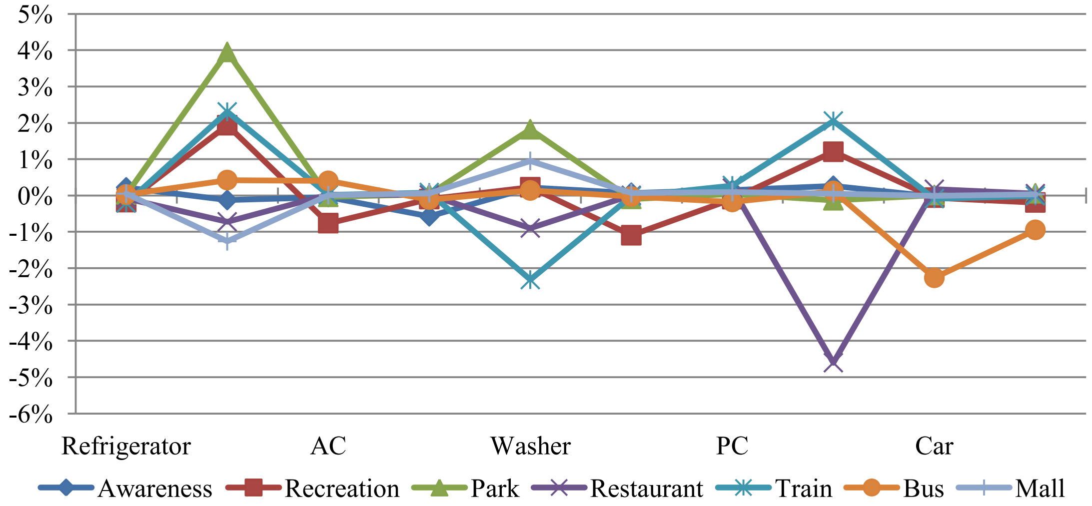


Figure 9- 2 Static policy sensitivity analysis (percentage change)

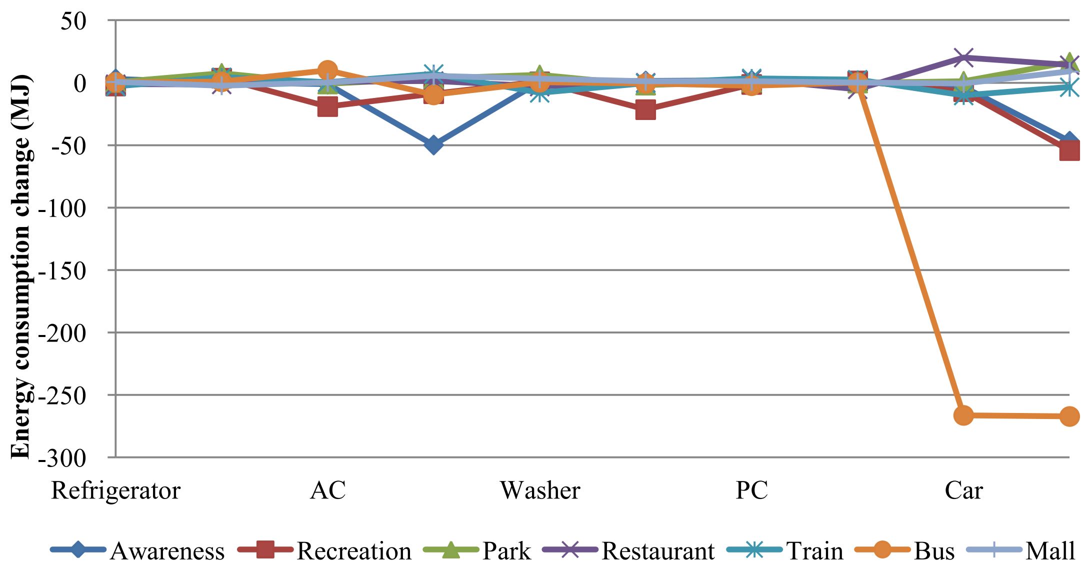


Figure 9- 3 Static policy sensitivity analysis (energy consumption MJ change)

9.3 Dynamic Simulation Program

9.3.1 Program Interface

Figure 9- 4 Simulation interface

A visual user interface is designed for the simulation (see Figure 9-4). From the interface, several parameters needed in the simulation program can be set externally based on the survey data. Besides, the policy makers can select the years to implement different types of policies so as to identify the influence of the policy timing on the energy conservation. It is thought that after the policy implementation, household energy consumption behavior might alter due to the end-use efficiency change, and/or the awareness change, and/or the lifestyle change, and these changes will in turn influence the market and the energy consumption of all the population due to the social interaction. Therefore, we believe that the timing will influence the efficacy of the package policies. Accordingly, we specifically configure this option for each type of policy.

Totally, six modules are included in the dynamic simulation: technology improvement/rebate module, awareness change module, land-use change module, social-demographic/economic factor (called as EV) change module, neighborhood social interaction module, and market change module. The former four modules are used to test the effects of technology improvement/rebate policy, soft policy, land-use policy and the natural change of social-demographic/economic factors on household energy consumption behavior, while the latter two modules are used to represent the dynamic influence of the market and the society which can also help to evaluate the efficacy of the measures of controlling the market end-use diffusion rate and giving the social context information.

The flowchart for simulation is detailed depicted in Figure 9-5. And how to give the values to parameters are explained in the subsequent sections.

9.3.2 Technology Improvement/Rebate Module

This module is mainly for the calculation of the new efficiency if households replace their old end uses with new more efficient ones. In this module, four groups of parameters are needed: the policy year, the household coverage rate, the end-use coverage rate, and the efficiency improvement rate which is assumed to follow a normal distribution. According to the rebate program which has already been conducted in 2010~2011 in Beijing, it is reported that almost 50% of households joined this program, and the maximum number of the updated end uses was restricted to 5, in addition, it is said that 20%~40% of energy is expected to be saved. Thus, in our program, the household coverage rate and end-use coverage rate are set to be 50% and 5, respectively. The efficiency improvement rates are normally distributed with mean 40% and standard deviation 20%.

During the simulation, we first check whether is the policy year of technology improvement/rebate program, if yes, then randomly choose 50% households in the sample and make them randomly renew no more than 5 types of end uses they own. The efficiency improvement rate of the renewed end uses is generated by following the normal distribution in which the mean and standard error is assigned by ourselves. Finally, the new efficiency for end uses can be computed.

Note that due to the lack of data about households' willingness to renew their old end uses and which type they prefer, we have to assume the household coverage rate and the efficiency improvement rate in the program which might make the results unrealistic. Therefore, we mentioned this point as a limitation in Section 9.1.2.

9.3.3 Environmental Awareness Change Module

Because the factors associated with self-selection effects are incorporated in the model, we can evaluate the effect of soft policy like environmental education on household energy consumption behavior. The parameters need to be pre-set in this module is the policy year, household coverage rate, the awareness improvement rate which is assumed to follow a normal distribution. In the simulation, we assume that not all households will be influenced by the soft policy, accordingly, the option of household coverage rate is given and the value of 50% is used in the program. Moreover, due to the lack of data about whether household will change to more efficient lifestyle if some soft policies are conducted and how they will do, therefore the awareness improvement rate is randomly generated based on the externally input mean and standard error. We also clarified this limitation in Section 9.1.2.

The simulation process is to first check whether the studying year is the policy year defined, if yes, then randomly select 50% of households in the sample to improve their awareness on the usage of end use k (k=1, 2,…, 9) by the generated value (normally distributed with mean 0.1 and standard deviation 0.1). In this way, the change of the unobserved attributes after the soft policy is simulated.

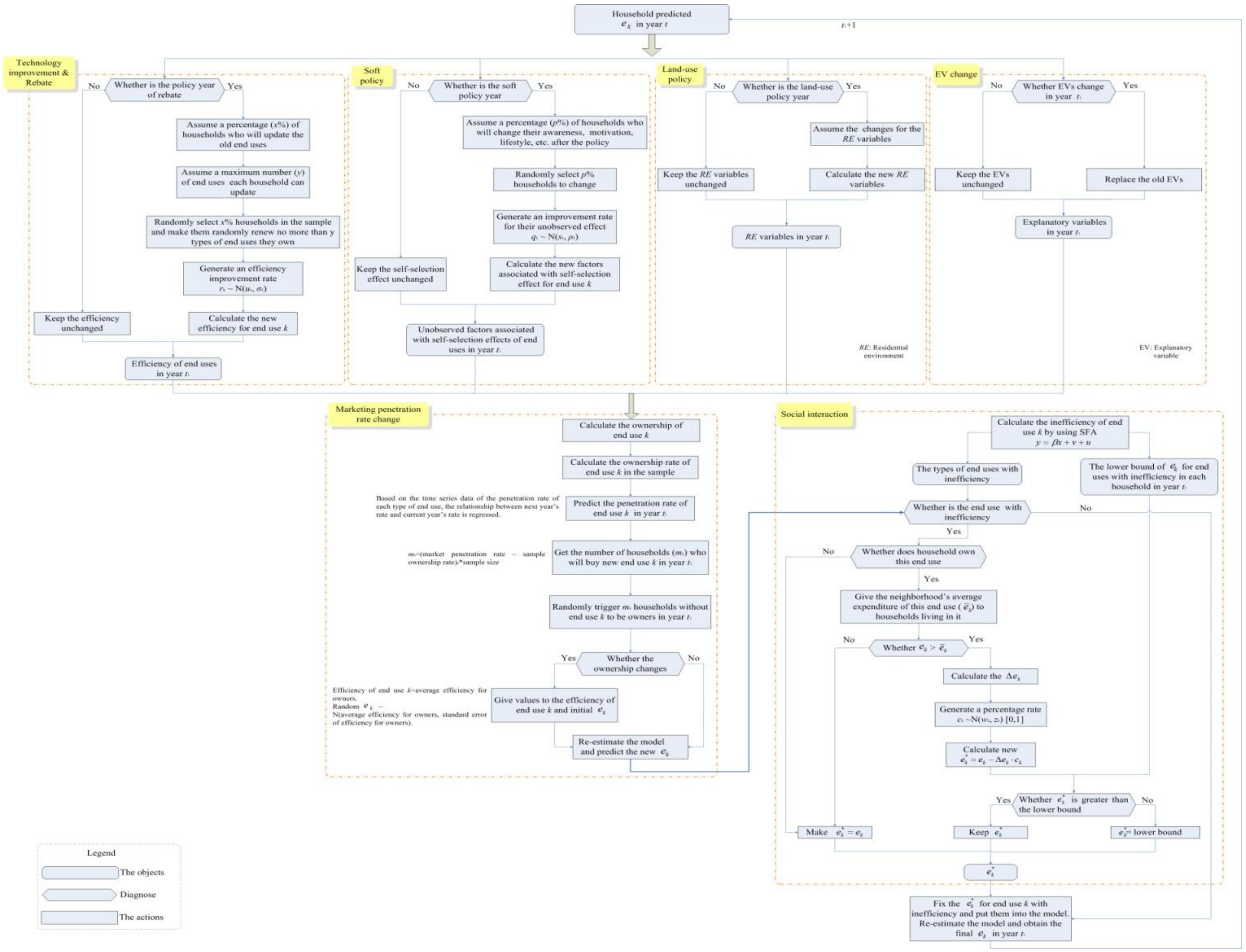


Figure 9- 5 Dynamic simulation flowchart

9.3.4 Land-use Change Module

In this module, only the details about the land-use policy (i.e., the year, and the contents) are needed to input to the program. By changing the value of residential environment attributes, how the land-use policy works can be easily captured. In the final simulation program, we will take the policy which increases one more bus lines in the neighborhood (i.e., number of bus lines +1) as an example to depict the collaborative influence of the land-use policy and other policies on the household energy consumption.

9.3.5 Explanatory Variable Change Module

Considering that the years 2010~2015 are targeted, thus the nature change of the social-demographic and social-economic variables involved in the model (i.e., income, retirement with the age increase, and the presence of children younger than 12 years old) will occur. Based on the data for each individual, the variable value of the employment and the children presence in the future 5 years are recursive. With regard to the household income, according to the average income in the past 10 years of Beijing residents, the income increasing rate is regressed by the time series data, and based on the regression equation ($y_{t+1} = 1.043 \cdot y_t + 3095.675,\ R^2 = 0.9905$), the income in the future years of each household in the sample is calculated by simultaneously considering the average age change of the main workers (whether is the age for retirement) in the household.

9.3.6 Market Change Module

It is assumed that the end-use penetration rate in the market will influence the ownership of household end uses. But in the model we cannot reflect this type of market environment influence. Therefore, in the dynamic simulation, the change of marketing rate is also considered. With the new end-use efficiency, factors for self-selection effect, *RE* attributes, and EVs (explanatory variables) calculated from the above four modules, the ownership of end use *k* (*k*=1, 2,…, 9) in each household will be known based on which the ownership rate of end use *k* in the sample can be figured out. Meanwhile, the relationship between the end-use penetration rate in the next year and the rate in the current year is regressed according to the time series data of the previous 10 years (see Table 9-2). After these, the sample ownership rate of end use *k* is compared with its market penetration rate and certain number of households (non-owners of end use *k*) in the sample is randomly triggered to be owners so as to keep the simulation consistent with the real market situation. Because we do not have any information of the end-use efficiency and its energy expenditure for household who newly buy the end use, thus, these values are assigned based on the average efficiency in the current sample and its standard deviation (see the flowchart for details). This process can be ameliorated by collecting the data about whether will households (non-owners) buy that end use in the future if giving the information of the market diffusion rate and which type they will choose (see the limitation ③in Section 9.1.2). Finally, we re-estimate the model and predict the new energy expenditure on each end use. In this way, we obtain the household energy consumption pattern which will appear if the social interaction is not considered.

Table 9- 2 Market end-use penetration rate regression results

End use	Intercept	Penetration rate in the current year	R-square
Refrigerator	21.126	0.799	0.715
Fan	31.217	0.775	0.551
AC	17.589	0.911	0.988
Shower	17.157	0.833	0.849
Washer	33.327	0.670	0.716
TV	56.473	0.593	0.528
PC	11.436	0.906	0.974
Microwave oven	15.025	0.803	0.902
Car	-12.486	1.233	0.995

9.3.7 Neighborhood Social Interaction Module

It is assumed that some households' energy consumption behavior might be influenced by the energy consumption level in the social context. If giving the public about the average end-use usage information, the households who use more than the average level are thought to be more likely to adjust their behavior[9]. However, considering that the usage of some end uses is merely for the basic life needs, that is to say, there is no potential space for households to reduce the energy consumption on these end uses. Only for end uses with inefficient usage, it is possible to make households cut down their energy expenditure when giving the social context information, and moreover the reduction will not be infinite considering households' basic service demand. With this consideration, the inefficiency analysis is first conducted by adopting the stochastic frontier analysis (SFA). Based on the results from SFA, the types of end uses with inefficiency can be identified and further, the lower bound of the energy expenditure for these end uses in each household in every year can be obtained as well. The simulation of social interaction module is carried out afterwards.

9.3.7.1 Inefficiency Analysis

Stochastic frontier analysis (SFA) has been one of the most popular tools for doing efficiency/inefficiency analysis. Numerous applications in the fields of finance, agriculture, environmental economics, public sector economics and development economics show the important role that SFA plays in inefficiency measurement (Fernández et al., 2005). To analyze the inefficiency of end uses, the frontier cost function is adopted. It is unlikely that all households will operate at the frontier. Failure to attain the cost frontier implies the existence of consumption inefficiency.

In this study, the mathematical expression is denoted as:

[9] http://www.carbonaware.eu/fileadmin/user_upload/Deliverables/CATCH_DEL_DOC_D1.1_20Behavioural_20Inception_20Report_orginal_V1.pdf

$$\ln Y_{ij} = \beta \ln X_{ij} + u_{ij} + v_{ij}, \qquad u_i \geq 0 \qquad (i = 1,2,\ldots,N \quad \text{and} \quad j = 1,2,\ldots,9). \quad (9.1)$$

In this specification, *i* and *j* index the households and the end uses, respectively. The error term is composed of two parts: the first u_{ij} is a one-side non-negative disturbance reflecting the inefficiency of end use *j* in household *i*; the second v_{ij} is a two-sided disturbance capturing the effect of measurement error and random factors. It is generally assumed that u_{ij} follows a half normal distribution which can be wrote as $u_{ij} \sim idN^{+}(0, \sigma_u^2)$, while v_{ij} follows a normal distribution, $v_{ij} \sim iidN(0, \sigma_v^2)$.

In the stochastic frontier setting, the inefficiency is measured as the ratio of actual costs (the actual energy expenditure) to the least cost level (the minimum energy expenditure):

$$\text{Inefficiency}_{ij} = \frac{(Y_{ij} | u_{ij}, X_{ij})}{(Y_{ij} | u_{ij} = 0, X_{ij})} = \frac{\beta \ln X_{ij} + u_{ij}}{\beta \ln X_{ij}} \geq 1 \qquad (9.2)$$

Table 9- 3 Variables in the SFA

Variable	Description
Y_{ij}	ln(the energy consumption per capita on end use *j* in household *i*)
x1	ln(household annual income level)
x2	ln(household size)
x3	ln(accessibility to bus stop/MRT station)
x4	ln(accessibility to supermarket)
x5	ln(energy intensity of end use)
x6	ln(accessibility to shopping mall)
x7	ln(accessibility to park)
Interacted terms between each two of the above X variables.	

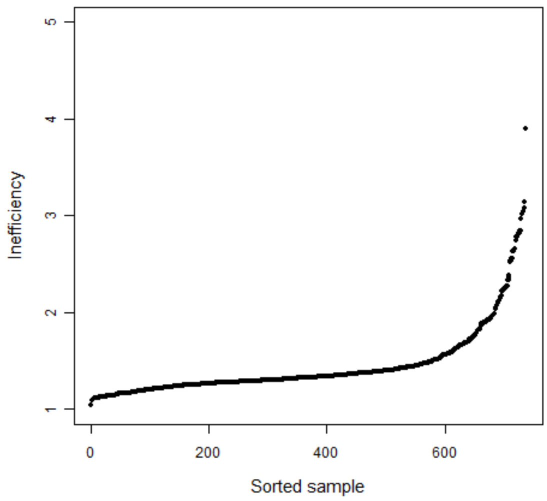
The variables included in the SFA model are listed in Table 9-3. After conducting the SFA analysis to all the end uses, it is found that not all of the end uses suffer from the inefficient usage. The inefficiency only occurs to the usage for refrigerator, washer, microwave oven, and car given their significant lambda ($\text{lambda} = \sigma_u / \sigma_v$) in the model (see Table 9-4). Based on the SFA results, the lower bound ($\underline{y_{ij}} = \beta \ln X_{ij}$) of the end-use usage in

Table 9- 4 Estimation results of SFA model

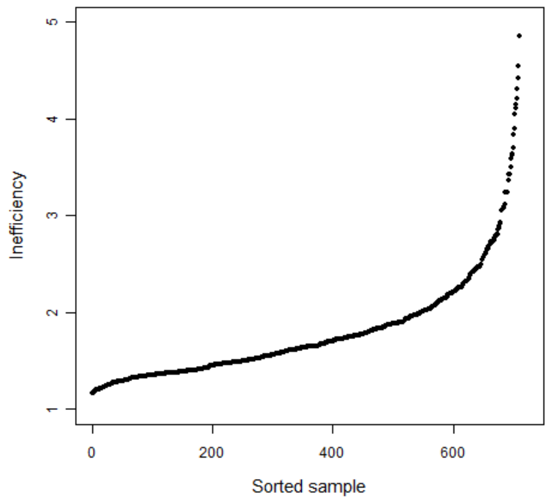
	Refrigerator	Fan	AC	Shower	Washer	TV	PC	Microwave oven	Car
Intercept	4.829 ***	0.314	5.914 ***	3.360 **	0.538	-6.024 *	-15.018 ***	-3.278	3.982 **
x1	0.032	0.234	-0.035	-0.545	-0.867 **	-0.510	1.335 **	0.413	-0.119
x2	-0.163	-2.579 ***	-0.722 **	0.773	-0.709	-1.439 *	-1.167 **	-1.650	-1.783
x3	0.336	-0.134	-0.011	0.251	-0.451	-1.421 **	0.783	0.239	3.382 ***
x4	0.214	0.551	0.296	0.579	1.739 ***	-0.144	-0.851	1.734	3.717 ***
x5	-0.634 ***	0.824 ***	1.232 ***	0.905	0.409	3.587 ***	7.093 ***	0.732	1.654
x6	-0.621 ***	0.991	-0.470	-1.627 **	-0.417	-0.651	-0.441	4.065 **	-3.382 **
x7	0.146	-1.421 **	-0.969 ***	-0.387	-0.458	0.699	0.516	-5.659 ***	-2.456 **
x11	0.044	-0.248 **	-0.022	-0.056	0.379 ***	-0.034	-0.059	-0.154	0.114
x12	-0.007	-0.126	-0.240 *	0.264	-0.007	0.321 ***	0.068	0.479 *	-0.233
x13	0.114 *	-0.183	0.102	0.276 *	0.046	-0.171	0.026	0.238	-0.372 *
x14	-0.169 **	-0.026	-0.276 **	-0.518 **	-0.545 ***	0.240 **	-0.180	-0.008	-0.787 ***
x15	0.017	-0.024	0.486 ***	0.002	0.034	-0.009	-0.171 **	-0.058	0.102
x16	0.089	0.078	0.313 **	0.369 *	0.112	-0.013	-0.110	-0.396	0.641 ***
x17	-0.055	0.217	0.111	0.285	0.313 **	0.120	0.029	0.370 *	0.372 *
x22	0.014	0.321 **	0.280 **	-0.042	-0.169	0.076	0.209 *	-0.210	0.023
x23	0.139 *	-0.208	-0.044	0.291	-0.033	0.137	-0.391 ***	0.476	-0.078
x24	0.008	-0.087	-0.040	-0.297	0.152	0.030	0.086	-0.464	0.019
x25	0.139 ***	0.286 **	-0.854 ***	-0.569 *	-0.008	0.066	-0.040	0.103	0.780
x26	-0.033	0.600 **	-0.049	0.171	0.105	0.178	0.221	0.131	0.175
x27	0.029	0.018	0.310 *	-0.422 *	0.115	-0.312 **	-0.195	-0.161	-0.450 **
x33	-0.069	-0.173	-0.137	0.332 **	-0.129	0.203 *	0.108	-0.310	-0.124
x34	0.042	0.283	-0.239	-0.477 **	0.156	-0.025	-0.277 *	-0.288	0.279
x35	0.089 ***	-0.039	0.200	-0.321	0.078	0.212 *	-0.175 *	-0.260	-0.875 *
x36	-0.019	-0.214	0.154	0.041	0.154	0.065	0.620 ***	0.760 ***	-0.488 *
x37	0.031	0.700 ***	0.104	-0.123	-0.042	-0.002	-0.160	0.405	-0.480 *
x44	0.068	-0.462 ***	0.123	0.229	-0.299 **	-0.202	0.029	0.303	-0.160
x45	-0.016	0.065	-0.488 **	-0.037	-0.164 *	0.009	0.289 ***	-0.141	-0.989 *
x46	-0.154 *	0.226	-0.293	-0.155	0.020	0.365 ***	-0.356 **	-0.062	-0.559 **
x47	-0.069	-0.305	0.214	0.456 *	-0.281	-0.302 **	-0.053	-0.349	0.264
x55	-0.099 ***	0.008	-0.017	0.039	0.057 **	-0.254 **	-0.601 ***	-0.007	-0.570
x56	-0.063 *	-0.267 **	-0.064	0.625 *	-0.058	0.184	0.063	-0.566 **	0.907
x57	0.003	0.175	0.330 *	0.030	-0.029	-0.089	-0.090	0.895 ***	0.974 *
x66	0.152 **	-0.076	0.395 **	0.147	0.299 **	-0.303 ***	-0.027	0.432 *	0.933 ***
x67	0.086	-0.481 **	-0.273	-0.159	0.002	-0.097	-0.073	-0.360	-0.422
x77	-0.107 *	0.414 ***	0.299 **	0.164	0.149	0.195 **	0.140	-0.079	0.492 ***
lambda	1.608 ***	0.732	1.272	1.437	1.453 ***	0.029	0.031	0.991 ***	2.630 ***
Sigma2	0.288	0.707	0.873	0.866	0.905	0.375	0.604	1.633	0.961
R-square	0.726	0.816	0.622	0.651	0.737	0.994	0.996	0.846	0.873

Note: $\text{lambda} = \sigma_u / \sigma_v$, Sigma2= $\sigma_u^2 + \sigma_v^2$.

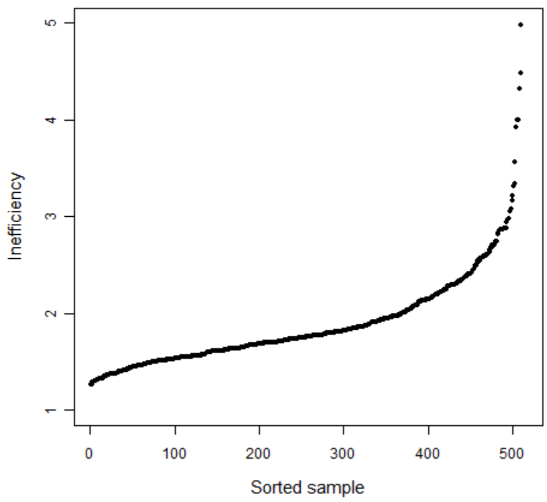
each household can be derived; besides the future lower bound can also be obtained by changing the variables with the time. All these outputs will be utilized in the simulation subsequently.



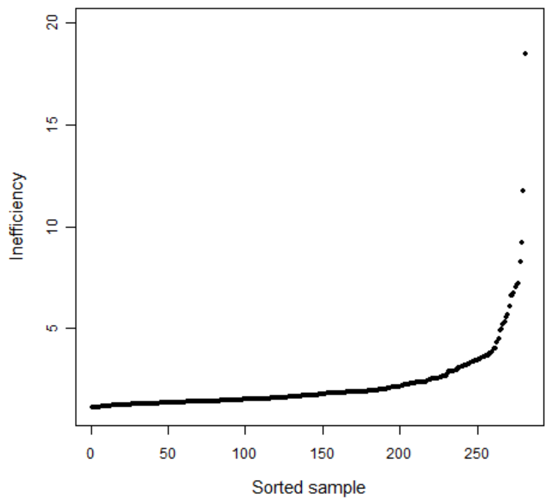
(a) Inefficiency measures of refrigerator



(b) Inefficiency measures of washer



(c) Inefficiency measures of microwave oven



(d) Inefficiency measures of car

Figure 9- 6 Inefficiency level of the end uses

The inefficiency level is depicted in Figure 9-6. As you can see that the inefficiency level of the domestic end uses ranges from 1 to 5 and almost 80% is below 3. In contrast, the inefficiency level of the car is much wider (i.e., between 1~19), indicating a substantial variance among the sample. In these contexts, it is inferred that the social interaction might play greater role on the energy consumption for cars.

9.3.7.2 Simulation Module

Following the inefficiency analysis, the simulation for the social interaction begins with the energy expenditure on each end use equals to the value finally derived in the market change module.

Focusing on the end uses with inefficiency, in the simulation program we will check whether the household owns these end uses, if yes, then the average expenditure on those end uses in the same residential neighborhood will be given to them. However, how much the household will reduce their energy consumption is unknown. Here, an expenditure change rate is generated by following a normal distribution. The mean and standard error of the distributions are externally input by the planners. Actually, this is also one of the limitations for the program, but it can be overcome by collecting the data about how households will response if the average usage or some context for the energy consumption is given. The new energy expenditure on end uses with inefficiency will be calculated based on the change rate and these values are constrained by their lower bounds. If the new expenditure is greater than its lower bound, then keep it; otherwise, replace it with the lower bound. Finally, by fixing the expenditure for end uses with inefficiency and re-estimating the model, the final energy expenditure on the other end uses in that year will be obtained. Then go to the next year.

There are two parameters in this module: the mean and the standard error of the change rate. Considering that in the social interaction module, only the energy expenditure on end uses with inefficiency are influenced, that is to say, the saving expenditure could be reallocated to other end uses which might finally reduce the expected saving or even increase the total energy consumption. With this concern, four scenarios are designed to determine the parameter, in which the respective mean values of the change rate are 0.05, 0.1, 0.15, and 0.2 (standard errors are all fixed at 0.1). By simulating these four scenarios without including the other five modules, how the energy consumption changes with the mean value of the change rate is tested. The average annual change rate of the energy consumption on each end use in these four scenarios is listed in Table 9-5. As you can see that, alongside with the influence of social interaction on refrigerator, washer, microwave oven and car, the consumption on the other end uses alter a lot, which partially (scenarios with mean equals to 0.1, 0.15, and 0.2) or fully (scenario with mean equals to 0.05) offset the initial savings. Consequently, the mean value in the final simulation program is set to 0.1 so as to reflect the above two types of phenomenon.

Table 9- 5 The energy consumption change in different scenarios

Mean value		Refrige-rator	Fan	AC	Gas shower	Washer	TV	PC	Micro-wave oven	Car	Total
0.05	(%)	-2.18%	54.72%	2.43%	-2.64%	-3.52%	4.67%	10.58%	-3.77%	-2.32%	0.02%
	(MJ)	-28.72	197.07	63.61	-217.67	-11.10	100.37	166.21	-4.00	-260.52	5.24
0.10	(%)	-3.28%	53.67%	3.46%	-2.01%	-5.83%	5.14%	11.35%	-6.33%	-3.17%	-0.02%
	(MJ)	-42.37	193.23	92.37	-167.87	-17.46	111.62	181.07	-6.25	-350.64	-6.31
0.15	(%)	-2.62%	54.02%	2.71%	-2.55%	-4.45%	4.60%	11.03%	-3.99%	-2.62%	-0.03%
	(MJ)	-34.32	199.66	71.24	-210.20	-13.98	99.00	175.50	-4.38	-292.18	-9.67
0.20	(%)	-3.95%	54.12%	3.78%	-1.90%	-7.41%	5.61%	11.86%	-7.41%	-3.58%	-0.04%
	(MJ)	-50.41	203.21	101.46	-158.89	-21.84	122.93	191.33	-7.55	-392.88	-12.64

9.4 Simulation Results

Considering the large variance of the random values, especially the parameters which are assumed to follow the normal distribution, in the simulation, each parameter is drawn 125 times and finally the average of all these draws is used to be the value of that parameter so as to lessen the possible bias. After determining all the parameter values, the dynamic simulation is carried out. The results of two policy groups are analyzed (see Table 9-6). The dynamic effects across 5 years of single policy and policy package are examined in the simulation under the predefined assumptions. We only test the effect of policy conducting in year 2012 to

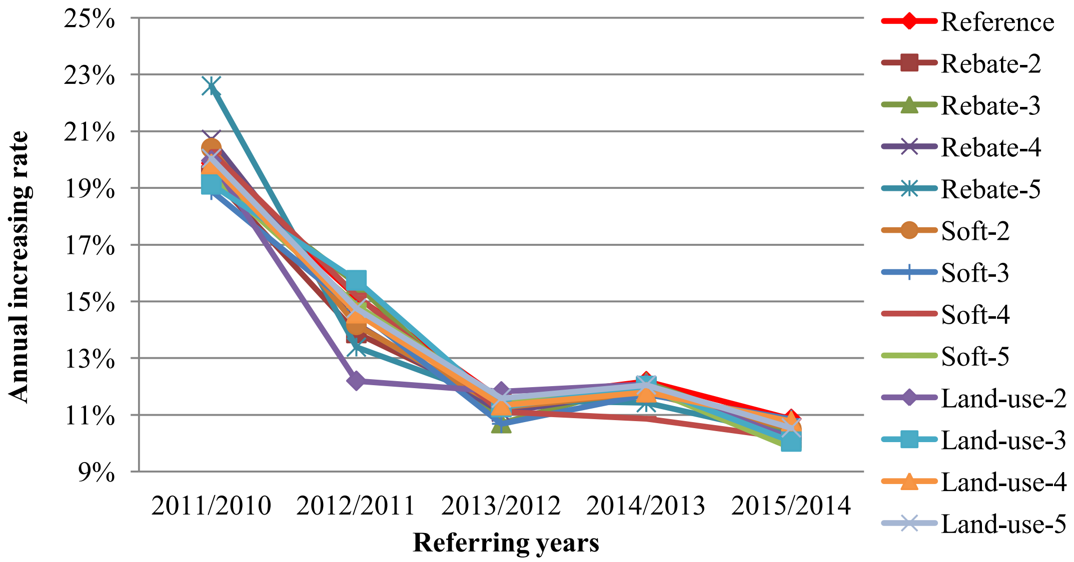
2015 due to the ended 2011.

Note that considering there are many random terms in the program, the different outputs in scenarios might result from the policy intervention and/or the random variance. Therefore, instead of comparing the final household energy consumption, the annual growth rate of the household energy use in policy scenario is compared with the value in the reference scenario.

Table 9- 6 Information of each policy group

Group	Technology improvement/Rebate	Soft policy	Land-use policy	Market rate	Social context
Single policy	Any one of these three policies			√	√
Policy package	√	√	√	√	√

9.4.1 Single Policy



(Note: The number follow the name of policy is the policy year)

Figure 9- 7 Annual increasing rate of household energy consumption for single policy

Figure 9-7 shows the annual increasing rate of household energy consumption in the single policy scenarios. The annual increasing rate is found decreasing with the year growing (from around 21% to around 10%). This might be caused by the gradually saturated market diffusion rate of end uses. It is further revealed that the increasing rates in the policy year in all scenarios are under the one in the reference scenario, indicating that the proposed policies do play a role on energy saving.

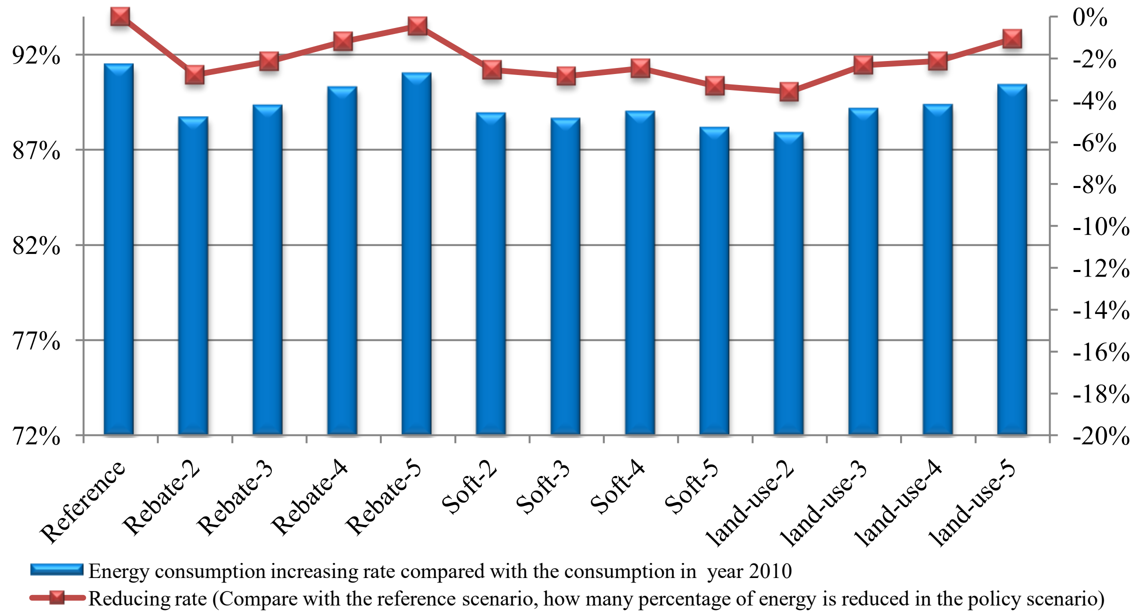


Figure 9- 8 Effect of single policy in the end of year 2015

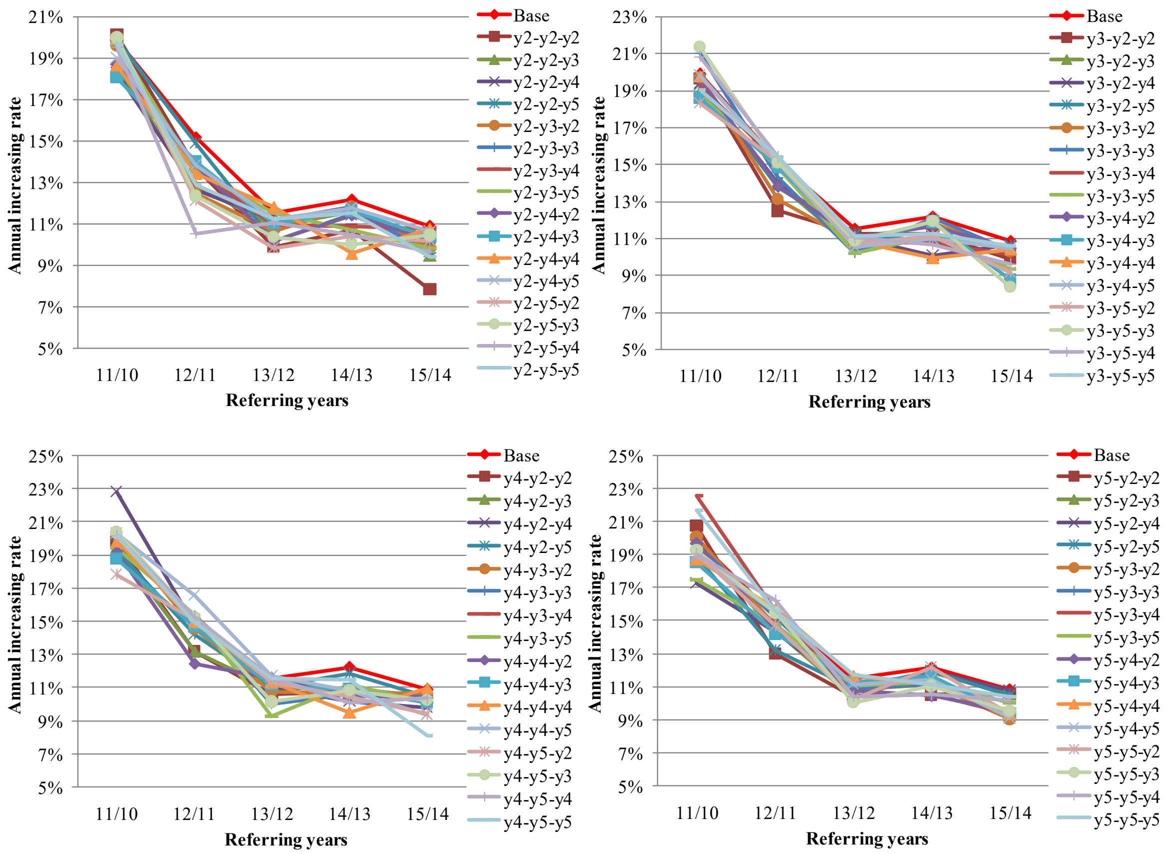
The effect of single policy in the end of year 2015 is shown in Figure 9-8. Compared with the reference scenario, all the single policy scenarios can somehow save the energy consumption (-0.5%~-3.6%). The effect of soft policy is more stable across the years than technology improvement/rebate and land-use policy. And its effect seems to be enhanced after reflecting the dynamic situation, probably due to the social interaction. For the land-use policy and technology improvement/rebate, it is found that the earlier the policy is carried out, the greater the effect of the policy is.

It is said in the twelfth five year programme, China plan to lessen 20% energy consumption in the whole society. This target is further allocated to each province[10]. The target for the household sector in Beijing by considering the economic development is to keep the annual growth rate of electricity consumption as 3.5% and the annual growth rate of

[10] http://china.lbl.gov/publications/target-allocation-methodology-provinces-china-chinese-version

transport consumption around 7%. It is easy to find that single policy is far from enough to achieve the target. Consequently, the necessity of the package policy is emphasized.

9.4.2 Policy Package



(Note: y2-y3-y4 is used to index the policy package, which means the rebate is carried in the second year, soft policy in the third year, and land-use policy in the fourth year.)

Figure 9- 9 Annual increasing rate of household energy consumption for policy package

Totally, there are 64 policy scenarios, the annual increasing rate in each scenario are given in Figure 9-9. With the increasingly saturated diffusion of end uses in the market, the annual growth rate of household energy consumption decreases a lot. This implies the importance of another type of policy which is not mentioned in this thesis, that is the market regulation policy (e.g., the car plate lottery policy). Compared with the red line (i.e., the reference scenario), almost all the lines after the policy year are under it, that is to say, the earlier the policy is carried out, the more likely the subsequent lines are under the red line.

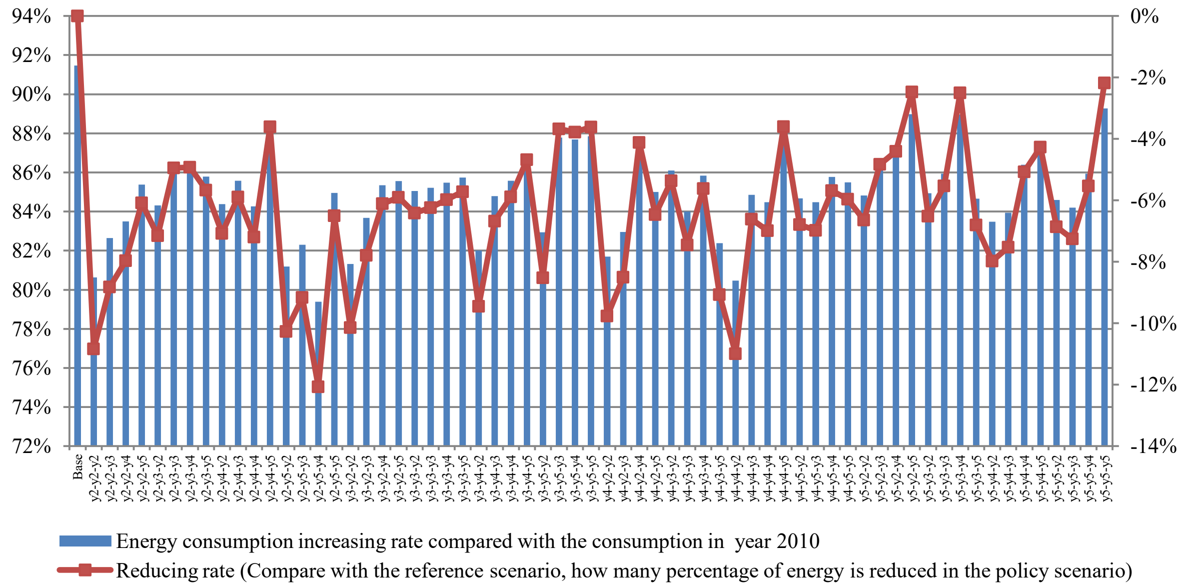


Figure 9- 10 Effect of package policy in the end of year 2015

Shedding light on the effect of package policy in the end of year 2015, it is seen that compared with the reference scenario, the predicted energy consumption can be cut down by at least 2% while at most 12%, suggesting a significant variance between the policy packages. Thereinto 77% of the packages can reduce energy use by no less than 5%. The substantial deviation mentioned above poses another concern: the timing to conduct the policy is also very essential when evaluating the policy efficacy. From Table 9-7, it is clear that with different timing, the policy effect differs. When fixing the policy year for soft policy and land-use policy but altering the year for technology improvement/rebate, the packages which can achieve the most reduction are found mainly to be the ones with the rebate carried out in the second year. While when fixing the policy year for rebate and soft policy but altering the year for land-use policy, it is revealed that sometimes the saving percentage rises with the policy year postponing, while sometimes it does not. Whereas, the packages with the land-use policy conducted in the earlier years are still more possible to have greater savings. When fixing the policy year for rebate and land-use policy but altering the year for soft policy, similar performance with the case of changing land-use policy year is shown. The aforesaid findings associated with the timing issue provide a warning to the policy makers that the policy effect is not the same across different time.

Table 9- 7 Timing effect on the policy performance

Scenario	15/10 change	Scenario	15/10 change	Scenario	15/10 change	Scenario	15/10 change
Reference	91.46%	Reference	91.46%	Reference	91.46%	Reference	91.46%
y2-y2-y2	80.62%	y3-y2-y2	81.32%	y4-y2-y2	81.69%	y5-y2-y2	84.82%
y2-y2-y3	82.64%	y3-y2-y3	83.67%	y4-y2-y3	82.96%	y5-y2-y3	86.63%
y2-y2-y4	83.49%	y3-y2-y4	85.35%	y4-y2-y4	87.34%	y5-y2-y4	87.05%
y2-y2-y5	85.38%	y3-y2-y5	85.56%	y4-y2-y5	84.99%	y5-y2-y5	88.99%
y2-y3-y2	84.31%	y3-y3-y2	85.04%	y4-y3-y2	86.10%	y5-y3-y2	84.94%
y2-y3-y3	86.51%	y3-y3-y3	85.22%	y4-y3-y3	84.01%	y5-y3-y3	85.93%
y2-y3-y4	86.54%	y3-y3-y4	85.48%	y4-y3-y4	85.84%	y5-y3-y4	88.96%
y2-y3-y5	85.79%	y3-y3-y5	85.74%	y4-y3-y5	82.39%	y5-y3-y5	84.66%
y2-y4-y2	84.38%	y3-y4-y2	82.01%	y4-y4-y2	80.47%	y5-y4-y2	83.48%
y2-y4-y3	85.57%	y3-y4-y3	84.78%	y4-y4-y3	84.85%	y5-y4-y3	83.93%
y2-y4-y4	84.26%	y3-y4-y4	85.57%	y4-y4-y4	84.47%	y5-y4-y4	86.39%
y2-y4-y5	87.85%	y3-y4-y5	86.78%	y4-y4-y5	87.86%	y5-y4-y5	87.19%
y2-y5-y2	81.19%	y3-y5-y2	82.94%	y4-y5-y2	84.67%	y5-y5-y2	84.60%
y2-y5-y3	82.30%	y3-y5-y3	87.78%	y4-y5-y3	84.48%	y5-y5-y3	84.21%
y2-y5-y4	79.39%	y3-y5-y4	87.68%	y4-y5-y4	85.78%	y5-y5-y4	85.93%
y2-y5-y5	84.96%	y3-y5-y5	87.84%	y4-y5-y5	85.50%	y5-y5-y5	89.28%

Focusing on the most effective policies which achieve more than 10% reduction (i..e, y2-y2-y2, y2-y5-y2, y2-y5-y4, y3-y2-y2, y4-y4-y2), it might conclude that with the land-use policy referring to the bus line increase conducted in the second year, it is more possible to obtain more savings. However, due to the assumptions predefined in the simulation, we have to say that this result might be inconsistent with the reality. But if the real data is collected, we can evaluate the true effect of package policies, and then quantified policies can be picked out.

Though all the above policy packages can play a great role in energy conservation, none of them can achieve the expected target. If the assumptions we set in the simulation are consistent with the reality, then it means that the collaborative efficacy of the policy packages comprised by the technology improvement/rebate, land-use policy, soft policy, and social-context based policy is not enough. To reach the final goal, one way is to intensify the implementation of the policy; another way is to ask help from other policies, such as the marketing regulation policy.

9.5 Summary and Potential Application

9.5.1 Summary

To achieve an environmentally sustainable society, it is important for policy makers to design proper policy or policies to regulate and direct household energy consumption behavior. However, due to the severe situation of the climate change and resource shortage, it is difficult to reach the target only with the help of certain policy. In other words, a policy system should be built up to substantially reduce the energy consumption in the household sector. Under this consideration, we develop a dynamic simulation program to evaluate the collaborative effects of package policies which include the technology improvement/rebate, land-use policy, soft policy, and social context based policy. Six modules comprise the simulation program, including technology improvement/rebate module, awareness change module, land-use change module, explanatory variable change module, market change module, and neighborhood social interaction module. Not only the influence of the technology change, residential environment change, socio-demographic/economics attribute change, and the awareness change acting on household energy consumption is represented in this simulation, but also the influence of the continuously changing market and society. This simulation program comprehensively considers the possible aspects which might be relevant to household energy consumption pattern, besides, the user-friendly interface make it easy to manipulate for the policy makers. As we know, such kind of policy design system is very rare currently. Therefore, it is essential to emphasize the importance of developing the dynamic system for policy evaluation, and to popularize it.

Based on the simulation results, it is found that the technology improvement/rebate, land-use policy, soft policy, and social context based policy do play a role in changing Beijing residents' energy consumption pattern. But none of them is enough to achieve the target by itself. Package policy is required. Concerning the effect of package policies, the timing of the policy significantly influence its performance. This admonishes the policy makers to realize that the policy effect is not the same across the time. Based on this simulation program, the quantified policy packages which can help reach the target of energy saving can be clear at a glance.

However, due to the limitation for the data, several assumptions are defined which makes the result not reliable. To obtain an accurate assessment, in addition to the data contents included in our survey, the supplementary information following the items mentioned in Section 9.1.2 should be collected.

9.5.2 Potential Application

The proposed simulation program in this study can be calibrated for any urban city. Moreover, it is able not only to evaluate the effect of policies mentioned above, but also to be applied to assess the influence of some macro-level policies on household energy consumption. Three examples are given as follows.

(1) In order to improve the national education level, China is vigorously expanding the enrollment of undergraduate and graduate students in these 5 years and this will continue in the future 5 years or longer. Based on our previous analysis, it is found that education level is a significant influential factor for household energy consumption behavior. In this context,

such kind of macro-level policy which seems irrelevant to the energy issue is essentially playing a great role in altering household energy consumption pattern. Because we considered the influence of education level in the dynamic simulation, it is possible to quantify the relationship between the educational policy and the energy conservation.

(2) Since 1976, China has implemented the family planning programme so as to slow down the population growth. And recently, the continuously declining birth rate in China (from 23.33% in 1987 to 12.1% in 2009) makes the government to think about the release of the family planning policy. Such kind of population policy might obviously affect the family structure (with or without children). In the dynamic simulation, we also incorporate the presence of children as an explanatory variable of the energy consumption behavior. Thus, by dynamically adjusting this factor following the macro-level population policy, these two aspects can also be linked.

(3) Focusing in Beijing, the car plate lottery policy has been carried out since 2011. After this policy, the severe growth of car ownership in Beijing is slowed. Our dynamic simulation program can reflect the influence of this policy on household energy consumption behavior as well by controlling the change of the market penetration rate in the future year.

All these potential applications verify the necessity of the development of such a dynamic simulation program again.

Chapter 10

Conclusions and Future Research

Sustainable energy consumption has been proposed several decades ago. The energy consumption always comes from four sectors, including industry, commercial, residential, and transportation sectors. This dissertation deals with the energy consumption related to the household daily behavior which always covers two parts: residential sector and transport sector. Two dimension analyses are conducted on the one hand to find out the diversity of household energy consumption pattern in Asian countries, on the other hand to deeply look at the household energy consumption behavior. The final purpose of this thesis is to develop a robust policy evaluation system to help solve the energy saving issue. To the author's knowledge, it might be the first study to deeply and comprehensively look at the household energy consumption issue from the behavioral perspective, and the first study to provide a robust policy evaluation system. To fulfill this research, several studies on model development, numerical analysis and policy simulation are implemented. This chapter presents some conclusions and recommendations for future research.

10.1 Conclusions

To in-depth talk about the household energy consumption, several sub-models have been developed. Based on the sub-models, specific policies are designed to identify their influence on the household energy savings.

Diversity of Household Energy Consumption Behavior

In order to understand the energy consumption patterns of Asian cities, as well as examine the effects of car ownership and self-selection on household energy consumption behavior, four representative megacities, Tokyo, Beijing, Jakarta, and Dhaka were selected and an international questionnaire survey about household energy consumption was conducted at each city in 2009. Based on the survey data, Heckman's latent index model is further built for each city by separating the effect of the car ownership itself and the effect of self-selection. Several conclusions can be made in this part of analysis.

(1) The influential factors of household energy consumption behavior vary among cities; furthermore, in the same city the influential factors are different within car owning households and no car households. Whereas, the top two influential factors in Tokyo, Beijing, Jakarta, and Dhaka, are all income and household size

(2) It is found that the greater maturity of economic development of a city, the larger effect of car ownership on household energy consumption increase, while the smaller effect of self-selection effect on it. This finding emphasized the importance of conducting the policy which is used to control the car ownership and the soft policies which is for reducing the self-selection effects in both developed cities and developing cities.

(3) Due to the existence of self-selection, the car ownership and household energy use should be analyzed together instead of separately treated

Joint Representation of Energy Consumption Behavior in Residential and Transport Sectors

Focusing on the necessity of the joint representation of energy consumption behavior in residential and transport sectors, this study adopted the mixed Multiple Discrete-Continuous Extreme Value (MMDCEV) model to describe the household energy consumption behavior referring to the ownership and usage of an array of end uses including both domestic appliances and vehicles. Several conclusions can be made in this part of analysis.

(1) The effectiveness of MDCEV model to simultaneously describe residential and transport energy consumption behavior is confirmed based on the model performance.

(2) Log-linear competitive relationships are found among expenditures of end uses, moreover, the correlation between the end uses caused by the unobserved factors are also verified. That is to say, the necessity and rationality of the integrated analysis of household energy consumption behavior across residential and transport sectors are clearly shown. This conclusion calls the policy makers' attention to the development of package policy which covers both the residential and transport sectors.

(3) Model estimation results provide additional insights about the influence of household attributes, housing attributes, and residential location on households' consumption behavior of different types of end uses in the context of the integrated analysis.

(4) It is revealed that the unobserved factors play a much more important role in explaining energy consumption behavior than the observed attributes of households and their members.

Time Use and Household Energy Consumption

Considering the intertwined relationship between the time dimension and energy dimension, this chapter develops a new household resource allocation model, which incorporates multiple interactions (including the interaction between time use and energy consumption, the inter-activity interaction, the inter-end-use interaction, and the intra-household interaction) based on multi-linear utility functions and endogenously represents zero-consumption for both time and energy within the group decision-making modeling framework. To the authors' best knowledge, this is the first model in literature to jointly accommodate all these behavioral mechanisms in a unified and consistent modeling framework, especially in the context of time use and energy consumption. Several conclusions can be made in this part of analysis.

(1) The model accuracy suggests that the developed model is acceptable to represent the household time use and energy consumption behavior.

(2) Multiple behavioral interactions are found in the empirical analysis, which on the one hand supports the rationality for the joint representation of time use and energy consumption behavior, while on the other hand confirms the necessity for describing the energy consumption behavior of in-home end uses and out-of-home vehicles simultaneously. The existence of the various interactions suggests that different policies should be packaged so as to enhance the synergetic effects of policy interventions.

(3) The effect of telecommuting policy on household energy consumption is evaluated based on the proposed model. It is found that telecommuting can help household save substantial energy use.

Residential Location Choice and Household Energy Consumption

It is expected that the residential location choice and household energy consumption behavior might correlate with each other. Besides, due to the existence of self-selection effects, the observed inter-relationship between them might be the spurious result of the fact that some unobserved variables are causing both. This chapter first builds an integrated model, termed mixed Multinomial Logit-Multiple Discrete-Continuous Extreme Value (MNL–MDCEV) model, which covers residential location choice, end-use (including in-home appliances and out-of-home cars) ownership, and usage behavior, and then applies the integrated model to identify the sensitivity of household energy consumption to changes in land use policy by considering a comprehensive set of residential environment (*RE*) variables, socio-demographic variables as well as multiple self-selection effects. Several conclusions can be made in this part of analysis.

(1) The effectiveness of the integrated model to describe the residential location choice and household energy consumption behavior by simultaneously incorporating the one-way causal relationship and the non-causal association (i.e., self-selection effect) between them is confirmed.

(2) The model results indicate that land-use policy do play a great role in changing Beijing residents' energy consumption pattern, while the self-selection effects cannot be ignored when evaluating the effect of land-use policy.

(3) Based on the policy scenario design, it is found that increasing recreational facilities and bus lines in the neighborhood can greatly promote household's energy-saving behavior. Additionally, the importance of "soft policy" and package policy is also emphasized in the context of Beijing.

(4) The rationality of joint representation for residential and transport energy

consumption behavior is verified attributing to the significant complementary effect between these two parts.

Technology Improvement and Household Energy Consumption

A general agreement has been reached among economists and scholars that energy efficiency improvement is always accompanied by an empirical issue: Does the rebound effect occur simultaneously? This chapter attempts to answer this question by examining the extent to which an increase in the energy efficiency of major household end uses (including refrigerator, electric fan, air conditioner, gas shower, clothes washer, TV, PC, microwave oven, and car) causes additional utilization on itself and on other end-uses in the context of Beijing from a short-run perspective. An integrated model is first developed by combining a Logit model and a resource allocation model with a multilinear function, where the former is used to represent the choice of owning each end use and the latter to describe the end-use usage decision. The prediction is implemented by assuming the efficiency change of specific end uses. The direct and indirect rebound effects are finally obtained from calculating the own- and cross-elasticities. Several conclusions can be made in this part of analysis.

(1) The effectiveness of adopting the integrated model described in this chapter to evaluate household energy consumption by different end uses is confirmed on the one hand by the relatively good model performance and on the other hand by the rational behavioral mechanism implied by the statistical significance of many interaction terms introduced into the model.

(2) It is found that not all the targeted end uses suffer from the rebound phenomenon. Among the nine objective end uses, the rebound effects occur only when the efficiency of air conditioner, clothes washer, microwave oven and car increases.

Further, backfire is observed for clothes washer and microwave oven, but this is not remarkable.

(3) After controlling for rebound effects, the efficacy of technological improvement for the above four end uses in saving total energy consumption is detected: increasing the efficiency of air conditioner and car can reduce the total household energy consumption during the use phase, but opposite for microwave oven.

(4) The need for the integrated analysis of household energy consumption behavior across residential and transport sectors is confirmed again due to the significant indirect rebound effect.

Policy Application Based on Dynamic Simulation

As a further improvement of previous chapters, an integrated modeling framework which is actually a combination of multiple essential models is introduced by using dynamic simulation program. The main motivation is originated from the construction of a robust policy system to meet the predefined energy conservation target. The dynamic collaborative effect of land-use policy, soft policy, the technology improvement, and the social context based policy is evaluated in this simulation. In addition, the influence of market end-use diffusion rate and the household inefficient consumption on the energy use is also incorporated. Several conclusions can be made in this part of analysis.

(1) Single policy is suggested not enough to achieve the expected target. Package policies should be developed.

(2) The policy timing does affect the performance of that policy due to the continuously changing market and society.

(3) The data sets needed for designing a robust policy evaluation system are summarized

which can contribute to support the future research.

(4) This proposed dynamic simulation program can be further applied to assess the influence of some macro-level policies which seems irrelevant to the household energy consumption issue, such as the educational policy, population policy, and market policy.

Conclusive Comments

As mentioned in the first chapter that the main tasks in this thesis include twofold: (1) confirm the necessity and rationality of the integrated analysis of energy consumption behavior across residential and transport sectors; (2) identify the effective policies to reduce the total household energy consumption. Regarding the first task, it is demonstrated not only in Chapter 5, but also in Chapter 6, Chapter 7, Chapter 8, and Chapter 9 from different perspectives. In other words, the standpoint of this thesis is always plausible in the context of Beijing. This suggests that the cross-sector package policy covering both residential and transport sectors should be developed. While focusing on the second task, Chapter 6, Chapter 7, Chapter 8, and Chapter 9 contribute to evaluate the effects of time use policy, land-use policy, soft policy, and technology innovation on household energy consumption. Based on this thesis, it is proved that all these policies play significant role on energy saving which can provide a support for the policy makers. Further, different types of policies should be packaged together so as to achiever the far target. By combining these two findings, we give the specific policy implication derived from the whole research here (see Table 10-1) which can be summarized as two words "Package policy":

(1) No matter for any single policy mentioned in Table 10-1, we cannot evaluate their effects only in the residential sector, or only in the transport sector, Instead, the cross-sector

effect of these policies should be evaluated. In other words, the package land-use, time-use, technology innovation, soft, “eco-point”/fee system policies are more needed in reality.

(2) Since none of the listed policy can achieve the sustainable society, the policy system which packages several types of policies should be developed.

Table 10- 1 Policy implication based on the whole research

		Only residential sector	Only transport sector	Residential & Transport sectors
No	Land-use policy	No	No	Yes
No	Time-use policy	No	No	Yes
No	Technology innovation	No	No	Yes
No	Soft policy	No	No	Yes
No	“Eco-point”/Fee system	No	No	Yes
Yes	Policy system which packages several types of policies			

10.2 Recommendations for Future Research

Having elaborated the main conclusions, there are several research issues and recommendations for future research that should be identified

(1) In this thesis, as mentioned before, we only focus on the direct energy consumption used in the household, while the indirect energy consumption embedded in goods and services purchased by households is not included. However, in order to effectively reduce household energy consumption, it seems also important to explore how households respond to impacts of the indirect household energy consumption. To address these issues, more detailed information is required and the method used to deal with the supply–demand issues can be combined with our research.

(2) To explore the diversity of the household energy consumption patterns, more

city-specific factors should be included in the model (e.g., motorcycle or other paratransits) in case that the self-selection effect is partially explained by these factors.

(3) In the whole thesis, the energy consumption is calculated based on the end-use efficiency and its usage which is reported by respondents. Reporting biases could occur at both the level of dependent variables and the level of explanatory variables in any type of questionnaire survey. It is also true in this study. Such reporting biases should be corrected by improving data collection methods and/or adopting more advanced modeling techniques. Some technologies, such as GIS, GPS, and ICT, could be used to reduce respondents' answering burden and consequently reduce reporting errors. Data fusion techniques might be helpful to correct reporting errors by combining different data sources, if available. Reporting biases could be accommodated in the modeling process (e.g., utilizing the concept of measurement equation in the structural equation models with latent variables, and discretizing the continuous variables).

(4) Since representing complex behavioral mechanisms usually requires advanced estimation techniques, which are difficult to implement in practice, it is necessary to develop user-friendly software packages.

(5) In the policy application chapter, due to the limitation of the data, some assumptions have to be made. In order to be consistent with the reality, several types of data information are needed which have been clearly listed in Chapter 9.

Appendix

A. Sampling Algorithms

The way of obtaining the draws of $\boldsymbol{b}$, Σ and $\Gamma_i \forall i$ are borrowed from Train (2003), in which the posterior distributions are specified by the same distributional families as the priors since normal and inverted gamma distributions are both conjugate distributions (Gill, 2008). The details of the sampling steps are described as follows.

Conditional on Γ and Σ, the posterior for $\boldsymbol{b}$ is $N(\overline{\Gamma}, \Sigma / I)$, in which I is the total sample size of observed households, and $\overline{\Gamma} = (1/I)\sum \Gamma_i$. A draw of $\boldsymbol{b}$ can be easily obtained through $\tilde{\boldsymbol{b}} = \overline{\Gamma} + C\kappa^0$, where C denotes the lower-triangular Choleski factor of Σ / I and κ^0 denotes a vector ($N \times 1$) independently drew from a standard normal density (N is the dimension of estimated parameters).

The posterior for the nth (n=1,2,…, N) diagonal element of Σ conditional on $\boldsymbol{b}$ and Γ is $\mathrm{IG}(I+1, (1+I\overline{V_n})/(I+1))$, in which $\overline{V_n} = (1/I)\sum_i (\Gamma_{in} - \boldsymbol{b_n})^2$. For ease of description, denote $s_n = (1+I\overline{V_n})/(I+1)$. The procedure of generating draws from inverted gamma distribution is first taking ($I+1$) draws from a standard normal distribution and label them as $\kappa_r (r = 1,...,(I+1))$; second, create $m_n = (1/(I+1))\sum_r (\sqrt{1/s_n}\kappa_r)^2$, and finally, the draw of the nth diagonal element of Σ can be derived from the inverse of m_n, that is $\Sigma_{nn} = 1/m_n$.

Applying Gibbs sampling to help obtain the draws of $\boldsymbol{b}$ and Σ.

The posterior for $\Gamma_i \forall i$ given b and Σ is proportional to $L_i(y_{ij}, e_{ijk} | \Gamma_i) f(\Gamma_i | \boldsymbol{b}, \Sigma)$. The Metropolis-Hasting (M-H) algorithm is used to take draws for Γ_i. Let Γ_i^t denote the value of

Γ_i at the tth iteration, and sample Γ_i^* at the (t+1)th iteration. Then the procedure is specified as below.

1. Calculate $q = \sigma D \kappa^1$, where κ^1 is a vector ($N \times 1$) independently drew from iid standard normal deviates, D is the Choleski factor of Σ, and σ is a scalar which is set to dynamically change with the acceptance rate among the I trail draws of $\Gamma_i \forall i$ in the previous iteration. Following Train (2003), σ is lowered if the acceptance rate is below 0.3, and is raised if the rate is above 0.3.

2. Sample Γ_i^* through $\Gamma_i^* = \Gamma_i^t + q$.

3. The transition probability from Γ_i^t to Γ_i^* is

$$R = \min\left\{ \frac{L_i(y_{ij}, e_{ijk} | \Gamma_i^*) f(\Gamma_i^* | \boldsymbol{b}, \Sigma)}{L_i(y_{ij}, e_{ijk} | \Gamma_i^t) f(\Gamma_i^t | \boldsymbol{b}, \Sigma)}, 1 \right\}.$$

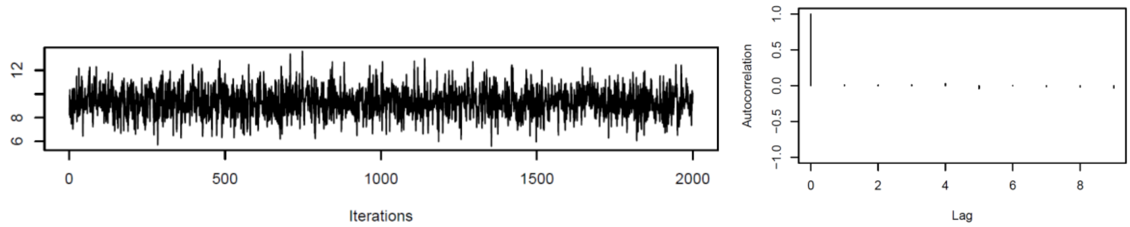
4. Draw variable $\mu \sim \mathrm{U}(0,1)$, the standard uniform distribution, and make

$$\Gamma_i^{t+1} = \begin{cases} \Gamma_i^* & \text{if } \mu < \mathrm{R} \\ \Gamma_i^t & \text{otherwise} \end{cases}.$$

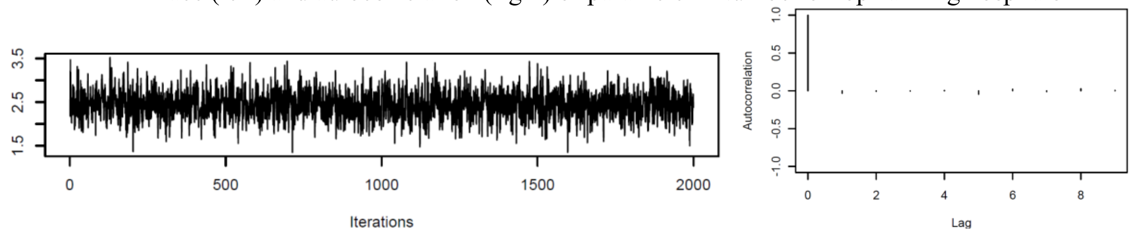
B. Convergence Diagnostic

The 2000 draws used to do the inference were exported first. The output analysis and diagnostics for MCMC were then implemented in software R by using the package “coda”. Here the trace plots, autocorrelation graphs and the Geweke diagnostic of the mean value of some selected parameters are used to check the convergence.

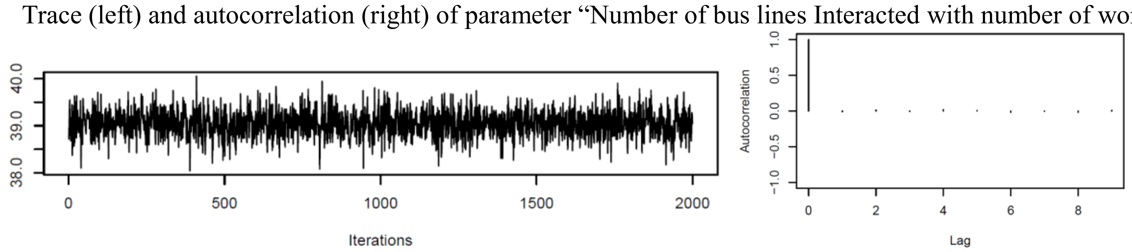
Both the graphs and the z-scores indicate that the parameters drawn from MCMC have achieved convergence.



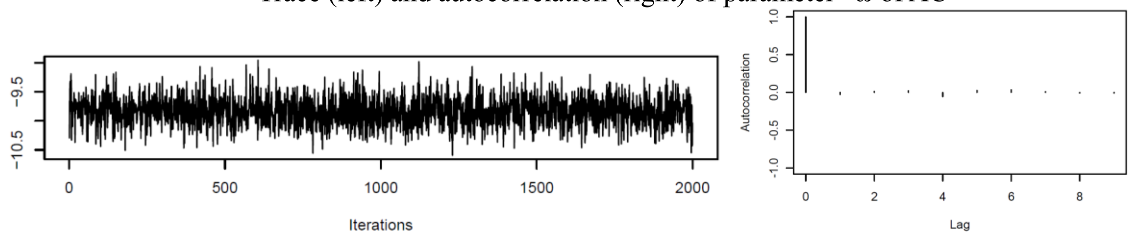
Trace (left) and autocorrelation (right) of parameter "Number of top-ranking hospitals"



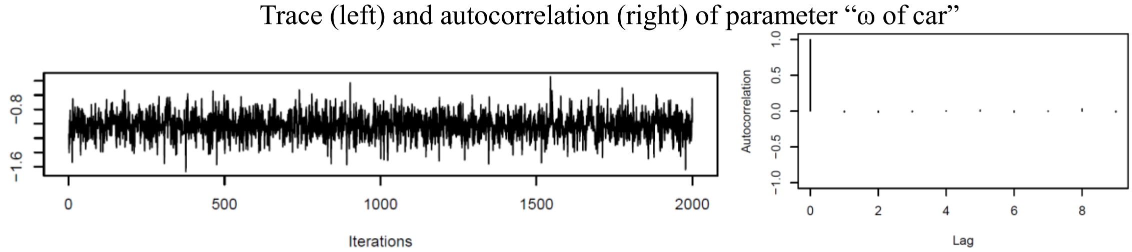
Trace (left) and autocorrelation (right) of parameter "Number of bus lines Interacted with number of workers"



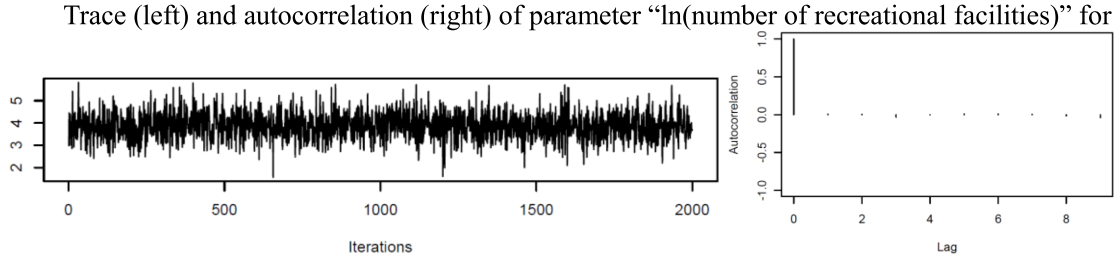
Trace (left) and autocorrelation (right) of parameter "ω of AC"



Trace (left) and autocorrelation (right) of parameter "ω of car"



Trace (left) and autocorrelation (right) of parameter "ln(number of recreational facilities)" for TV



Trace (left) and autocorrelation (right) of parameter "CBD area" for car

Figure 7-B1 Trace plots and autocorrelation graphs of parameters

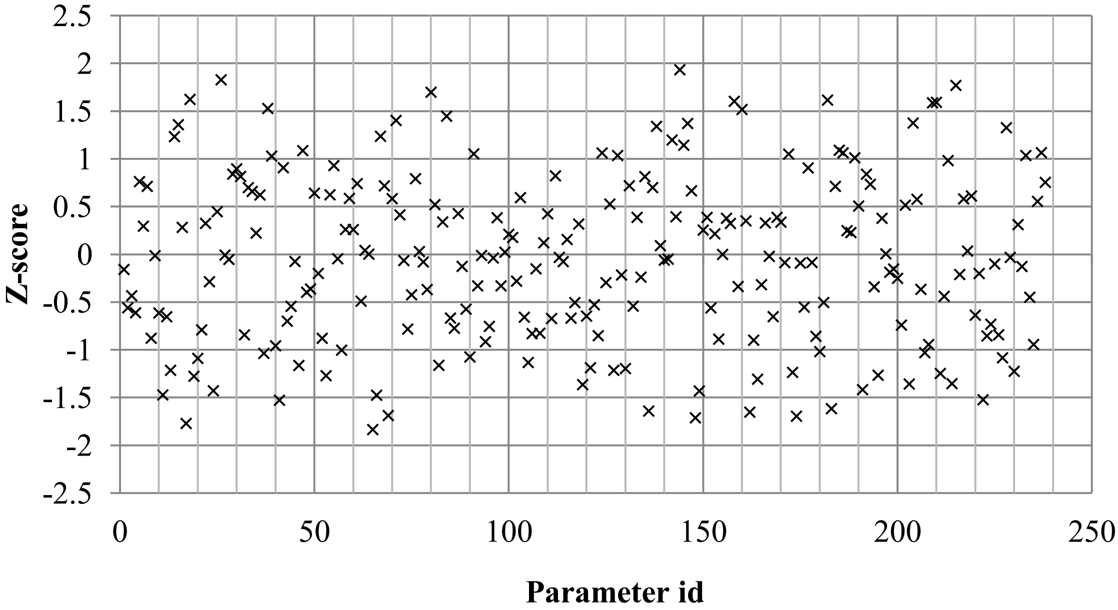


Figure 7-B2 Geweke diagnostic for the mean value of each parameter

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