Simulation of Household In-home and Transportation Energy Use: An Integrated Behavioral Model for Estimating Energy Consumption at the Neighborhood Scale

By

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Abstract

Household in-home activities and out-of-home transportation are two major sources of urban energy consumption. In light of China's rapid urbanization and income growth, changing lifestyles and consumer patterns – evident in increased ownership of appliances and motor vehicles - will have a large impact on residential energy use in the future. The pattern of growth of Chinese cities may also play an intertwined role in influencing and being influenced by consumption patterns and, thus energy use. Nonetheless, models for evaluating energy demand often neglect the evolution of appliance & vehicle ownership and directly correlate consumption with static characteristics without explicit behavioral links. In this thesis I aim to provide a comprehensive method for understanding household energy behavior over time. Using household survey data and neighborhood form characteristics from Jinan, a mid-sized Chinese city, I explore the relationship between neighborhood design and household-level behaviors and their impact on final energy consumption. My ultimate goal is to provide the modeling engine for the "Energy Proforma©" a tool intended to help developers, designers, and policy-makers implement more energy-efficient neighborhoods.

To predict in-home and transportation energy use, and their trade-offs, I develop an integrated household-level micro-simulation framework. The simulation tool is based on a total of eight inter-related behavioral models which estimate out-of-home energy use by predicting trip generation, mode choice and trip length for each household and in-home energy use according to different energy sources. In the various sub-models, relevant dimensions of neighborhood form and design are included as explanatory variables. These models are then combined with modules that update household demographics, appliance & vehicle ownership information, and activity trade-off patterns. These inter-linked models can then be used to estimate the long-term effects of neighborhood design on household energy consumption and greenhouse gas emissions.

Unlike separate in-home or out-of-home energy demand models, I develop an integrated simulation framework for forecasting. It captures estimated trade-off effects between in-home and transportation energy-consuming behaviors. The approach produces indicators of detailed behavioral outcomes such as trip mode and trip length choice, making it easier to relate policies, such as mode-oriented strategies, to ultimate outcomes of interest. I ultimately aim to provide urban designers, developers, and policy makers a decision support tool to explore and compare long-term energy performance across proposed neighborhood development projects.

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To my grandpa, thank you for inspiring and supporting me all the way from my childhood to MIT. I still remember the dream that you told me and that's always the extra motivation to push me forward.

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Chapter 1: Introduction

1.1 Motivation and Thesis Context

The turn of the twenty-first century finds China under rapid and intense urbanization. Between 2010 and 2030, China will add approximately 350 million people – more than the entire population of the USA – to its cities (Woetzel et al, 2009). This unprecedented demographic shift is intertwined with economic transformations and changing consumer patterns and lifestyles, such as demand for larger living spaces, more appliances and more motor vehicles (McNeil & Letschert, 2005; Hao et al, 2010). These trends will undoubtedly be matched by rising energy consumption and greenhouse gas emissions. While the nation has made impressive strides in reducing the greenhouse gas (GHG) intensity of its economy in recent decades, emissions per capita have been on the rise, sharply so in recent years (Figure 1.1). If the Chinese government is to fulfill its ambitious efforts to further reduce the carbon intensity of its economy (by 40-50% between 2005 and 2020), it will likely have to focus on the urbanization process.

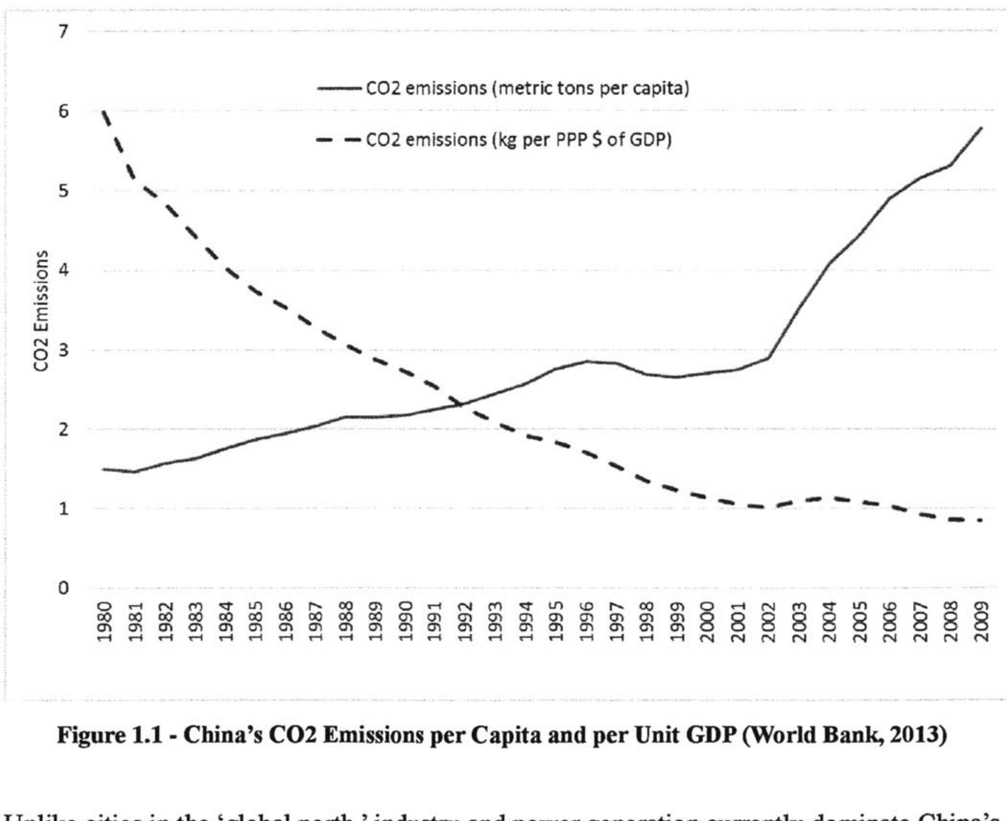

Figure 1.1 - China's CO2 Emissions per Capita and per Unit GDP (World Bank, 2013)

Unlike cities in the 'global north,' industry and power generation currently dominate China's cities emissions profiles (Wang et al, 2012); however, future energy demand and related emissions will be driven by massive increases in the urban buildings and transport sectors (Woetzel et al, 2009). In light of this forecast growth in energy and emissions, intensifying urbanization, and the need to realize sustainable urban development, the "Clean Energy City" concept has been promoted at both national and local levels in China (Yao et al, 2005). Changing the patterns of urbanization now holds great promise for mitigating short-term urban energy use and emissions and ensuring a long-term, lower-carbon urban development trajectory.

Given the sheer scale of urbanization in China, the pent-up demand for space and consumer goods and services, and the underlying political economy of urban development (e.g., the land lease system; see Liu and Salzberg, 2012), moving China's urban development towards a lower-carbon future requires intervening at the development scale – that is the neighborhood.

Neighborhoods constitute the fundamental building block of the modern Chinese city, epitomized by the Da Pan, large-scale (e.g., 30-300 hectares), predominantly suburban, developments driven by the dynamic real estate industry (Chen, 2008). In turn, neighborhoods, the physical places where people live and often undertake a number of their daily activities, condition residential energy consumption. Households, living in a neighborhood, aim to maximize their quality of life, given their capabilities. More formally, households choose their daily in-home activities (e.g., eating, sleeping, watching TV) and out-of-home activities (e.g., eating out, going to work, attending school) to maximize their utility subject to time, money, physical and other constraints. These activities result in energy consumption. In addition, households implicitly consume energy "embodied" in the neighborhood physical structure they inhabit – that is, the energy "invested" in constructing the physical spaces we inhabit. Therefore, we can partition neighborhood-level energy consumption into three aspects (CEC report, 2012): 1) Embodied – the energy used in the manufacturing, transporting, and processing construction materials; 2) Operational – the energy consumed to maintain the operations and life-supporting functions of households in the neighborhood; and 3) Transportation – the energy involved in household travel.

This research is a component of the ongoing project – "Making the clean Energy City in China"[1]. The overall project aims to understand the relationship between urban form and all three types of energy consumption (Embodied, Operational, and Transportation) at the

[1] The project is supported by China Sustainable Energy Program-The Energy Foundation and the Low Carbon Energy University Alliance

neighborhood scale. This research examines in-home operational energy, out-of-home transportation energy, and their trade-offs in an integrated way with previous efforts made in this project. To be specific, the project first directly calculates the embodied energy used in manufacturing, transporting the materials to the site, and in the construction process. Then it considers the operational energy for the public areas of a development, such as elevators, water pumps, and lighting (Zhang, 2008). These components are added to the energy estimate that comes out of the integrated in-home and transportation energy models developed in this thesis. Together they form the engines of the "Energy Proforma©", a tool that this project aims to provide to help developers, designers, and policy-makers implement more energy-efficient neighborhoods.

1.2 Research Objectives

The objective of this thesis is to develop and demonstrate an integrated model that incorporates in-home and transportation energy to better understand the impact of human behavior and lifestyles on energy use and GHG emissions. The ultimate intention is to enhance the behavioral modeling engine underlying the "Energy Proforma"© to provide urban designers, developers, and policy makers a means to explore and compare long-term energy performance across proposed neighborhood development projects (Frenchman et al, 2013)[2]. These objectives are pursued by researching the following tasks in detail.

1) Most of the existing studies investigate these two energy sectors separately, while total household energy use arises from both sets of activities and, their interactions. The overall simulation framework must find a way to incorporate both in-home and transportation energy and their trade-offs. The development of integrated in-home and transportation framework should also consider data constraints for model estimation.

2) Dynamic features should be added to the modeling framework. In a rapidly evolving place like China, we must account for the evolution of demographics, appliance & vehicle ownership and the explicit underlying behavioral links.

3) The relationship between urban form and energy at the neighborhood scale should be explored and understood with behavioral models embedded in the overall simulation framework. The impact of form variables on energy might be direct with energy-related behavior or indirect through energy equipment stocks or intermediate behavior choices.

[2] An on-line version of the tool can be viewed here: energyproforma.mit.edu.

As such, each behavioral model should be correctly specified and estimated and links and transitions between different behavioral models must be clearly identified.

4) In order to be applied in a practical tool like the "Energy Proforma"©, the simulation model developed in this research must be validated with real data and the ability to analyze impacts of policy scenarios should be demonstrated as well.

1.3 Research Approach

The objectives of understanding and quantifying the in-home and transportation energy use will be achieved in the context of Jinan, a typical mid-sized city in China. Methods and models that have already been developed in the "Clean Energy City" project will be the basis of this research (Jiang, 2010; Zhang, 2010; Wang, 2012; and Chen, 2012).

Instead of focusing solely on the analysis of energy and urban form, I take an integrated approach to understand human behavior within neighborhoods through empirical analysis. Microsimulation is the modeling technique applied here since it has the ability to account for interactions and dynamics within the complex decision-making system. The simulation tool is based on a total of eight inter-related behavioral models which estimate out-of-home energy use by predicting trip generation, mode choice and trip length for each household and in-home energy use according to different energy sources. To specify and estimate those behavioral models, I utilize a series of statistical techniques including linear regression models, discrete choice models (MNL & Nested-Logit), and event count models (Negative Binomial Regression).

In the various sub-models, relevant dimensions of neighborhood form and design are included as explanatory variables. These models are then combined with modules that update household demographics, appliance & vehicle ownership information, and activity trade-off patterns. These inter-linked models can then be used to estimate the long-term effects of neighborhood design on household energy consumption and greenhouse gas emissions.

While the city of Jinan is used as the case study in this research, differences between cities and behavior/consumption patterns should be recognized. The approach taken in this research aims to demonstrate a feasible way of estimating neighborhood-level energy consumption given target population, quantified design indicators, and general city-based factors. This does not indicate that the estimated models can directly move to other cities and produce energy and emission calculations. Rather, the model is built based on the idea of tracing human behavior and the overall framework can be applied as a starting point to think about how urban form and energy are connected via human activities.

1.4 Thesis Structure

The rest of the thesis is organized as follows:

Chapter 2 reviews the literature on modeling techniques applying to household in-home and transportation energy use. First, I summarize previous efforts on developing separate household in-home and transport energy demand models. Then, I present three potentially related integrated microsimulation models. I conclude with discussion of precedents and challenges in modeling both transportation and in-home energy and their trade-offs.

Chapter 3 presents the conceptual framework and methods. I summarize the calculation methods for in-home and transportation energy consumption and CO2 emissions. Then, I discuss the advantages of microsimulation. Within this approach, I introduce the overall model framework and techniques.

Chapter 4 describes the data used to estimate the models related to in-home and transportation energy use and the model estimation processes. I introduce the data source and conduct descriptive analysis for variables used in the model. With the data survey, I estimate the models for appliance ownership, vehicle portfolio choice, lifestyle trade-off patterns choice, and sub-models within two energy estimation modules.

Chapter 5 presents the simulation process, model validation procedure and the forecast results. Three types of scenarios are developed to simulate the changes of energy consumption and CO2 Emissions, including a baseline forecasts with only the evolution of demographics and equipment stock and two other scenarios with fuel efficiency improvement or design interventions.

Chapter 6 concludes the thesis. I summarize the findings, research limitations and directions for future research.

Chapter 2: Literature Review

The aim of this chapter is to review the literature on modeling techniques applying to household in-home and transportation energy use. Most household-level analyses tend to model in-home and transportation energy consumption separately. The first two sections of this chapter review previous efforts on developing separate household in-home and transport energy demand models. The third section traces several potentially related integrated microsimulation models. The last section of this chapter summarizes the precedents and discusses challenges in modeling both transportation and in-home energy and their trade-offs.

2.1 In-home Energy Consumption Modeling

There are two general modeling techniques to research household in-home energy demand and various impact factors – "top-down" and "bottom-up" approaches. The top-down technique treats residential energy consumption as a whole, without further considering the difference among individual end-uses. It attributes the total estimated residential energy consumption to characteristics of the entire housing sector (Swan et al, 2009). Macroeconomic indicators are commonly used by top-down models, such as GDP, employment rates, climate conditions, appliance penetrations, and housing unit numbers. They are applied at an aggregated level and normally aim to provide better understandings of the relationship between the energy sector and the economy. On the other hand, bottom-up models typically calculate the end-uses of individuals, households, or groups of households and utilize samples to extrapolate the total energy consumption by the neighborhood, region, or the entire nation. Common input data include built forms, appliances, climate conditions, and occupants' demographics and behavior (Suganthi and Samuel, 2012). Bottom-up models can be further categorized into two approaches: econometric (statistical) and engineering (Swan et al, 2009).

The econometric approach correlates in-home energy demand with certain chosen explanatory variables given the historical data. The relationship is built after coefficient estimation and it can then be utilized for forecasting considering changes in the values of explanatory variables. Statistical methods rely on assorted types of regression analysis and a variety of relevant models have been introduced to estimate factors related to in-home energy demand. Dubin and McFadden (1984) provide the seminal work, proposing a unified model of the demand for appliances and the derived demand for electricity, utilizing economically consistent discrete-continuous regression models. Fung et al (1999), using regression techniques, find that energy price, demographics, weather, and appliance ownership significantly relate to residential energy consumption in Canada. Santin et al (2009) find, using regression, that both physical attributes and occupant characteristics explain the variations of in-home electricity energy consumption. To capture potential non-linear relationships, Aydinalp et al (2002) proposed a comprehensive residential consumption model using neural networks and utilized demographics, appliance, and heating system information as the inputs to train the neural networks. Wang (2012) reviews a number of recent analyses in China which find income growth, urbanization, demographic changes, and related elements like increased consumer goods as important factors driving household energy consumption.

The engineering approach simulates energy consumption of the end-use devices/systems themselves based on power ratings and usage patterns. For in-home operation, appliances, equipment age, thermodynamic principles, customer behavior, and house unit size are normally included (Vassileva et al, 2011). Bottom-up engineering models are capable of analyzing the impact of new technologies and are usually used for estimating energy efficiency of new device/system technologies. The analysis units can be pretty flexible. Several methods focusing on appliances themselves have been developed. They utilize the distribution of the appliances and assume common appliance unit power to calculate energy consumption (Capaso et al, 1994; Jaccard and Baille, 1996; Kadian et al, 2007). Apart from appliances, some of the previous models treat houses as the basic units and categorize houses according to their size and thermal/air conditions (MacGregor et al, 1993; Huang and Broderick, 2000; Parekh, 2005). Another way to classify the houses is based on an actual sample, and those methods are normally applied to represent high/low energy consumption regions (Farahbakhsh et al, 1998; Larsen and Nesbakken, 2004).

As mentioned, in-home energy can be calculated with a top-down scheme, at an aggregated level, or with a bottom-up (statistical or engineering) scheme, from the user side. The top-down approach only requires simple macroeconomic input information but cannot distinguish energy consumption for various individual end-uses. Bottom-up statistical approaches have a theoretically close link with occupant behavior but also rely on detailed historical consumption data. In addition, self-selection in housing is a theoretical challenge in the regression analysis underlying the bottom-up statistical methods. That is, households desiring low energy consumption might choose more efficient homes, appliances, etc.. The bottom-up engineering approach has the advantage of accounting for new technologies but is usually based on simplified consumer behavior. Each of the three major in-home energy consumption approaches have their own pros and cons and therefore can only meet a specific need for energy modeling.

2.2 Transportation Energy Consumption Modeling

Energy demand in the transportation sector is directly related to individuals/households' travel patterns (e.g., trips, distances, modes) and the fuel type and efficiency of involved motor vehicles. The purpose of this section is to review the relationship between urban form and travel patterns, and further, on transportation energy consumption. Apart from direct aggregated-level comparative analysis, most of the existing disaggregated transport energy models can be categorized into two types: multivariate-regression and Structural Equation Modeling (SEM).

Multivariate-regression is a flexible data analysis method to explore and quantify the relationship between variables of interest (transportation energy or its related travel patterns, in this case) and a set of explanatory variables. It typically involves linear regression, discrete choice, event count and other modeling techniques based on types of variables (continuous or discrete) and forms of equations (linear or non-linear). On the transportation side, researchers have long been interested in utilizing multivariate-regression analysis to explore the empirical relationships between neighborhood built form and travel behavior. Typically, such analyses focus on specific behavioral dimensions underlying energy use, but not energy use per se. The reviews by previous researchers conclude that it is not only the socio-economic and lifestyle differences between residents, but also the urban form itself - its massing, road layout, location and amenities - that influence inhabitants' behavior and therefore energy consumption (Boarnet & Crane, 2001; Goudie, 2002; Newbold et al, 2005). Ewing and Cervero (2010) recently conducted a meta-analysis of more than 50 such empirical studies (all but four apparently in North America), and find private vehicle kilometers traveled (VKT) to be consistently related to population density, land use mix, street configuration as well as relative location (e.g., distance to jobs). They find roughly comparable effects with respect to public transport use and walking. In China, a number of recent studies, using disaggregate data, have focused on various related aspects of urban travel in China, including the relationship between neighborhood form and travel distances (Pan et al, 2009), neighborhood form and household vehicle ownership and travel energy use

(Jiang, 2010) and relative neighborhood location and travel energy use (Naess, 2010). Multivariate-regression has the advantage of predicting from multiple impact factors and accounting for the correlation and confounding effects of these predictors. An important issue raised from Multivariate-regression analysis when applied to the built environment-behavior question is the role of self-selection in residents' behavior. For example, residents might choose to live in certain urban areas because of convenience vis-a-vis desired travel behaviors.

Structural Equation Modeling (SEM) is one of the advanced techniques to address those "self-selection" issues (see reviews of other approaches from Mokhtarian and Cao, 2008). The most essential part of SEM is its ability to handle complex relationships between endogenous and exogenous variables in transportation studies (Golob, 2003). Bagley and Mokhtarian (2002) established a nine-equation structural equation model to test the direct, indirect, and total effects of attitudes, lifestyle, and urban form variables on travel demand, mode, and distance. Focusing on a specific mode like public transit, Bailey et al (2008) find complex relationships among public transportation availability, demographics, and urban form and travel patterns. The authors confirm their hypothesis with SEM estimations that higher transit accessibility enables more efficient land uses and in turn will reduce carbon footprint (negative estimated total effect between public transportation availability and vehicle miles traveled). Structural Equation Modeling approach allows modeler to take measurement error into account and test complex patterns of relationship in a simultaneous fashion (Ullman, 2001). In the meantime, to achieve MLE estimation of those complex link patterns, assumptions are usually made to require a large data set and a multivariate normal distribution of indicator variables. In practice, variables are rarely multivariate normal and data limitations are commonly encountered in a developing context like China.

2.3 Integrated Energy Consumption Modeling

The previous two sections have reviewed modeling techniques for in-home and transportation energy consumption. Those approaches are static and treat components of the urban development system as separately for in-home operation and out-of-home travelling. However, households consume energy as a derived demand from their daily needs. That is, people within a household decide to conduct either in-home or out-of-home activities to maximize their quality of life subject to various time and resource constraints. In this sense, energy demands of different sectors are internally linked through individuals' activity and decision systems. In practice, improved data and econometric techniques have led to a growing interest in developing integrated models to incorporate both in-home and transportation sectors simultaneously (Almeida et al, 2009; Tirumalachetty et al, 2009). Apart from those newly developed models (still limited in numbers), several existing integrated land use transportation models have the great potential to be extended as multi-sector urban energy models. Some of these land use transportation models reproduce travel behavior at the individual/household level, in theory enabling them to be behaviorally augmented with a bottom-up estimation module for agents' in-home energy demand. The reminder of this section first reviews a potentially related land use transportation model - ILUTE. After that, two newly evolved integrated urban energy models are examined.

2.3.1 ILUTE

The Integrated Land Use, Transportation, Environment (ILUTE) framework is an agent-based microsimulation tool designed to forecast an urban region's development by accounting for agents' evolution and interactions (Miller et al, 2004). ILUTE consists of various types of agents that interact within the urban environment – including individuals, households, dwelling units, firms, etc. The underlying behavioral engine simulates the evolving attributes and behavior of these agents over time. Figure 2.1 presents the most recent modeling framework of ILUTE as it is still under development (Miller et al, 2011).

The integrated model is initialized from a base year census in 1986 using a modified Iterative Proportional Fitting (IPF) procedure (Pritchard and Miller, 2009). Population demographics, labor market, housing market (residential location) and auto ownership are updated each year (although shorter periods are possible for simulating these longer term decisions). Then these four dimensions of agent attributes along with other exogenous information serve as inputs for generating activity/travel patterns with a sub-model named TASHA (Travel and Activity Scheduler for Household Agents; see Miller and Roorda, 2003). A traffic assignment module then can simulate the performance of road and transit network serving movements of people and goods with the generated activity/travel patterns. Ultimately, transportation emissions can be estimated with the simulated transportation system.

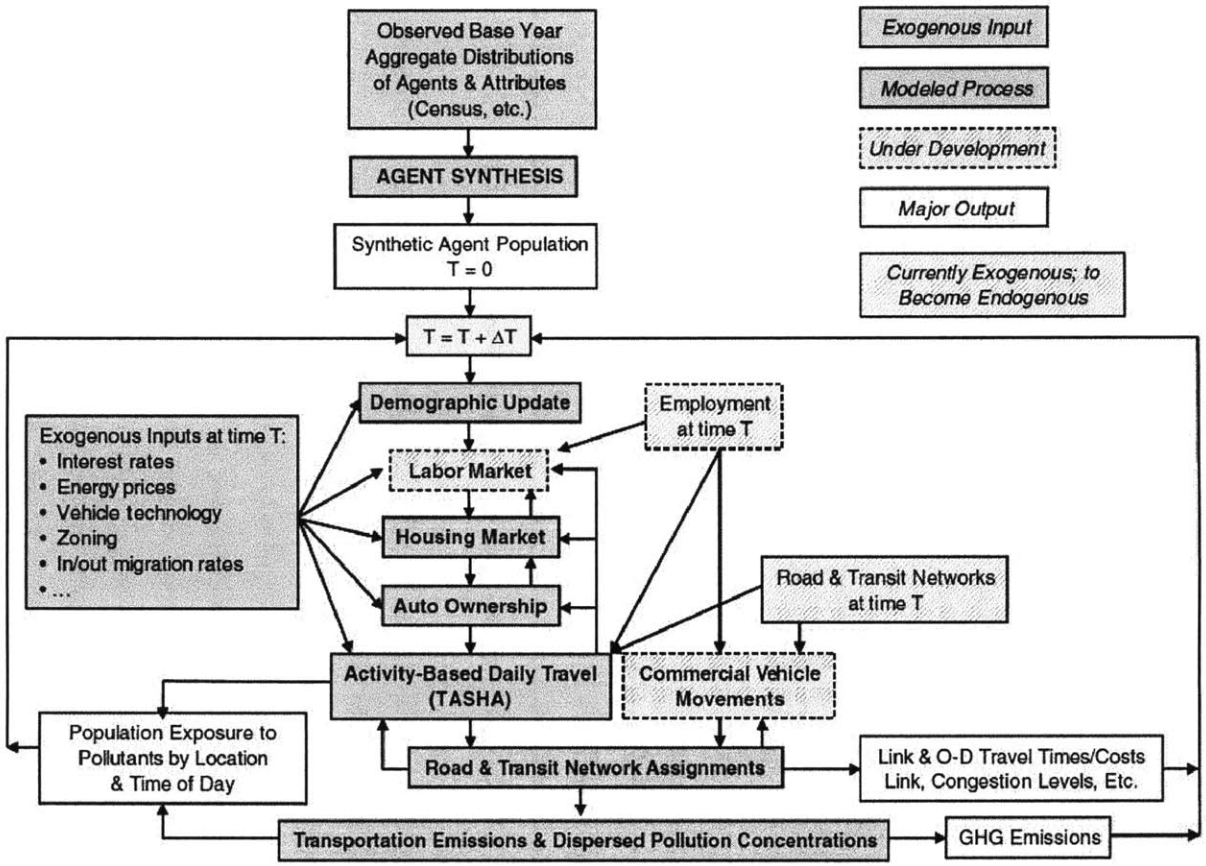

Figure 2.1 – Flow chart of ILUTE processes (Source: Miller et al, 2011)

Within each detailed module, rule-based and utility-maximizing models are employed depending on the process being modeled (Miller et al, 2011). Table 2.1 summarizes key features of four longer time-period modules. The activity/travel module simulates activity, trip start time, and activity duration using 5 minute intervals for a typical 24-hour workday. TASHA is designed to fit into a number of network assignment models, such as EMME and MATSIM to enhance representation of network performance (Gao et al, 2010).

Modules	Features and Sub-models
Demographics	Updating attributes include birth, death, marriage, divorce, education, driver's license, and in- and out- migration
Labor Market	Considering 1) persons quitting and entering the market; 2) move of jobs for persons within the market; 3) allocation of workers searching jobs to available positions in the market; and 4) evolution of worker's wages by industry, location, and job type
Housing Market	Supply of housing (type and location); Choice of sales prices and rents
Auto Ownership	Vehicle type choice model and vehicle transactions model (Mohammadian & Miller, 2003)

Table 2.1 – Key features of long-term time-period modules in ILUTE

Currently ILUTE is only applied to modeling energy consumption and GHG emission for the transportation sector by integrating with TASHA. However, it has the potential to be extended to other sectors like in-home residential energy. From the above review, we can detect that ILUTE incorporates several key modules (demographic evolution, vehicle ownership, residential location, activity patterns, etc.) that would benefit from an extension to an in-home energy consumption module. In fact, a number of other land use transportation models have similar potential, such as ILUMASS (Moeckel et al, 2003), and CEMDAP (Bhat and Waller, 2008). These simulation-based models typically treat individuals/households as the analysis units and recognize their interactions within activity and decision systems. As a result, an extra in-home operation component can be theoretically embedded in such disaggregate analytical frameworks.

2.3.2 iTEAM

Integrated Transportation and Energy Activity-Based Model (iTEAM) was proposed by a collaborative team at MIT for the evaluation of "green policies" (Almeida et al, 2010). iTEAM provides an integrated agent-based simulation framework focusing on behavior of social actors (individual/household) and organizations (firms) at a micro level. The aggregation of simulation results aim to reflect the complex relationships between urban form, transport, and energy demand and enable the design of more sustainable urban areas. It proposes human activity as the connecting bridge between complex systems of a city. Accordingly, behavior of two involved agents is identified in Figures 2.2 and 2.3 (Ghauche, 2010).

The behavioral models within iTEAM recognize the fact that both exogenous and endogenous factors could result in a range of decisions in different temporal and spatial scales. In the short term, immediate decisions like daily activity patterns, mode choice and fleet dispatching condition on equipment ownership and location availability. In the medium term, the purchase/replace of equipment could be affected both by short-term usage patterns and long-term location constraints. In the long term, apart from the market provision and agents' demographic conditions, residential/organization location choice also depends on the motivation of the short-term activities. The interactions between short, medium, and long term behavior indicate a two-way causal relationship and require an integrated framework to capture the complex agent decision-making mechanisms.

Figure 2.4 presents the overall framework of iTEAM (Ghauche, 2010). The transportation part of the framework consists of several dynamic equilibrium models reflecting demand/supply interaction. To be specific, travel choices of households and firms constitute the demand for related locations. Then, those demands are transferred to OD matrix between zones and they are distributed to routes connecting origins and destinations through traffic assignment modules. After several iterations, equilibrium is achieved when supply and demand are balanced in the road network. The performance of the network after traffic assignment will provide feedbacks to agents and impact their later travel activities. For the energy consumption part, equipment usage and duration module is designed to convert activities of households/firms to energy demand. The feedback mechanism is similar as the consumption information could influence the subsequent activity decisions.

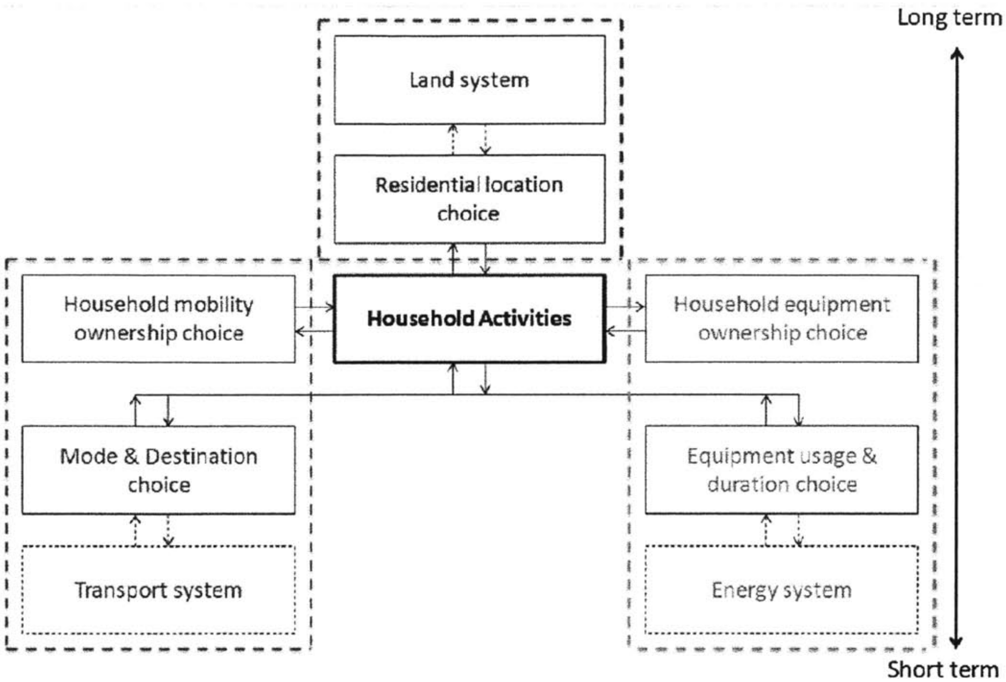

Figure 2.2 – Household behavioral model in the iTEAM (Source: Ghauche, 2010)

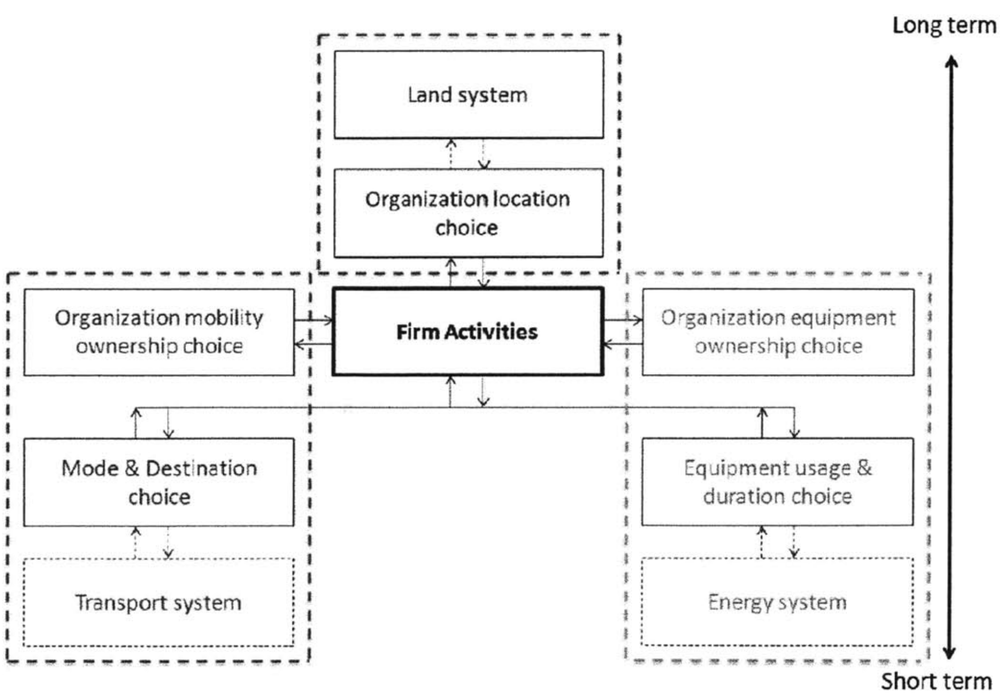

Figure 2.3 - Firm behavioral model in the iTEAM (Source: Ghauche, 2010)

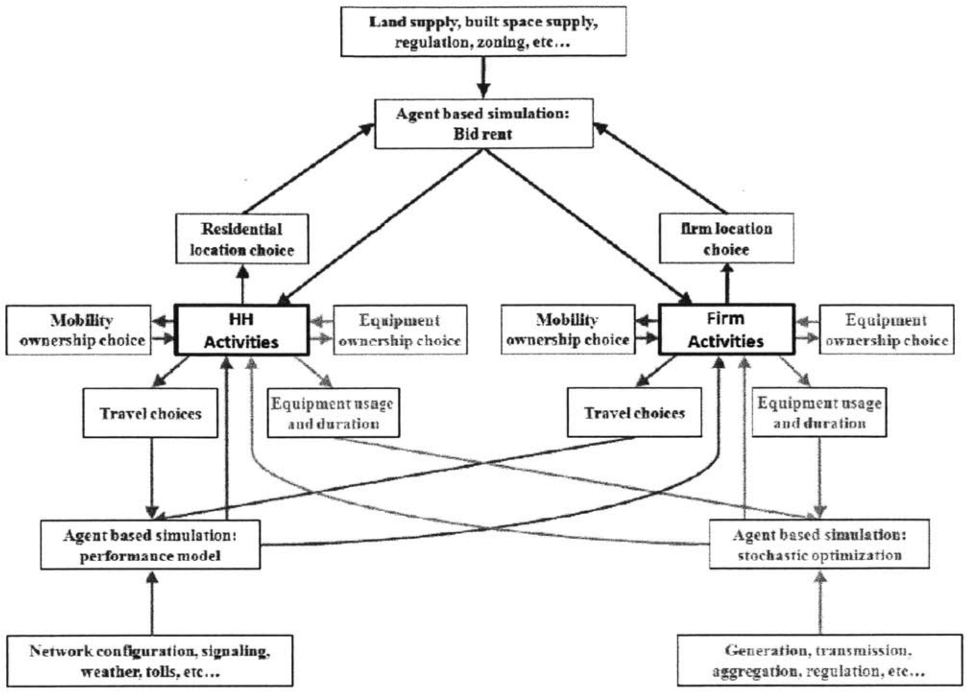

Figure 2.4 – Overall Framework of the iTEAM (Source: Ghauche, 2010)

In practice, this sophisticated large-scale microsimulation model would require a large amount of data that can hardly be fully collected through traditional paper surveys. Ghauche (2010) proposed several data collection strategies based on new methodologies like smartphones, online survey, telemetry, and bio-tracking devices and sheds some light on future direction of this state-of-art activity-based framework. Theoretically, with the development of better data collection techniques, iTEAM would be capable of modeling the energy consumption and related GHG emissions in both the transportation and home operation sectors.

2.3.3 Austin Greenhouse Gas Emission Model

Another integrated urban energy model has been developed and applied by researchers at University of Texas, Austin to evaluate greenhouse gas emissions over a 25-year forecasting period in the Austin area (Tirumalachetty et al, 2009). It includes a number of sub-models to represent households and firms, traces the evolution of their attributes and decisions, and converts those decisions to energy consumption in related sectors. The key feature of this integrated model is that it accounts for both transportation and appliances/energy sources energy consumption and compares aggregated regional energy performances under 5 anticipated future scenarios (Tirumalachetty et al, 2009).

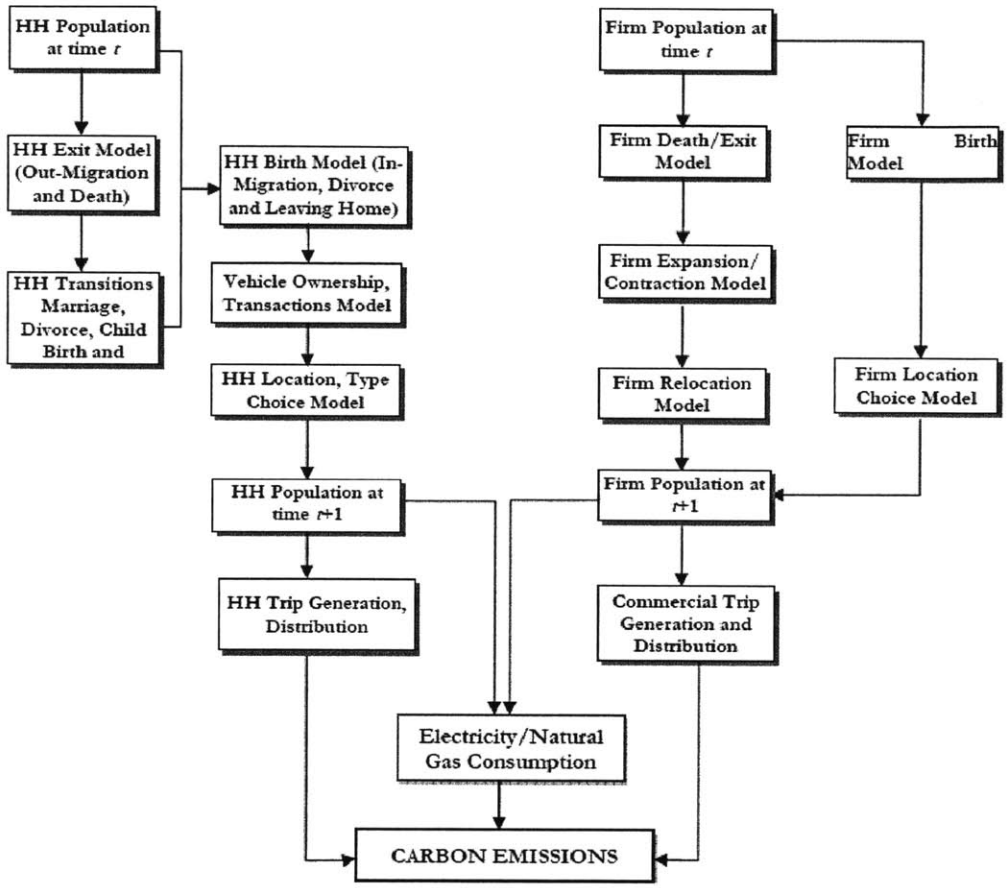

Figure 2.5 – Simulation Framework for Austin Greenhouse Gas Emission Model (Source: Tirumalachetty and Kockelman, 2009)

As framed by Tirumalachetty (Figure 2.5), the overall simulation model consists of several interrelated processes like household/firm transitions, travel demand generation/distribution, and energy/emissions estimation. The model is initialized with a base year population generated using Public Use Microdata Sample (PUMS) seeds (Tirumalachetty et al, 2009). At each time step, updating agent attributes (demographics and locations) are central to future energy consumption/emissions calculations. For households, Monte Carlo simulations are used to represent key processes (birth, death, divorce, marriage, and income growth) influencing household demographics. Household locations and vehicle stocks are considered with relevant choice and transaction models. For firms, a sequence of sub-models is employed to simulate the processes of firm death/exit, expansion/contraction, and relocation (Kumar and Kockelman, 2008). With updated household and firm information, household and commercial trips are generated and distributed by a set of count- and choice- based models. The electricity/natural gas consumption is also estimated with agent updating characteristics using standard OLS regressions.

2.4 Summary of Precedents and Challenges

A shortcoming to the approaches reviewed in section 2.1 and 2.2 is the treatment of in-home and out-of-home activities separately, while total household energy use arises from both sets of activities and, their interactions. In recent years, activity-based modeling has emerged as the 'state-of-the-art' in transportation systems analysis, based on the basic idea that travel demand derives from the demand for activities (e.g., Bowman and Ben-Akiva, 2001) – people do not want to travel, per se, rather they want access to daily wants and needs. In-home energy demand can be considered analogously; people do not want energy consumption, rather they want lighting, comfort, food, entertainment, etc. An activity-based framework, thus, provides a formal way of integrating individual- and household-level energy consumption by accounting for the activities that demand energy and travel as well as potential trade-offs between them (e.g., in-home entertainment vs. traveling to leisure elsewhere). Such trade-offs cannot be captured with separate in-home or transportation models. Only recently, however, have efforts moved towards developing activity-based models for fully estimating household energy (and other resource) use at the urban scale and these efforts remain partial, either as proposed approaches (e.g., Almeida et al, 2009) or focusing only on part of the consumption picture (Keirstead and Sivakumar, 2012). One challenge to implementing the activity-based approach is the typical lack of adequate data. Even for the integrated models applied in the Austin Greenhouse Gas Emission Model (Tirumalachetty et al, 2009), the lack of detailed panel data results in a number of simplifying and sometimes heroic assumptions (Tirumalachetty and Kockelman, 2009).

In addition, empirically understanding the relationships between neighborhood form and behavior faces the classic causality challenge, sometimes referred to as "self-selection" (Mokhtarian and Cao, 2008). In aiming to show whether neighborhood form produces different household activity patterns and energy use, at least two related forms of bias may be present: simultaneity bias (e.g., individuals who prefer a low-energy lifestyle choose to live in low energy-oriented neighborhoods); and omitted variable bias (unobserved variables, like preferences for lower energy use, produce the low-energy outcomes, but also correlate with the neighborhood). In other words, the presumed exogenous causal variable, the neighborhood, is actually endogenous, which can produce inconsistent and biased estimators.

In other words the behavioral models underlying the simulation might be incorrect.

Furthermore, as mentioned, the neighborhood may well influence both durable goods ownership (e.g., motor vehicles, air conditioners) and energy use and emissions. Within the ownership and use decisions, endogeneity bias may also be present. For example, if one specifies a regression model of, for example, household vehicle use using the household's observed number of motor vehicles included as an explanatory variable, the choice variable may be correlated with unobserved variables (e.g., households with more energy-intensive travel lifestyles being more inclined to own private vehicles) and, thus, with the second stage model's error term. This violates a basic regression assumption. One way to correct for this endogeneity bias is by developing an instrumental variable; for example, the predicted number of air conditioning (AC) units (estimated from the AC choice model) and substituting this predicted value (as an instrument) in lieu of the actual number of ACs in the household (Dubin and McFadden, 1984). Such an approach, in theory, 'purges' the independent choice variable (in this case, number of ACs) of its correlation with the error term in the electricity use model.

Finally, in order to predict effects into the future, particularly in a rapidly evolving place like China, we must account for the evolution of demographics, appliance & vehicle ownership and the explicit underlying behavioral links. To understand the role of the neighborhood in household total energy consumption in China, I develop a model of in-home energy use, transportation energy use, and their trade-offs. The in-home component attempts to capture two related choices made by households - the choice of equipment/energy source type and the choice of how frequently to use the equipment/energy source to fulfill demands for in-home activities. For transportation energy, several aspects of the household decision-making process are crucial, including the choice of vehicle ownership, the number of activities to undertake, where to realize those activities, and how to get to them. As mentioned, I can also imagine that some activities might lead to trade-offs between in-home and transportation energy consumption.

Unfortunately, I only have access to a trip-based survey of household travel information and reported energy bills for different energy sources. Thus, I cannot implement a full activity-based model. Furthermore, for in-home consumption, I do not have detailed appliance usage information; instead, I have self-reported electricity, gas, coal, and centralized heating bills. While I can compute household energy use with those bills, I cannot model the underlying activity behaviors. For the transportation part, the trip-based survey allows me to model trip frequency, mode, and distance but I cannot explicitly link the in-home and out-of-home parts together by trade-off behaviors.

Chapter 3: Conceptual Framework and Methods

3.1 Measures of Energy Consumption

3.1.1 In-home Operation Energy Use and CO2-Equivalents Emissions

In this research, four major types of energy sources are incorporated for in-home operation sector – electricity, gas, coal, and centralized heating. Consistent with the overall project, standard units of output – Megajoules (energy consumption) and ton/kg of CO2 (GHG Emissions) per household per annum – are used for comparisons across different neighborhoods. The measures for those four energy sources are first adapted by Zhang (2010) based on self-reported utility bills. The empirical context for which these specific measures are derived is Jinan, the capital of Shandong Province, which will be described in more detail in the following Chapter.

3.1.1.1 Electricity

In the context of urban China, electricity is the major source to power electronic appliances for the purposes of lighting, comfort, food, entertainment, etc. Besides, electricity is commonly used for heating in households without the provision of centralized heating or in units that desire to have additional heating appliances. The household monthly electricity bill is introduced as the weighted average of typical spring/fall, summer, and winter months to capture the fluctuations throughout the year (Wang, 2012). With the monthly bill, household electricity energy consumption can be calculated in Megajoules as follows (Zhang, 2010):

$$\mathrm{EE} = \frac{\mathrm{BE} * 12}{\mathrm{PE}} * q_E \div (1 - \beta) \div \varepsilon \qquad \text{- } \textbf{Equation 1}$$

EE – Household annual electricity energy consumption (MJ)

BE – Household monthly electricity bill (Yuan RMB)

PE – Electricity price (Yuan/KWH, 0.5469 in survey city)

q_E – Thermal-electricity conversion factor (MJ/KWH, 3.6 in this case)

β – Electricity transmission loss rate (7.08% in this case)

ε – Coal power plant conversion rate (35.47% in this case)

3.1.1.2 Gas

Natural gas is the primary source for cooking and water heating in Jinan Three typical types of gases are consumed by households in the survey city: liquefied natural gas (LNG), liquefied petroleum gas (LPG) and coal gas (Wang, 2012). The measurement of gas energy consumption is based on gas type and reported monthly gas bill. The calculation equation is summarized as below (Zhang, 2010):

$$\mathrm{EG} = \frac{\mathrm{BG} * 12}{\mathrm{PG}} * \gamma_{\mathrm{g}} \qquad \text{- } \textbf{Equation 2}$$

EG – Household annual gas energy consumption (MJ)

BG – Household monthly gas bill (Yuan, RMB)

PG – Gas price (Yuan/m^3; 2.4 for LNG, 13.9 for LPG, and 1.3 for coal gas in survey city)

γ_g – Gas unit thermal value (MJ/m^3; 36.4 for LNG, 118.2 for LPG, and 16.74 for coal gas)

3.1.1.3 Coal

Households directly consume coal for the purpose of cooking and heating. With the introduction of pipeline gas and centralized heating system, coal usage has been decreasing in China. Similar to the gas energy calculation, the following equation presents the measurement of coal energy consumption (Zhang, 2010):

$$\mathrm{EC} = \frac{\mathrm{BC}}{\mathrm{PC}} * \gamma_{\mathrm{C}} \qquad \text{- } \textbf{Equation 3}$$

EC – Household annual coal energy consumption (MJ)

BC – Household annual coal bill (Yuan, RMB)

PC – Coal price (Yuan/ton, 876 in survey city)

γ_C – Coal unit thermal value (MJ/ton; 26700 in this case)

3.1.1.4 Centralized Heating

Centralized heating is primarily designed and used for space heating. In Jinan, centralized heating does not allow individual control over switching on/off or adjusting temperature for specific dwelling units. As required by the local government, the heating fee is charged on a general construction-area basis, not on actual consumption levels. Accordingly, energy consumption for centralized heating can only be estimated based on dwelling unit area as follows (Zhang, 2010).

$$\mathrm{ECH} = 86.4 * \mathrm{A} * \mathrm{N} * \mathrm{q_h} * \frac{\mathrm{t_i} - \mathrm{t_a}}{\mathrm{t_i} - \mathrm{t_{o,h}}} \div \mu_b \div \mu_p$$ - **Equation 4**

ECH – Household annual centralized heating energy consumption (MJ)

A – Dwelling unit area (m^2)

N – Heating period per year (140 days in survey city)

q_h – Building heating index (W/m)

t_i – Indoor designed temperature during heating period (18 ℃ in survey city)

t_a – Average outdoor temperature during heating period (-0.9 ℃ in survey city)

$t_{o,h}$ – Outdoor designed temperature during heating period (-7 ℃ in survey city)

μ_b – Cogeneration boiler efficiency (0.87 in this case)

μ_p – Pipe network efficiency (0.98 in this case)

3.1.1.5 CO2-Equivalents Emissions

As mentioned above, electricity, gas, coal, and centralized heating are four major sources for in-home energy consumption. The CO2-Equivalent emission associated with those energy sources can be calculated using the method developed by the Intergovernmental Panel on Climate Change (IPCC). The relationship between CO2-Equivalent emission and fuel consumption can be expressed as follows (Zhang, 2010):

$$\mathrm{CO2_{fuel}} = \mathrm{E_{fuel}} * \mathrm{EF_{fuel}}$$ - **Equation 5**

$CO2_{fuel}$ – CO2-Equivalents emission of a certain fuel (ton)

E_{fuel} – Amount of fuel combusted (TJ)

EF_{fuel} – Emission factor (ton/TJ)

In Jinan, almost all of the electricity and centralized heating are coal-based. This research assumes that all the coal used in industry is bituminous coal while anthracite coal is used in the residential sector (Table 3.1). Other emission factor values for different types of gases are summarized in Table 3.1.

Fuel Type	EF_{fuel}	Associated Energy Source
Bituminous coal	94.6	Electricity & Centralized heating
Anthracite coal	98.3	Household coal
Natural Gas	56.1	Household gas
LPG	63.1	Household gas
Coal Gas	44.4	Household gas

Table 3.1 – CO2 Emission Factors for different energy sources (from Zhang, 2010)

3.1.2 Transport Energy Use and CO2 Emissions[3]

Household transport energy use depends on how many trips the household generates, the modes involved, fuel types, and trip distances. Measurement of household transport energy use is adapted by Jiang (2010) based on reported weekly travel patterns. Theoretically, the weekly scope better captures individual/household routine travel schedules than a single day. Within the household, shared trips should also be considered to avoid double counting of the energy consumption. Equations 6 – 8 present the calculation method for household travel and energy use (Jiang, 2010).

$$E^{T}_{i} = \sum_{m} E_{i}^{m} \quad \text{- } \textbf{Equation 6}$$

$$E_{i}^{m} = \sum_{j}\sum_{k}(TF^{m}_{i.j.k} * \frac{TD^{m}_{i.j.k}}{TO^{m}_{i.j.k}}) * EI^{m} \quad \text{- } \textbf{Equation 7}$$

$$EI^{m} = FU^{m} * EC^{m} \quad \text{- } \textbf{Equation 8}$$

$i -$ i^{th} Household

$j -$ j^{th} Person in the household

$k -$ Purposes, including work, maintenance, leisure, and school

$m -$ Modes, including EBike, motorcycle, car, and bus

$E_i^{\,T} -$ Total household weekly transport energy consumption (MJ/HH/Week)

$E_i^{\,m} -$ Household weekly transport energy consumption with mode m (MJ/HH/Week)

$TF^{m}_{i.j.k} -$ Trip frequency for person j in household i for purpose k with mode m

[3] Transportation emissions are calculated for CO2 only, which differs slightly from CO2-Equivalents from the in-home side. Hence, the calculated emissions from the transport sector are slightly lower that total CO2-Equivalents.

(Trips/Week)

$TD^m{}_{i.j.k}$ – Average trip distance for person j in household i for purpose k with mode m (km/Trip)

$TO^m{}_{i.j.k}$ – Trip occupancy for person j in household i for purpose k with mode m

EI^m – Energy intensity factor for mode m (MJ/km)

FU^m – Fuel economy factor for mode m (L/km or KWH/km)

EC^m – Energy content factor for mode m (MJ/L)

The detailed fuel economy, fuel energy content, and energy intensity factors are summarized in Table 3.2. Those estimations do not consider specific traffic conditions (e.g. congestion) and their impact on fuel consumption.

Mode	FU^m	EC^m	EI^m
EBike	0.021 KWH/km	——	0.076 MJ/km
Motorcycle	0.019 L/km	32.2 MJ/L	0.612 MJ/km
Car	0.092 L/km	32.2 MJ/L	2.962 MJ/km
Bus	0.3 L/km	35.6 MJ/L	10.680 MJ/km

Table 3.2 – Fuel economy, energy content, and energy intensity factors (Jiang, 2010)

Similar to the energy intensity factor (EI^m), I introduce the CO2 emission factor (EF^m) to estimate emissions associated with fuel consumption. To be specific, EI^m in Equation 7 should be replaced with EF^m and EF^m and can be calculated as follows (Jiang, 2010):

$$\mathrm{EF^m = FU^m * CC^m} \quad \text{- } \textbf{Equation 9}$$

FU^m – Fuel economy factor for mode m (L/km or KWH/km, see details in Table 3.3)

CC^m – CO2 content factor for mode m (kgCO2/L or kgCO2/KWH, see details in Table 3.3)

Mode	FU^m	CC^m	EF^m
EBike	——	——	0.026 kgCO2/km
Motorcycle	0.019 L/km	2.165 kgCO2/L	0.041 kgCO2/km
Car	0.092 L/km	2.165 kgCO2/L	0.199 kgCO2/km
Bus	0.3 L/km	2.470 kgCO2/L	0.741 kgCO2/km

Table 3.3 - Fuel economy, CO2 content, and CO2 emission factors (Jiang, 2010)

3.2 Advantages of Micro-Simulation

This research aims to develop and demonstrate an integrated model that estimates the long-term effects of urban form on household in-home and out-of-home energy use and related trade-off behaviors. Microsimulation is a possibly well-suited modeling technique here since it has the ability to account for interactions and dynamics within the complex decision-making system (Lemp et al, 2007). Microsimulation is a social scientific analysis tool that has been in existence since the 1950s (Orcutt, 1957). The essential core of microsimulation is that it logically represents agent behavior at the disaggregate level, typically taking firms or individuals/households as the fundamental analytic units. Microsimulation models simulate the change of state and behavior of agent units, normally referred to as "ageing" of the data (Zaidi & Rake, 2001). There are two types of ageing approaches – static and dynamic. Static ageing requires the direct replacement of data inputs (panel data) or reweighting of the base records to trace the changes in related variables and behavior. On the contrary, dynamic ageing captures the evolution of agent attributes at time t+1 by applying behavioral probabilistic equations or sub-models to the same agent attributes at time t (typically with Monte Carlo simulation). The ageing process provides necessary information needed for underlying behavioral modules within the overall microsimulation framework and together they are capable of predicting future scenarios of complex system.

The basic concept and features of a microsimulation approach offer major advantages for both theoretical research and practical applications. Orcutt (1957), Ballas (1999), Mitton (2000), Vovsha (2002), and Lemp (2007) have outlined several key strengths of microsimulation. These include the ability to consider population heterogeneity, aggregate, and modularize.

Compared to traditional macroeconomic theory, using micro-level data allows one to account for a wide range of heterogeneity in both populations and related behaviors. For example, most macroeconomic approaches utilize representative agents to account for heterogeneity in the residential sector. They typically group households based on several key demographic variables like income and household type. However, in order to achieve maximum homogeneity within each group, a large combination of characteristic variables are inevitably needed. In theory, a 10-variable combination with 3 levels each would require nearly 60,000 population groups (3^10), probably exceeding the sample size itself. In this sense, microsimulation provides a better and natural way to represent data heterogeneity by keeping the characteristics of each agent as an individual unit and forming an initial or raw database for the subsequent modeling process.

Despite the behavioral attractiveness of microsimulation, decision makers are typically interested in macro effects of policies in a complex system. Using microsimulation, underlying econometric analysis is able to trace behaviors at the level where decisions are actually taken by agents. This disaggregated level allows macro effects to be studied and aggregated without bias that might result from macro-level models. In complex systems, inputs and outputs are normally linked in a nonlinear fashion. It is difficult or sometimes inappropriate to utilize a direct formula to represent the relationships. Instead, a number of internal links and transitions determine the state and behavior of the agents. Microsimulation can be conducted at great detail to simulate behaviors and in turn provide a flexible output by aggregating interested clusters of agents.

Another important strength of microsimulation comes from its modularized structure. Modules are typically introduced as inter-correlated processes within the overall simulation framework. One advantage of modularization is that it can break down the complex system into a set of single manageable processes. For example, with a standard statistical approach, tracking agent evolution requires detailed panel data, incorporating lagged variables and rigorous constraints and assumptions for time series theory. Microsimulation adopts a simpler idea to realize the decision at each time step, predicting the future based on the fact that the decision has been made instead of by multiplying a set of conditional choice probabilities. That is, suppose we have a choice B conditional on choice A. Microsimulation simulates what decision the agent has made for A and then deduces her decision for B based on the actual result of A. Traditional statistical approaches, on the other hand, multiply the conditional probability $P(B|A)$ by $P(A)$. If the choice set is large, there would be a huge number of combinations of possible choices in a statistical approach. Microsimulation only focuses on the current state of the system and the transition probability for next time step. As such, evolution can be broken down into two processes – initialization and transition - by considering only one time step at a time. Panel data are usually hard to collect, especially for disaggregate-level analysis. But data needed for initialization and transition can be pooled together from different sources without the continuation of multi-year efforts. In addition, microsimulation modules are flexible enough to adapt different types of econometric models within one modeling framework.

3.3 Model Framework

Considering the modeling challenges and data constraints identified in Section 2.4, I develop a simplified integrated microsimulation model (Figure 3.1). First, I define trade-off lifestyle pattern variables to reflect some potential in-home/out-of-home activity substitution. Second, I model in-home energy use via linear regression, incorporating the trade-off variables but ignoring the underlying activities. Third, I disaggregate travel behavior into trip generation, internal/external trip choice, and trip mode-distance choice models. Finally, since we ultimately want to model energy performance over time I incorporate modules to update demographics and vehicle and appliance ownership.

The simulation tool is based on a total of eight inter-related behavioral models which estimate out-of-home energy use by predicting trip generation, internal/external trip rate[4], mode choice, and trip length for each household and in-home energy use according to different energy sources. Table 3.4 presents those behavioral models and techniques applied in relevant modules. The detailed modeling techniques can be found in the following Section 3.4. In the various sub-models, relevant dimensions of neighborhood form and design are included as explanatory variables. These models are then combined with modules that update household demographics, appliance & vehicle ownership information, and activity trade-off patterns, as represented in Figure 3.1. These inter-linked models can then be used to estimate the long-term effects of neighborhood design on household energy consumption and greenhouse gas emissions.

Sub-models	Modeling techniques
AC ownership choice	Multinomial Logit Model
Trade-off lifestyle pattern choice	Instrumental variables, Binary Logit Model
Vehicle portfolio choice	Multinomial Logit Model
Electricity energy consumption	Instrumental variables, Linear Regression
In-home energy consumption	Instrumental variables, Linear Regression
Trip frequency choice	Instrumental variables, Negative Binomial Regression
Internal/external trip choice	Binary Logit Model
Trip Mode/distance choice	Nested Logit Model

Table 3.4 - Summary of behavioral models in the overall simulation framework

[4] I assume, perhaps strongly, that no energy consumption takes place for "internal" trips, usually less than 500m.

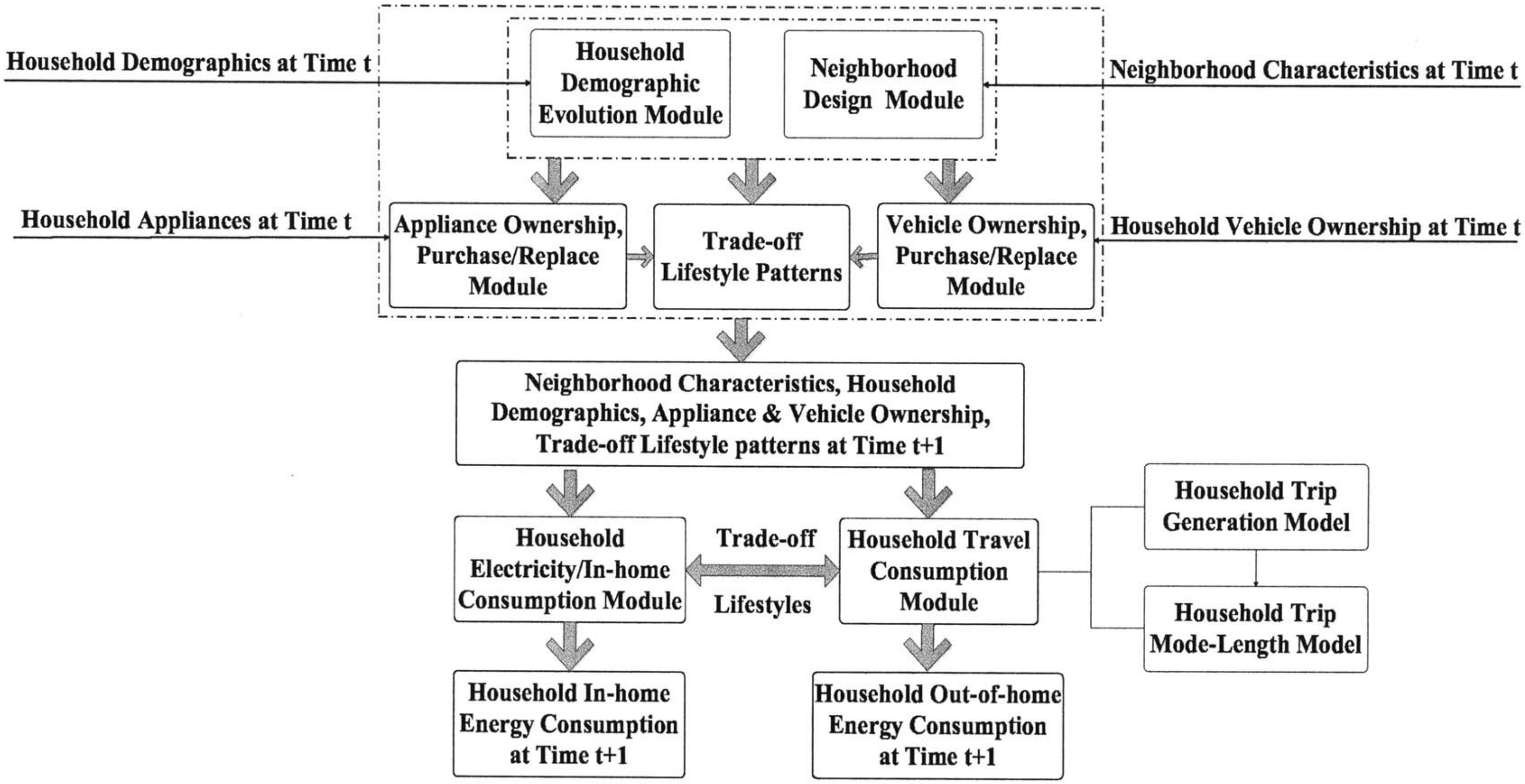

Figure 3.1 - Integrated modeling framework

3.4 Methods

3.4.1 Binary and Multinomial Logit Choice model[5]

Random utility models (RUMs), of which logit choice models are the proverbial "work horse," are the backbone of my behavioral models. In the basic model structure, if the decision-maker, n, selects one and only one alternative from a choice set $C_n = \{1,2\}$ with only two alternatives, the problem can be formulated as a Binary Logit Choice. We can introduce the random utility for each alternative:

$$U_{1n} = V_{1n} + \varepsilon_{1n} \qquad \text{- Equation 10}$$

$$U_{2n} = V_{2n} + \varepsilon_{2n} \qquad \text{- Equation 11}$$

Here V_{in} is the systematic utility expressed as a function of explanatory variables and ε_{in} is the random utility error component.

The decision rule is that individual n selects the alternative with the highest utility, U_{in}, among those in the choice set C_n. Therefore, the probability of choosing alternative 1 can be expressed as:

$$\begin{aligned} P_n(1) &= P(U_{1n} \geq U_{2n}) \\ &= P(V_{1n} + \varepsilon_{1n} \geq V_{2n} + \varepsilon_{2n}) \\ &= P(\varepsilon_{2n} - \varepsilon_{1n} \leq V_{1n} - V_{2n}) \end{aligned} \qquad \text{- Equation 12}$$

Choosing the Type I Extreme Value distribution for the error term, we get the following:

$$\varepsilon_{1n} \sim \text{Extreme Value}(0, \mu);\ \varepsilon_{2n} \sim \text{Extreme Value}(0, \mu);\ \varepsilon_{2n} - \varepsilon_{1n} \sim \text{Logistic}(0, \mu).$$

The Type I Extreme Value distribution has two parameters – location parameter and scale parameter. Here the location parameter is equal to zero and the scale parameter is set to μ for all alternatives. Thus,

$$\begin{aligned} P_n(1) &= P(\varepsilon_{2n} - \varepsilon_{1n} \leq V_{1n} - V_{2n}) \\ &= \frac{1}{1 + e^{-\mu(V_{1n} - V_{2n})}} \\ &= \frac{e^{\mu V_{1n}}}{e^{\mu V_{1n}} + e^{\mu V_{2n}}} \end{aligned} \qquad \text{- Equation 13}$$

[5] Based on the book from Ben-Akiva et al, 1985

We can then estimate the model using maximum log-likelihood estimation (MLE) to get the coefficients embodied in the systematic utilities V_{1n} and V_{2n}. The parameter μ scales the coefficients and they are estimated together if scale parameter μ is not pre-identified.

With more than two alternatives, we can use the Multinomial Logit choice model. Now we have the choice sets $C_n = \{1,2,\dots,i,\dots,J_n\}$ with J_n alternatives. Again, with the utility maximization decision rule, the probability of choosing i can be expressed as:

$$\begin{aligned} P(i|C_n) &= P(U_{in} \geq U_{jn}, \forall j \in C_n) \\ &= P(V_{in} + \varepsilon_{in} \geq V_{jn} + \varepsilon_{jn}, \forall j \in C_n) \\ &= P(\varepsilon_{jn} - \varepsilon_{in} \geq V_{in} - V_{jn}, \forall j \in C_n) \end{aligned} \qquad \text{- } \textbf{Equation 14}$$

If ε_{jn} are independently and identically distributed (IIA assumption) as Extreme Value $(0, \mu)$, we obtain the choice probability for individual *n*:

$$P(i|C_n) = \frac{e^{\mu V_{in}}}{\sum_{j \in C_n} e^{\mu V_{jn}}} \qquad \text{- } \textbf{Equation 15}$$

Again, we can estimate the model coefficients using MLE.

3.4.2 Nested Logit Model[6]

If two types of choices are decided jointly (e.g., the trip mode and distance choice), the IIA assumption described above for Multinomial Logit choice will be violated. Therefore, we need to model the joint choice with two-level Nested Logit techniques. For decision-maker, n, the alternatives are divided into K nests and each nest k contains B_k alternatives. Accordingly, for alternative $i \in B_k$, we can define the utility function for i:

$$U_{ni} = W_{nk} + Y_{ni} + \varepsilon_{ni} \qquad \text{- } \textbf{Equation 16}$$

Here W_{nk} is a function of variables that only describe nest k and Y_{ni} depends on variables related to alternative i.

The probability of decision-maker n choosing alternative i (P_{ni}) can be decomposed into a marginal probability (P_{nB_k}) and a conditional probability $(P_{ni|B_k})$:

[6] Based on the book from Train, 2003

$$P_{ni} = P_{ni|B_k} P_{nB_k} \qquad \text{- Equation 17}$$

The marginal and conditional probabilities take the Logit form and they are linked by the so-called "Logsum" (or inclusive value), the denominator from the lower-level nest, i.e.:

$$P_{nB_k} = \frac{\exp(W_{nk} + \lambda_k I_{nk})}{\sum_{l=1}^{K} \exp(W_{nl} + \lambda_l I_{nl})} \qquad \text{- Equation 18}$$

$$P_{ni|B_k} = \frac{\exp(Y_{ni}/\lambda_k)}{\sum_{j\epsilon B_k} \exp(Y_{nj}/\lambda_k)} \qquad \text{- Equation 19}$$

$$I_{nk} = \ln \sum_{j\epsilon B_k} Y_{nj}/\lambda_k \qquad \text{- Equation 20}$$

Here I_{nk} is the Logsum value and λ_k is the coefficient on the Logsum. In most cases, the scale parameters associated with the lower level utilities are normalized at 1, allowing the upper level scale parameter and hence the Logsum parameter λ_k to be unrestricted. λ_k is a measure of correlation within each nest k and it should take values between 0 and 1. If λ_k is larger than 1, a basic assumption of the nesting structure is violated.

3.4.3 Event Count models – Poisson and Negative Binomial Regressions[7]

For trip frequency, I apply event count models. A commonly used model for count data is the Poisson. For decision-maker, n, the conditional mean of the frequency Y_n can be written as a function of explanatory variables X_n and parameters β_n:

$$E(Y_n|X_n) = e^{X_n \beta_n} \qquad \text{- Equation 21}$$

Then, the probability for individual n to choose frequency Y_n can be expressed as a Poisson distribution:

$$P(Y = y_n) = \frac{e^{-\lambda_n} {\lambda_n}^{y_n}}{y_n!} \qquad \text{- Equation 22}$$

Here λ_n is the mean of the Poisson distribution and $\lambda_n = E(Y_n|X_n) = e^{X_n \beta_n}$. Therefore, the log-likelihood function can be written as:

$$\ln L(\beta) = \ln \prod_n \frac{e^{-\lambda_n} {\lambda_n}^{y_n}}{y_n!} = \sum_n y_n(\beta' X_n) - \exp(\beta' X_n) - \ln(y_n!) \qquad \text{- Equation 23}$$

7 Based on the paper from Jang, 2005

and the model can be estimated using MLE. The Poisson model makes a strong assumption – the conditional mean equals the conditional variance. I expect unobserved heterogeneity in our empirical application so that this assumption will probably be violated. Therefore, I also test a negative binomial model to account for the potential overdispersion of the trip frequency data. The Negative Binomial regression relaxes the assumption of equal mean and variance by adding the unobserved heterogeneity, ε, into the parameter λ_n:

$$\lambda_n = E(Y_n|X_n) = e^{X_n\beta_n+\varepsilon} \qquad \text{- Equation 24}$$

Here, ε is Gamma distributed, leading to the Negative Binomial distribution of the frequency. With this relaxation of the Poisson regression model, we can then estimate the Negative Binomial Regression with MLE as well.

3.4.4 Endogeneity and Instrumental Variables

As we can see, the overall model framework requires the lower level models to use outputs from the upper level choice models. This can cause endogeneity problems, as described above. Suppose we have a response variable Y, say, electricity use and several explanatory variables X_i in the lower level model:

$$Y = f(X_1, X_2, \dots, X_i, \dots X_I) + \varepsilon \qquad \text{- Equation 25}$$

If X_i is a choice result variable from the upper level model, such as number of air conditioners, we will possibly fail to include all the explanatory variables when modeling X_i in a choice model. Those omitted variables could also be related to Y (e.g. in-door temperature preference in the AC and electricity case) and incorporated in the ε. This violates the Exogeneity assumption $E(X_i|\varepsilon) = 0$. A method to solve this endogeneity problem is to introduce an instrumental variable – the fitted probability of X_i. Since this fitted probability is only estimated with observed explanatory variables, it is no longer correlated to the omitted variables in the error term for the lower level model.

Another important potential source of endogeneity is "self-selection," as mentioned above. We attempt to mitigate this problem by incorporating household attitude information, as collected in the surveys, in the choice models. This represents the "statistical control" approach, whereby the attitudinal variables included in the relevant behavioral models serve to make some of the unobserved characteristics (e.g., attitudes towards energy consumption) "observed," and thus at least partly "purging" the model of endogeneity (Mokhtarian and Cao, 2008). This approach faces practical challenges, including those related to the validity and reliability of the attitudinal variables themselves. Ideally, more advanced models could solve the "self-selection" problem, but those remain an area of future research (including better data).

Chapter 4:Data and Model Estimation

4.1 Data Sources

The main data used for estimation and simulation of the models in this thesis come from a survey of households in Jinan in 2010. Jinan is a reasonably typical medium-sized city in China (see Wang, 2012) with a population of approximately 3.5 million people in 2010. MIT-Tsinghua (2010) identifies four neighborhood typologies prevalent in the city: "Traditional", "Grid", "Mixed Enclaves", and "Superblock" (see Table 4.1). These typologies form the basis for the stratified random sampling approach used. The research team chose 14 typical neighborhoods, representing the different typologies; within these neighborhoods, households were sampled randomly in 2010, producing 1523 households and nearly 9000 trip records[8]. Figure 4.1[9] shows the location of those 14 neighborhoods. After data cleaning, we were left with 1203 observations for model estimation and simulation. The household data consist of demographics and attitudes, home attributes, energy bills, and travel records. In addition, detailed data characterizing the physical form of the neighborhoods and their environs were collected (Table 4.2).[10]

Typology	Building/Street/Function
Traditional	1-3 story courtyards; fractal/dendritic fabric off a main shopping street, on-site employment
Grid (1920s)	Block structure with different building forms contained within each block; retail on connecting streets
Enclave (1980-1990s)	Linear mid-rise walk-ups; housing integrated with commercial facilities
Superblocks (2000s)	Towers in park with homogeneous residential use

Table 4.1 - Descriptions of four neighborhood typologies in Jinan (MIT-Tsinghua, 2010)

[8] The survey was conducted by Shandong University.
[9] Figure drawn by Johnna Cressica Brazier from MIT
[10] The physical characteristics were developed in a Geographic Information System (GIS) by Beijing Normal University.

Figure 4.1 - Location distribution of 14 neighborhoods in Jinan 2010 Survey

Measure	Description	Mean	Std.	Min	Max
Neighborhood Size	Area (m^2)	189461.0	72936.33	25572	302507
Total Households	Number of households per neighborhood	2899.9	1557.38	515	5992
Residential Density	Number of households per acre	63.3	21.94	26	104
FAR	Ratio of floor area of buildings to size of neighborhood land	1.884	.6453	.78	3.16
Building Coverage	Building footprint as share of neighborhood area	.292	.1166	.07	.53
Green Coverage	Green space as share of neighborhood land area	.086	.0803	.01	.29
Entry_m	Entry interval distance in meters	319.6	201.31	81	929
Function mix	Building function mix	.149	.1244	.03	.46
Lumix_500m	Land use mix w/in 500 meter buffer	.660	.0749	.54	.81
Underground Parking	Average underground parking area (m^2) per household	7.339	8.5850	.00	24.00
Surface Parking	Average surface parking area (m^2) per household	9.6	10.19	0	35
Walking Facility	Percentage of roads with walking facilities	.265	.2201	.00	.82
Distance to Center	Distance from the neighborhood center to the center of Jinan (kms)	4.90	2.133	.7	8.7
Street Level Shop	Percentage of street level shops	.095	.0994	.00	.35
Road Density	In the neighborhood (km/m^2)	30.280	14.6540	10.16	56.72
Motor_width	Average motorway width (m)	6.575	3.1104	3.17	13.00
SEI	Southern Orientation Index (area of projection of façade onto the south plane)*	.3490	.02640	.274	.391

Table 4.2 - Descriptive statistics: Variable measures of neighborhood form

Measure	Description		Mean	Std.	Min	Max
Porosity	Ratio of volume of open spaces to the total volume (buildings+open spaces)*		.6980	.09035	.557	.907
Surface to volume ratio	Ratio of building surface area to the total volume		.499	.2287	.267	.944
Footprint	Average site coverage area (in square meters)		583	381.8	48	1179
Façade continuity	Measure of the continuousness of the building facade		.6988	.05571	.5978	.7892
cul_de_sac	Percentage of "dead end" roads		.109	.1972	.00	.73
Factory Accessibility	Regional accessibility for factory**		12.423	11.0893	3.75	44.88
Office Accessibility	Regional accessibility for office**		10.196	13.6261	.94	45.25
Public Accessibility	Regional accessibility for public**		5.319	8.4899	.69	32.10
Shopping Accessibility	Regional accessibility for shopping**		153.920	133.2590	26.12	426.84
School Accessibility	Regional accessibility for school**		8.448	8.9295	1.28	34.05
BRT Routes	BRT routes with stops within 200m of the neighborhood	0	0.393			
		1	0.455			
		2	0.088			
		3	0.064			

Table 4.2 (continued) – Descriptive statistics: Variable measures of neighborhood form

Notes: * Calculated using GIS maps (figure ground maps and building height information) and simulation tools (see MIT, 2012). ** Calculated as a gravity-based measure, using calculated road network times (see Chen, 2012).

Household Demographics & Equipment ownership			Household Energy Consumption, Emission and Attitudes				
				Emission (kgCO2)		Consumption (MJ)	
Family Structure	Single	6.68%	Electricity	Min	227	Min	2397
	Couple	23.64%		Max	22672	Max	239665
	Couple & kids	42.11%		Mean	2962	Mean	31945
	Couple & parents	4.76%		Std.	1929	Std.	20396
	Grandparents & grandchild	2.92%	In-home	Min	227	Min	2397
	Three generations	19.97%		Max	32203	Max	342195
Household Size	1	4.90%		Mean	6235	Mean	67679
	2	25.30%		Std.	3128	Std.	33570
	3	40.90%	Transportation	Min	0	Min	0
	4	16.70%		Max	74681	Max	371366
	>4	12.20%		Mean	647	Mean	5909
Annual Income (Yuan)	Min	4300		Std.	2043	Std.	17734
	Max	720000	Driving is a sign of prestige***				34.0%
	Mean	93066	It is convenient to take buses***				67.5%
	Std.	74756	I like riding bicycles***				53.7%
Air Conditioner	0	12.7%	Time spent on travel is a waste to me***				35.6%
	1	36.7%	I'd like to live in bigger house***				55.2%
	>1	50.6%	I like traveling***				66.7%
Vehicle Portfolio	No vehicle owned	30.6%	Plastic shopping bags in supermarkets should be free***				50.6%
	E-bikes only	23.9%	High-rank officials do not take buses or ride bicycles to go				57.9%
	Motorcycles	5.2%	Rich men do not take buses or ride bicycles to go out***				52.4%
	Cars only	24.1%	I exercise regularly outside***				62.3%
	Cars and other vehicles)	16.2%	I reuse things like plastic bottles or bags***				69.3%

Notes: *** Percentage of positive responding: scores of more than 3 are counted as positive responding

Table 4.3 - Descriptive statistics: Household characteristics

Table 4.3 presents the descriptive statistics for several key demographic variables, equipment ownership, and energy consumption. For family structure, the two main household types are "couple & kids" and "couple & parents", consistent with the most common household size of 3. The average household income in the 14 neighborhoods is more than 90K (approximately US$15,000). Most households already have more than 1 AC while about 40% have at least one car. The sample may be biased towards higher income households. Here the in-home energy is the sum of electricity, gas, coal and centralized heating energy. The standard deviations of electricity and in-home energy consumption and emission are less than their means which helps in modeling since we don't need to predict too many extreme values. However, transportation energy consumption data appears to be overdispersed, indicating a number of outliers with large travel energy use, making predictions more difficult.

4.2 Appliance Ownership Modeling

We do not have appliance purchase information for households, only current ownership levels. Furthermore, we only have consistent ownership information for air conditioners (AC). AC ownership may be correlated with other energy consuming devices, but, together with heating demand AC is more likely related to neighborhood form than other appliances (such as refrigerators and clothes washers). Furthermore ownership of ACs has been the most rapidly increasing energy consuming appliances among urban Chinese households since 2000 (Zhou et al, 2011). As such, we model AC ownership; specifying and estimating a discrete choice model (Table 4.4). Household income and unit size are positively related to AC ownership, while renters and those living in neighborhoods with high surface-to-volume ratio have lower likelihood of owning ACs.

Variables	AC_1		AC_2_and_more	
	Coef.	t-value	Coef.	p-value
Constant	-.722	-0.53	-8.52	-5.35
Income (1000)	.0158	4.61	.0226	6.49
Rent	-.843	-3.39	-1.15	-3.89
Unit Area (log)	.480	1.77	2.22	7.05
Surface-to-Volume Ratio	-1.67	-2.57	-2.53	-3.52

Reference choice: No AC; Rho-square: 0.291; $n = 1203$; $L(0) = -1321.631$; $L(\hat{\beta}) = -936.620$....

Table 4.4 - Estimation Results for AC ownership

4.3 Vehicle Portfolio Ownership and Car Purchase Intention

Household motor vehicle ownership logically drives household travel energy demand. Jinan's households have a range of ownership patterns, or "vehicle portfolios" (Chen, 2012) (see Table 4.3), approximately increasing in energy intensity from: zero motorized vehicles, to electric bikes (e-bikes) only, motorcycles (MCs) only (or plus e-bikes), cars only, or cars plus other motorized modes (MCs and/or e-Bikes).

We specify and estimate a multinomial logit model of vehicle portfolio choice (Table 4.5) and find that household type, income, and employment status, and some neighborhood design variables significantly impact vehicle portfolio choice. In addition, given the dynamism of private car ownership in China and its importance to travel energy consumption, we attempt to model the likelihood of car purchase. For this, estimate a binary choice model of the intention to purchase a car (Table 4.6). Household income, current vehicle portfolio and several neighborhood form variables play significant roles in this intention "choice." This car intention model is not used in the simulation model as it does not reflect the attitude in the next year. Rather, it provides interesting insights into household long-term car purchase decisions.

Variables	EBike_Only		Motorcycle		Cars_Only		Cars_and_Others	
	Coef.	t-value	Coef.	t-value	Coef.	t-value	Coef.	t-value
Constant	.672	3.40	-1.71	-9.39	-10.6	-7.73	-5.13	-3.79
Income (log_K)	--	--	--	--	.949	6.25	.760	4.70
No_Employed	-.955	-4.69	-.976	0.383	-2.51	-5.69	-2.91	-4.71
Single	-.870	-2.65	--	--	--	--	-1.37	-2.18
Unit Area (log)	--	--	--	--	1.56	5.84	.618	2.29
Bus_Convenient	-.452	-2.50	--	--	-.746	-3.92	-1.07	-5.17
Adult_3+	.438	2.58	.718	2.47	--	--	.725	4.01
Walking Facility	--	--	--	--	-1.06	-2.35	-1.21	-2.42
Function Mix	-2.39	-3.92	--	--	--	--	-2.41	-2.53
Park_Under	--	--	--	--	.0293	2.89	--	--

Reference choice: No_Vehicle; Rho-Square: 0.212; n=1203; $L(0) = -1936.154$; $L(\hat{\beta}) = -1525.557$

Table 4.5 – Estimation of vehicle portfolio choice

Variables	Buy_Car	
	Coef.	t-value
Constant	-2.58	-4.66
Income (log_K)	.280	2.44
P_EBike_Only	.488	2.83
P_Motorcycles	.723	2.42
P_Cars_Only	-2.80	-8.27
P_Cars_and_Others	-2.43	-6.42
Child	.438	3.17
Attitude – LoveTravel	.572	3.44
Residential Density	-.00896	-2.48
Distance to city center	.136	3.74

Reference choice: Not_Buy_Car; Rho-Square: 0.364; n=1203; $L(0) = -833.856$; $L(\hat{\beta}) = -530.236$

Table 4.6– Estimation of car intention choice

4.4 Lifestyle Trade-Off Patterns

As discussed in the previous section, total household energy use will partly be determined by activities performed in-home versus out-of-home. I model household propensity to undertake different relevant activities: work outside vs. work-at-home, dine-out vs. cook at home, leisure out vs. in-home entertainment. From the household's perspective, members working outside the home may result in additional transportation energy use, while working at home may create additional in-home energy consumption. Similar trade-offs can exist in the cases of dining and leisure activities. These patterns will then possibly influence later-stage models of household trip frequencies (i.e., trip generation) and in-home energy consumption.

To quantify these three trade-off behavior patterns, I define three binary variables for work, eating, and leisure to indicate whether household preferences for going outside or staying at home for the same type of activity. I hypothesize that household and neighborhood design characteristics will impact those three aspects of lifestyle trade-off patterns. Table 4.7 presents the estimation results for the three trade-off patterns. The results intuitively suggest that higher incomes increase the likelihood of working at home, but also increase the likelihood of going out for leisure activities, consistent with intuition. Household attitudes, predicted vehicle portfolio (instrumental variable), demographics and neighborhood characteristics have influence, particularly for more flexible activities (i.e., leisure and dining).

Variables	Work at Home		Dine at Home		Leisure at Home	
	Coef.	t-value	Coef.	t-value	Coef.	t-value
Constant	-5.45	-4.04	3.60	8.03	-1.60	-3.56
Income (log)	.264	2.20	--	--	--	--
Income (per 1000 Yuan)	--	--	--	--	-.00173	-1.75
Three Generation family	.448	2.26	--	--	-.415	-2.41
Elder	--	--	.275	3.21	-.179	-2.06
House Owner	.381	1.97	--	--	--	--
Reside elsewhere	--	--	-1.08	-5.84	--	--
Residence Year 1+	--	--	--	--	-.476	-2.77
P_Motorcycles	--	--	-17.5	-5.33	--	--
P_Car_Only			-3.15	-5.43		
P_Car_Other			-3.52	-4.88		
Attitude – LoveTravel	--	--	--	--	-.417	-3.10
Attitude – Not prefer bus or bike	--	--	--	--	.682	5.16
Attitude – Prefer big house	.438	2.52	--	--	--	--
Attitude – regular exercise	--	--	--	--	-.720	-5.17
Building story	--	--	--	--	.0831	4.18
Building coverage	--	--	--	--	2.76	3.40
Residential Density	--	--	-.00759	-2.32	--	--
Motor width	--	--	-.0490	-3.88	--	--
Distance to city center	--	--	--	--	.0847	2.67
Cul_de_sac	--	--	--	--	1.18	3.45
RA_Total	--	--	-.00140	-2.64	--	--
Reference	Work Outside		Dine Outside		Leisure Outside	
# of observations	1203		1203		1203	
Rho-Square	.439		.125		.111	
L(0)	-833.856		-833.856		-833.856	
$L(\hat{\beta})$	-467.506		-729.538		-741.199	

Table 4.7- Estimation of trade-off lifestyle choice

4.5 Household Travel Consumption

To estimate household transportation energy use, I develop three models: a trip frequency model, a model estimating whether generated trips are internal or external to the neighborhood and a trip mode & length choice model. These models are applied to four trip types: work, maintenance, leisure, and school.

As mentioned in Section 3.4.3, Negative Binomial Regression models are applied to account for the potential overdispersion of the trip frequency data. Tables 4.8~4.11 present estimation results for work, maintenance, leisure, and school trips[11]. In these tables, the variable "Negative binomial" is an estimate of the dispersion coefficient. A Poisson Regression Model is one with a zero "Negative binomial" value. For all trip purposes, estimates of this value are greater than zero indicating over-dispersion and hence the necessity to use Negative Binomial Regression models. The trip frequency model results show that household characteristics, the predicted vehicle portfolio (instrumental variable), neighborhood form, and regional accessibility variables are all significant.

Variables	Coef.	Wald Chi-Square	Sig.
(Intercept)	-.225	1.354	.245
Employ_2	.486	59.714	.000
Employ_2+	.710	49.919	.000
Elder	-.375	133.718	.000
P_EBike_Only	3.745	71.873	.000
P_Motorcycles	13.793	102.022	.000
P_Cars_Only	3.495	128.123	.000
P_Cars_and_Other	3.256	113.345	.000
parking_under	-.019	18.274	.000
parking_surface	.017	4.509	.034
RA_office	.008	17.563	.000
Residential Density	-.005	13.831	.000
(Negative binomial)	.537	--	--

Table 4.8– Estimation of work trip generation

[11] For school trips, the trip frequency models are estimated based on families with kids. Those without any child are assumed not to generate any school trip.

Variables	Coef.	Wald Chi-Square	Sig.
(Intercept)	.683	3.411	.065
P_Cars_Only	-.599	14.326	.000
Income (log)	.071	6.329	.012
Unit Area (log)	.093	3.364	.067
Road_density	.010	54.065	.000
BRT routes 1+	.238	20.213	.000
Distance to city center	-.019	5.440	.020
Attitude – Bus Convenient	.085	5.185	.023
(Negative binomial)	.185	--	--

Table 4.9– Estimation of maintenance trip generation

Variables	Coef.	Wald Chi-Square	Sig.
(Intercept)	1.035	23.301	.000
Road_density	.024	22.863	.000
BRT routes 1+	.468	9.667	.002
Distance to city center	-.124	23.246	.000
Elder	.194	11.319	.001
Floor	-.031	5.160	.023
Rent	-.547	14.777	.000
Total_hh	1.4 E-4	10.585	.001
Residential density	-.016	19.068	.000
Attitude – Exercise regularly	.700	55.306	.000
(Negative binomial)	1.923	--	--

Table 4.10 – Estimation of leisure trip generation

Variables	Coef.	Wald Chi-Square	Sig.
(Intercept)	1.922	885.025	.000
RA_School	.018	9.659	.002
Kid_1+	.661	14.669	.000
(Negative binomial)	1.000	--	--

Table 4.11– Estimation of school trip generation

The internal/external trip choice model results (Tables 4.12 – 4.14) show, as expected, that numerous neighborhood design variables – such as sidewalks, green coverage, and BRT routes – play a significant role.

Variables	Internal Trip	
	Coef.	t-value
Constant	-.891	-2.71
BRT	-.888	-3.94
Residential Density	.0172	2.58
Attitude - LoveTravel	-1.12	-5.56
Park_Under	-.0965	-6.46
Road Density	-.0409	-3.94
Single	1.42	4.40

Reference: External Trip; Rho-Square: 0.671; n=1658; $L(0) = -1149.238$; $L(\hat{\beta}) = -348.142$

Table 4.12– Estimation of internal work trip choice

Variables	Internal Trip	
	Coef.	t-value
Constant	-2.82	-14.52
BRT	-.286	-2.46
Walking Facility	.945	3.88
Single	.612	2.62
Street Level Shop	3.54	8.43

Reference: External Trip; Rho-Square: 0.380; n=2729; $L(0) = -1891.599$; $L(\hat{\beta}) = -1173.317$

Table 4.13 – Estimation of internal maintenance trip choice

Variables	Internal Trip	
	Coef.	t-value
Constant	-7.29	-8.76
Residential Density	.0672	7.72
Elder	.466	3.93
Green Coverage	3.81	5.37
Neighborhood Size	3.53e-6	6.96
Footprint	-.00289	-5.92
Distance to city center	.161	3.36

Reference: External Trip; Rho-Square: 0.388; n=2273; $L(0) = -1575.524$; $L(\hat{\beta}) = -963.963$

Table 4.14 – Estimation of internal leisure trip choice

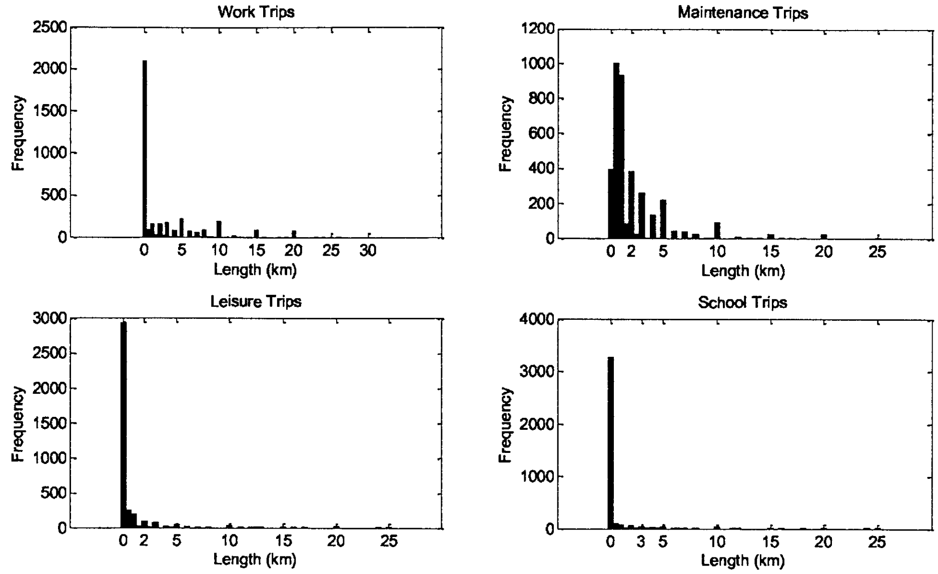

Figure 4.2 – Trip length distributions for work, maintenance, leisure and school trips

For the external trips, I then model trip mode & length choice together as a nested logit model. The modes include walk, bike, E-Bike, motorcycle, car, and public transit. I categorize trip distance as short, medium, and long, since survey reporting of this variable tended to be in rough distance estimates (see the histograms in Figure 4.2). Two nesting structures are theoretically possible (Figure 4.3). The nesting structure does not represent a sequential decision-making process, per se, but shows the pattern of similarities within a decision process that is simultaneous (e.g., Small and Winston, 1999). In other words, in the depiction in Figure 4.3 - Version 2, the traveler views the different modes for traveling short distances as more similar to each other than the different travel distances that one can choose by a particular mode. As described in the modeling techniques (see Nested Logit Model in Section 3.4.2), the logsum from the lower level nest (e.g., mode choice in Figure 4.3 - Version 2), figures directly into the utility function for the upper level choice and the coefficient on the logsum in the upper nest determines whether the nest structure is consistent with the model assumptions. For work, maintenance and leisure trips, the model estimation process suggests that "Version 2" in Figure 4.3 is the appropriate model structure (Final estimation results in Tables 4.15 – 4.21).

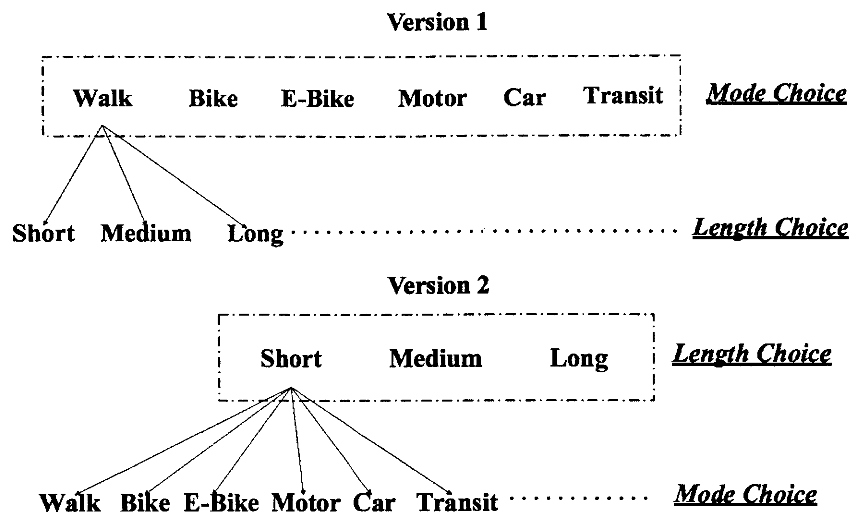

Figure 4.3 - Alternative nesting structures for mode-distance joint choice model

For school trips we take a different approach. Rather than specify an internal/external choice model, we account for the normal size of a school district in the city: 1.5km by 2.5 km[12]. So we use the length of a diagonal – 3km – as the threshold for short and long trips (i.e., we do not further divide them into internal or external trips). Tables 4.22 and 4.23 show the estimation results for school trip mode-distance choice, indicating the predominance of household characteristics, although a few form-related and relative location variables do play a role.

Apart from household socio-demographics and neighborhood form variables, travel time and cost are important factors influencing trip mode-distance choice. For travel cost, I use energy efficiency (see Table 3.2) and energy unit price data[13] to estimate the cost for each mode given the distance approximation of short, medium, and long trips. The resulting unit prices are summarized below:

※ Gasoline: 5.54 Yuan/km
※ Electricity: 0.547 Yuan/KWH
※ EBike: 0.0115 Yuan/km
※ Motorcycle: 0.1053 Yuan/km
※ Car: 0.5097 Yuan/km
※ Transit: 3 Yuan if Long Trip; others 2 Yuan

[12] http://zhuanti.sdnews.com.cn/2013/xuequ/
[13] Data collected from Jinan Price Administration Bureau's website: http://www.qpn.gov.cn/index.html

For travel time, I use in-vehicle travel time (IVTT) and out-of-vehicle travel time (OVTT) for the model estimation. Since I have the distance approximation associated with short, medium, and long trips, I only need the average speed to get the IVVT. Here I calculate the average speed with trip records in 2010 Jinan survey according to different modes.

※ Walk: 10 minutes/km
※ Bike: 5 minutes/km
※ EBike: 3.7 minutes/km
※ Motor: 3.4 minutes/km
※ Car: 2.5 minutes/km
※ Bus: 3.5 minutes/km

OVTT is related to the time to access the vehicles and is pre-determined for different modes as follows.

※ Walk: 0 minutes
※ Bike: 1 minutes
※ EBike: 1.5 minutes
※ Motor: 2 minutes
※ Car: 5 minutes
※ Bus: 10 minutes

Variables	Coef.	t-value
Constant - WA	.481	1.36
Constant - BI	.898	2.44
Constant - EB	.471	1.60
Constant - CA	1.50	5.93
Constant - TR	1.08	3.96
Cost	-.103	-2.67
IVTT	-.0515	-5.76
OVTT	-.307	-5.71
Female - WA	.758	3.60
Female - EB	.957	4.99
Female - TR	.718	4.85
Income(10K)- BI	-.0665	-2.40
Income(10K)- EB	-.0644	-4.12
Income(10K)- TR	-.0466	-4.28
BRT - WA	-1.12	-5.44
BRT - BI	-.684	-3.12
BRT - EB	-.429	-2.28
Travel_Waste_Time - WA	-.782	-3.50
Travel_Waste_Time - BI	-.318	-1.39
Travel_Waste_Time - TR	-.628	-4.15

Alternatives: WA (Walk), BI (Bike), EB (EBike), MO (Motorcycle, reference), CA (Car), TR (Transit)

Rho-Square: 0.325; n=1534; $L(0) = -1917.061$; $L(\hat{\beta}) = -1294.254$

Table 4.15– Estimation of work trip mode choice (lower level)

Variables	Coef.	t-value
Constant - Medi	4.81	5.67
Constant - Long	7.39	4.32
LOGSUM	.680	1.42
RA_Factory - Medi	-.0138	-2.24
RA_Factory - Long	-.0206	-1.49
Elder - Medi	-.0100	-1.64
Elder - Long	-.0336	-2.90
Rent - Medi	-.396	-2.35
Rent – Long	-.618	-1.84
Continuity – Medi	-4.93	-4.21
Continuity - Long	-8.34	-3.75

Alternatives: Short (reference), Medi (Medium), and Long trips

Rho-Square: 0.172; n=1534; $L(0) = -1685.271$; $L(\hat{\beta}) = -1395.534$

Table 4.16 – Estimation of work trip distance choice (upper level)

Variables	Coef.	t-value
Constant – WA	1.76	5.47
Constant – BI	.335	1.10
Constant – EB	-.831	-2.00
Constant – CA	-.482	-.95
Constant – TR	.383	-1.06
Cost	-.109	-1.95
IVTT	-.0601	-10.30
OVTT	-.136	-6.29
Female – WA	1.51	2.94
Female – BI	1.18	2.25
Female – EB	1.14	2.12
Female – CA	1.22	2.31
Female – TR	1.35	2.62
Footprint – EB	.00176	3.31
Footprint – CA	.00299	4.39
Footprint – TR	.00134	3.86

Alternatives: WA (Walk), BI (Bike), EB (EBike), MO (Motorcycle, reference), CA (Car), TR (Transit)

Rho-Square: 0.227; n=2286; $L(0) = -2711.158$; $L(\hat{\beta}) = -2095.390$

Table 4.17– Estimation of maintenance trip mode choice (lower level)

Variables	Coef.	t-value
Constant - Medi	1.19	1.92
Constant - Long	3.51	4.58
LOGSUM	.682	2.39
Income - Medi	.00303	2.52
Income - Long	.00194	1.54
Elder - Medi	-.582	-4.51
Elder - Long	-.805	-5.28
RA_Shopping - Medi	-.00332	-2.99
RA_Shopping - Long	-.00274	-1.93
Street Level Shop -Medi	-1.00	-1.94
Street Level Shop - Long	-2.97	-5.18
Nsize - Medi	2.72e-6	7.29
Nsize - Long	1.76e-6	4.52
Land Use Mix - Medi	-2.51	-2.62
Land Use Mix - Long	-4.21	-4.43

Alternatives: Short (reference), Medi (Medium), and Long trips

Rho-Square: 0.095; n=2286; $L(0) = -2511.428$; $L(\hat{\beta}) = -2273.969$

Table 4.18 – Estimation of maintenance trip distance choice (upper level)

Variables	Coef.	t-value
Constant - WA	6.14	2.86
Constant - BI	4.13	1.85
Constant - EB	4.24	1.80
Constant - CA	4.92	2.25
Constant - TR	6.80	3.17
Cost	-.189	-3.42
IVTT	-.100	-6.80
OVTT	-.146	-2.51
Entry_Distance - WA	-.541	-1.38
Entry_Distance - BI	-.622	-1.51
Entry_Distance - EB	-.838	-1.92
Entry_Distance - CA	-.593	-1.48
Entry_Distance - TR	-.972	-2.45

Alternatives: WA (Walk), BI (Bike), EB (EBike), MO (Motorcycle, reference), CA (Car), TR (Transit)

Rho-Square: 0.381; n=1894; $L(0) = -2245.471$; $L(\hat{\beta}) = -1389.732$

Table 4.19 – Estimation of leisure trip mode choice (lower level)

Variables	Coef.	t-value
Constant - Medi	-0.539	-0.80
Constant - Long	6.64	7.49
LOGSUM	.454	4.15
Income - Medi	.00779	5.51
Income - Long	.00946	6.57
Elder - Medi	-1.08	-8.28
Elder - Long	-1.10	-6.33
Household_Member_3+ - Medi	-.622	-4.75
Household_Member_3+ - Long	-.713	-4.89
Continuity - Medi	2.62	2.83
Continuity - Long	-4.96	5.19
Residential Density - Medi	-0.0138	-3.06
Residential Density - Long	-0.0249	-4.60

Alternatives: Short (reference), Medi (Medium), and Long trips

Rho-Square: 0.146; n=1894; $L(0) = -2080.772$; $L(\hat{\beta}) = -1776.618$

Table 4.20– Estimation of leisure trip distance choice (upper level)

Variables	Coef.	t-value
Constant - WA	1.93	6.63
Constant - BI	.930	4.22
Constant - CA	.428	.94
Constant - TR	2.96	6.56
Cost	-.226	-2.98
IVTT	-.0703	-7.60
OVTT	-.212	-4.43
Entry Distance - TR	-.00119	-2.91
Age less than 20 - TR	-1.67	-4.70
Nuclear Family - CA	.834	2.11

Alternatives: WA (Walk), BI (Bike), EB (EBike, reference), CA (Car), TR (Transit)

Rho-Square: 0.317; n=626; $L(0) = -762.181$; $L(\hat{\beta}) = -520.427$

Table 4.21 – Estimation of school trip mode choice (lower level)

Variables	Coef.	t-value
Constant - Long	.955	1.15
LOGSUM	.645	1.91
Total_hh	-.000165	-4.44
Income (log)	.132	2.48
RA_School	-.0209	-1.67
Household Member 3+	-.526	-2.81
2 Employed parents	-.575	-2.77
Parking_under	.0510	4.17

Alternatives: Short (reference) and Long trips

Rho-Square: 0.121; n=626; $L(0) = -433.910$; $L(\hat{\beta}) = -381.338$

Table 4.22 – Estimation of school distance choice upper level)

4.6 Household Electricity/In-home Energy Use Models

As mentioned, due to the lack of activity data for in-home appliance use, I cannot model in-home energy consumption with the quasi-activity-oriented approach as in the transportation energy consumption estimates. Therefore, I use a linear regression model to estimate in-home electricity and total energy consumption. The model includes in-home energy type, i.e., electricity, gas, coal, and centralized heating. Note that variables coming from upper level choices (e.g., trade-off behaviors) may be a source of endogeneity so that we employ instrumental variables (the expected values of these upper-level choices).

Tables 4.23 - 4.25 present the estimation results for electricity and total in-home energy consumption and CO2-Equivalents emissions. Here the in-home energy is the sum of electricity, gas, coal and centralized heating energy. Beyond household income and some demographics and dwelling unit attributes (i.e., size), we see that several form variables play a direct role, as well as indirect role, via, for example, the fuel choices and the AC choices[14]. We can also see that all three of the trade-off variables are significant, which partly supports my hypotheses. The signs on the work and leisure trade-off variables make sense since working at home and leisure at home are "in-home" versions of these two possible out-of-home activities. However, the sign on the dine-home variable is negative for in-home energy consumption, which is counter-intuitive. We can imagine some plausible explanations for this result. Perhaps households with a tendency to dine out have other unobserved characteristics that lead to more in-home energy consumption. In any case, this particular result requires additional research to better understand what is going on.

Variables	Coef.	t-value
Constant	-3.658	-2.761
P_Telecommute	4.412	4.074
P_Dine_Home	-.631	-1.636
P_LeisureHome	1.949	4.681
Income (log)	.336	3.706
Elder	.369	2.575
Household member 3	.242	1.868
Household member 3+	.436	2.619
Unit Area (log)	1.053	7.838
Function mix	1.149	2.597
Southern_Exposure_Index	-10.747	-4.656
AC1	.304	1.755
AC2_and_more	.858	4.540

Dependent variable: electricity energy consumption (10,000 MJ); R-Square: 0.212; n=1203

Table 4.23 – Estimation of electricity energy consumption

[14] The fitted probabilities of AC choices provide counter-intuitive signs of coefficients, and thus replaced by actual number of AC numbers in the model estimation.

Variables	Coef.	t-value
Constant	-12.244	-7.443
P_Telecommute	5.474	4.067
P_Dine_Home	-.534	-1.077
P_LeisureHome	2.929	5.631
Use_Coal	2.946	10.244
Centralized_Heating	2.714	12.396
Income (log)	.464	4.165
Elder	.388	2.188
Household member 3+	.402	2.192
Unit Area (log)	3.086	18.421
Southern_Exposure_Index	-17.268	-5.912
Porosity	1.612	1.656
AC1	.279	1.286
AC2_and_more	1.097	4.627

Dependent variable: in-home energy consumption (10,000 MJ); R-Square: 0.592; n=1203

Table 4.24 – Estimation of total operational energy consumption

Variables	Coef.	t-value
Constant	-9.677	-6.314
P_Telecommute	5.352	4.282
P_Dine_Home	-1.3304	-3.131
P_LeisureHome	2.852	5.959
Use_Coal	2.902	10.900
Centralized_Heating	2.494	12.301
Income (log)	.340	3.298
Elder	.286	3.094
Household member 3+	.387	2.558
Unit Area (log)	2.904	18.725
Southern_Exposure_Index	-17.917	-6.578
Porosity	1.697	1.949
AC1	.228	1.135
AC2_and_more	.942	4.268

Dependent variable: in-home CO2-Equivalents (tonCO2); R-Square: 0.596; n=1203

Table 4.25 – Estimation of total in-home CO2-Equivalents emissions

Chapter 5: Simulation of Energy Use

Using the estimation results from the models described above, I now develop and implement a simulation of household in-home and transportation energy at the neighborhood scale, as depicted in Figure 3.1. This chapter includes three sections. In section 5.1, overall simulation processes are summarized, including model initialization, design input, demographic/equipment/lifestyle evolution, and energy/emissions estimation. Section 5.2 conducts a series of validation analysis to assess the reliability of the microsimulation model. In section 5.3, a sequence of scenarios are developed and examined to demonstrate the application of the integrated model.

5.1 Simulation Processes

The simulations utilize MATLAB[15] to run 1000 iterations to provide forecasts of energy consumption and CO2 emissions over time via the following steps. The simulation provides annual results (i.e., a time step of one year, or t+1). As discussed above, the simulation framework involves numerous sub-models dealing with behavioral choice probabilities. To connect household decisions at multiple levels, I realize the choice probabilities at each level with Monte Carlo simulation techniques. Take a two-alternatives choice for example. Suppose the probability of choosing alternative 1 is 0.4 and the chance of selecting alternative 2 is 0.6. I just need to generate a uniformly distributed random variable between 0 and 1. The cut point here is 0.4 and the agent will take alternative 1 if the generated random variable is less than 0.4.

5.1.1 Model Initiation

The model is initiated with a base neighborhood (existing or new design), which provides the relevant base year built form characteristics, and base household demographics, which in combination, and using the relevant model estimation results (described in the previous section) provide estimates of appliance & vehicle portfolio ownership, lifestyle trade-off lifestyle patterns, and the in-home and transportation energy consumption.

5.1.2 Household Demographics Evolution Module

The inputs of this module are household demographics at time t (from the model initiation) and the outputs are household demographics at time t+1. The household characteristics

[15] Student version of R2012a obtained from MIT Information Services & Technology

include household size, household type, household income, etc. The evolution of these characteristics alone will impact energy use. Taking this evolution into account allows us to predict energy consumption of a certain household 5 or 10 years later.

The module designed here simulates future household characteristics with assorted assumptions. Those assumptions assign change probabilities to birth and death and generate new characteristics at next time step. For childbirth, we use a birth rate of 12.1 per thousand people (World Bank, 2013). We have a total of six household types ("family structure" in Table 4.3): 1) Single, 2) Couple, 3) Couple & Kids, 4) Couple & parents, 5) Grandparents & Grandchildren, and 6) Three Generation family. If a certain type of household has a child, the household size will increase by 1 and the household type will change (from Couple to Couple & Kids, for example). This child birth rule is applied to household types including Couple, Couple & kids, Couple & Parents, and Three-Generation Family. The death rate comes from life tables stratified by gender and age in China (Cai, 2005) and applying it decreases household size and possibly changes family structure as well.

For income, I use the government-reported forecast average annual income growth rate of 10.7%[16]. However, using a constant growth rate applied to all households is naïve. So, I apply an assumed triangular distribution to simulate annual income change across the households (Figure 5.1, adapted from Tirumalachetty and Kockelman, 2009). In addition, the average annual income rate decays every year, eventually declining to 3% in 20 years. The average household income updating results can be found in Table 5.1.

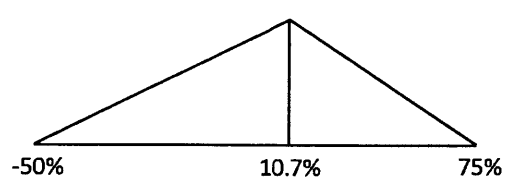

Figure 5.1– Triangular distribution for income growth rate

16 http://news.iqilu.com/shandong/yaowen/2013/0125/1435312.shtml

Year	Income	# of ACs	No vehicle owned	E-bikes only	Motorcycles	Cars only	Cars and others
1	93070	1.67	30.6%	23.9%	5.2%	24.1%	16.2%
2	96210	1.95	24.8%	18.9%	7.0%	26.2%	23.2%
3	99420	2.07	18.6%	19.1%	7.0%	26.9%	28.4%
4	102620	2.12	17.4%	15.7%	6.3%	29.7%	30.9%
5	105770	2.16	16.3%	13.3%	6.5%	29.8%	34.1%
6	108820	2.19	15.5%	11.3%	5.4%	31.4%	36.4%
7	112000	2.20	14.4%	9.2%	5.4%	32.1%	38.9%
8	114890	2.22	13.4%	8.2%	5.2%	32.2%	41.1%
9	117790	2.23	10.9%	8.1%	5.2%	34.5%	41.3%
10	120640	2.24	9.9%	8.4%	4.3%	34.3%	43.1%
11	123350	2.24	10.9%	5.8%	4.5%	34.7%	44.1%
12	125970	2.25	9.1%	6.7%	4.3%	34.2%	45.6%
13	128400	2.25	8.7%	6.5%	4.2%	33.3%	47.3%
14	130840	2.25	8.1%	7.2%	3.2%	33.8%	47.8%
15	133160	2.25	8.5%	6.4%	2.9%	35.7%	46.5%
16	135440	2.25	9.6%	4.4%	3.1%	34.1%	48.8%
17	137630	2.25	8.2%	5.3%	3.1%	35.3%	48.1%
18	139410	2.26	7.5%	5.0%	3.6%	36.3%	47.6%
19	141020	2.26	8.2%	4.2%	3.2%	37.7%	46.7%
20	142690	2.26	6.8%	4.8%	3.5%	38.5%	46.4%

Table 5.1– Estimated evolution of average household income, AC ownership, and vehicle portfolios over 20 years

5.1.3 Neighborhood Design Module

This module takes as inputs the neighborhood characteristics at time t and then provides, as outputs, the neighborhood characteristics at time t+1. This module involves no actual calculations; rather it represents the change of neighborhood characteristics as a result of design interventions.

5.1.4 Equipment Ownership Modules

Households may buy/replace a new/retired appliance or vehicle in each time step. I account for this via "appliance & vehicle purchase/replace" modules. Household appliance ownership is quite dynamic with the purchase of new appliances or replacement of break-down appliances. For appliance replacement, we assume constant energy efficiency performance (i.e., we do not account for potential changes in this attribute), an assumption which could be relaxed if efficiency improvements wanted to be explicitly included. This simplifying assumption enables us to avoid having to predict appliance breakdown. As discussed above, we currently only account for AC ownership, an assumption which could also be relaxed with more information on household appliance holdings.

For vehicle portfolio ownership, vehicle replacement is not considered due to the lack of such data in the survey.

For both AC and vehicle portfolio simulations, the inputs are household demographics, ownership levels and neighborhood characteristics at time t and the outputs are AC ownership and vehicle portfolio ownership at time t+1. The updating results for AC ownership and vehicle portfolio are present in Table 5.1 as well.

5.1.5 Transportation and In-Home Energy Use

These modules use the neighborhood and household characteristics and apply the relevant models to predict at times t, t+1, etc.: household lifestyle trade-off lifestyle patterns, household trip generation, mode choice, and length, conditional upon expected vehicle ownership portfolios; and household electricity and total operational energy use conditional upon AC ownership and lifestyle trade-off patterns.

5.2 Validation

Microsimulation is a technique designed to model complex systems by simulating the effects of changes (e.g., new policies) on agent behaviors and associated aggregate projections. The validation of the models is equally essential as the results of policy simulations since it assesses whether the model generated outcomes are credible as empirical evidence for policy development (Caldwell & Morrison, 2008). Despite the growing interest in applications of microsimulation models, literature on systematically validating the results of microsimulation approaches is relatively limited. There are generally two types of validation methods. One is to directly compare the model projections against historical statistics and another is an indirect approach known as the "multiple module approach" (details and examples from Caldwell, 1996). Most of the previous microsimulation frameworks utilized ex-post analyses of the previous periods to ensure the model is credible (see reviews from O'Donoghue, 2001).

In this research, I implement the direct comparison approach, using the actual (i.e., survey) and simulated base year data. The base year data comparison here is only a validation of model fitness since I use the same model estimation data set for simulation validation.

Figures 5.2 and 5.3 compare the simulated versus actual energy consumption and CO2 emissions for the base year in the form of cumulative distribution functions (CDF). The CDF curve depicts the overall distribution of energy use among all households in the base year. Overall, we can see that the simulation works well for all three energy categories: electricity, in-home operation, and out-of-home transportation. The fitted model does a reasonable job, except for some households with high levels of energy consumption and CO2 emissions.

We can also validate performance at the level of neighborhood (Figures 5.3 and 5.4). Among them, we have two "Traditional (T)", two "Grid (G)", three "Enclave (E)", and seven "Superblock (S)" neighborhoods. We can conclude that the simulated energy and emissions are close enough to the actual energy consumption for most of the neighborhoods. Comparing across typologies, we can see that superblocks have higher consumption levels for in-home energy. For transportation, most of the superblocks have higher consumption levels. Traditional neighborhoods have the lowest transportation energy use. Energy and emission in transportation side is much lower than in-home part across the 14 different neighborhoods.

By further breaking down the simulation of trip frequency, internal trip rate, trip mode and distance distribution, we can validate the detailed dimensions of transport energy consumption and emissions. Figure 5.6 compares the simulated average trip number per household with the survey data. The simulated and actual bars are reasonably close, showing that work is the most frequent purpose, followed by maintenance, school and leisure trips. Regarding internal trips, from Figure 5.7, we can observe that the model slightly underestimates the internal trip rate for maintenance and leisure trips (as discussed in the previous Chapter, school trips are not categorized as internal/external trip but rather distinguished based on size of school district). Although I utilize a joint nested choice model for trip mode and distance, I present the separate simulated distributions of mode and distance in Figures 5.8 and 5.9 to enable the comparison with the survey data. For modes, both the actual and simulated results indicate that EBike, Car, and Transit are the three major ways of travel for work trips while walking has the largest share for the other three purposes. As for distance, the simulation replicates the survey well – with short and medium trips dominating work, maintenance, and leisure purposes. For school trips, the share of short (inside the school district) and long trips (outside the school district) is relatively close to each other.

In summary, the simulation results compare favorably to values from the base year survey data. Of course, this only validates the first year prediction. When it comes to a longer time period (20 years in this case), the ability for the model system to provide a reasonable prediction of the future depends on a range of uncertainties. In the following section I discuss some of the uncertainties and how they are represented in the forecasts.

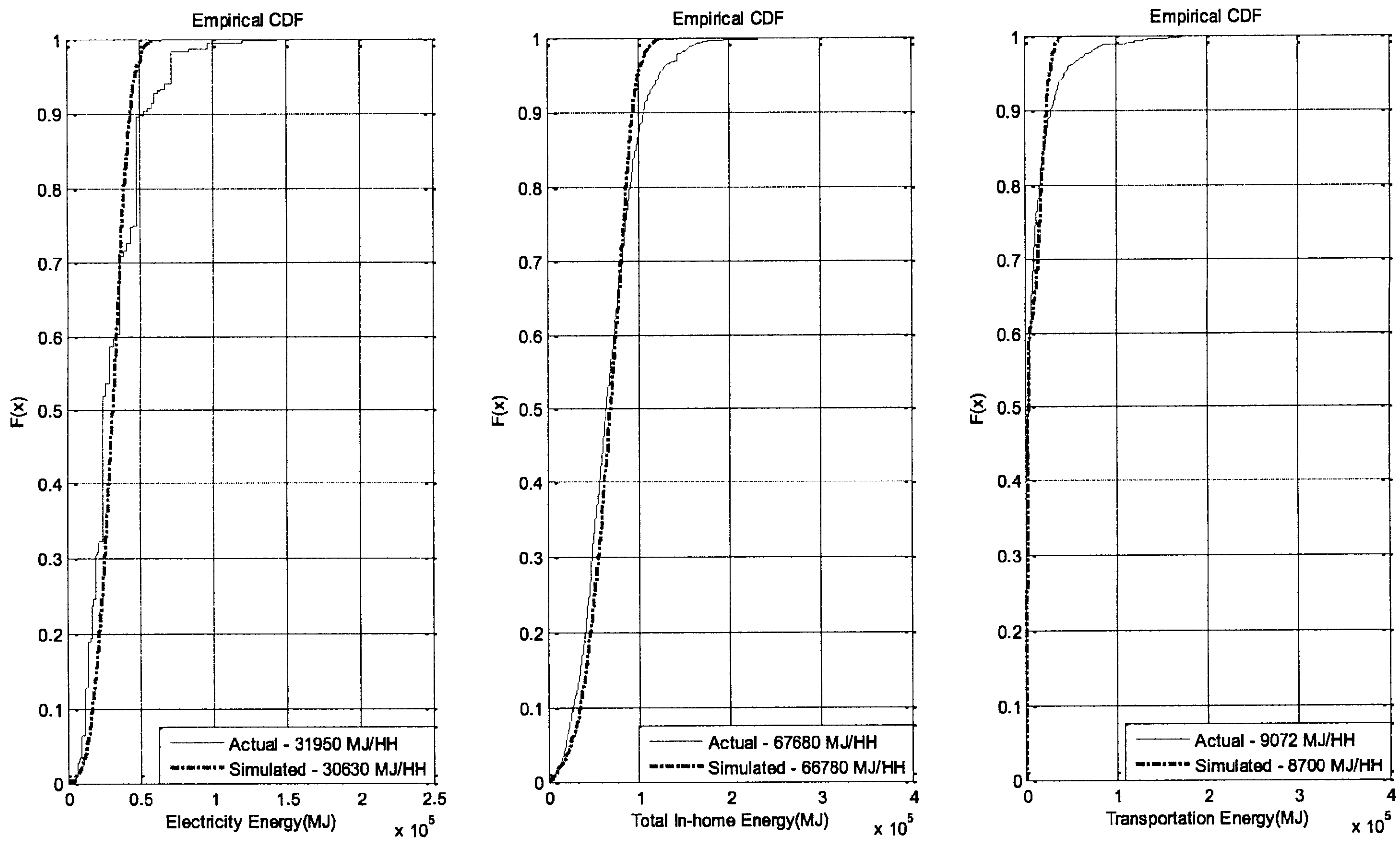

Figure 5.2 - Simulated vs. actual energy consumption in the base year (CDFs)

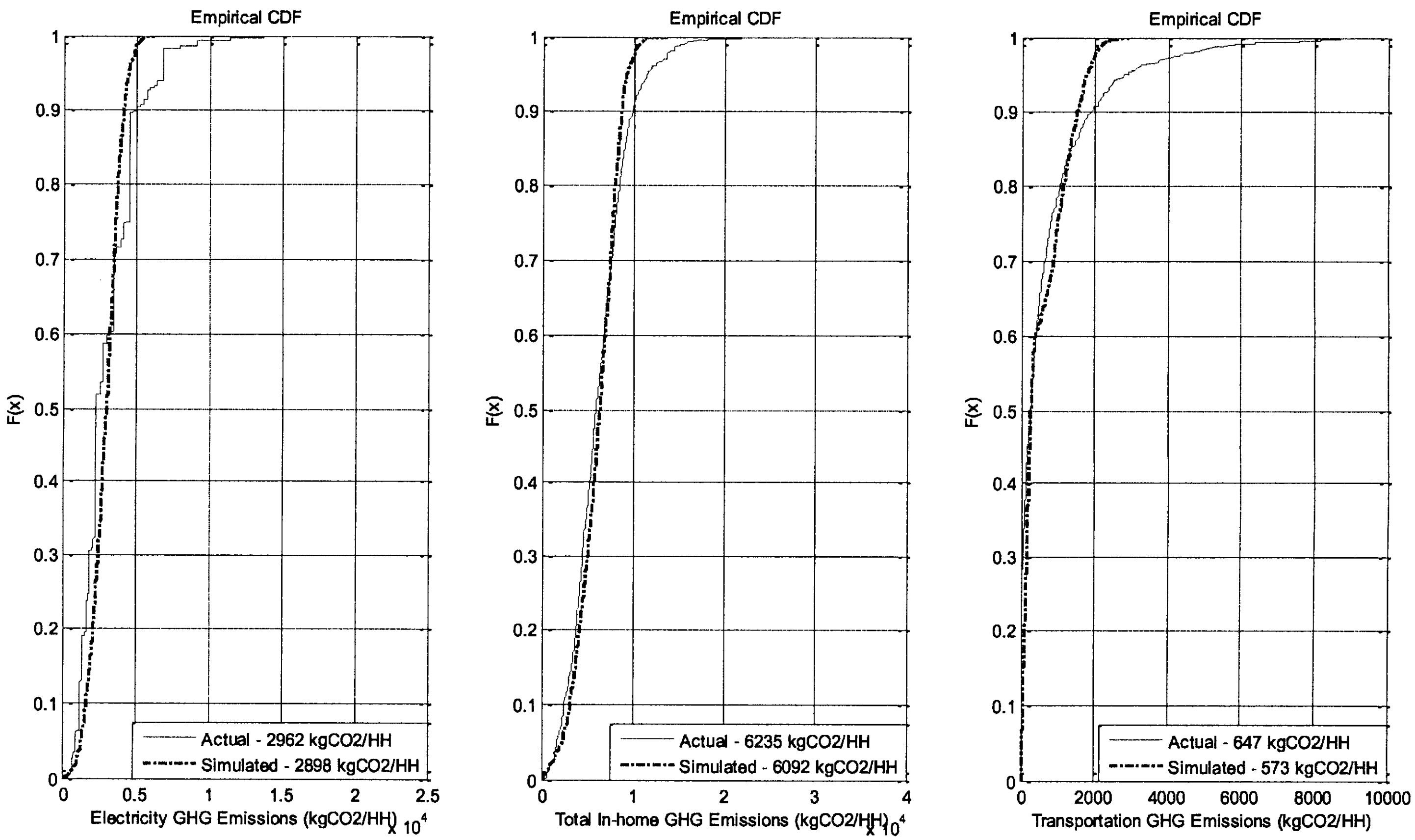

Figure 5.3- Simulated vs. actual CO2 Emissions in the base year (CDFs)

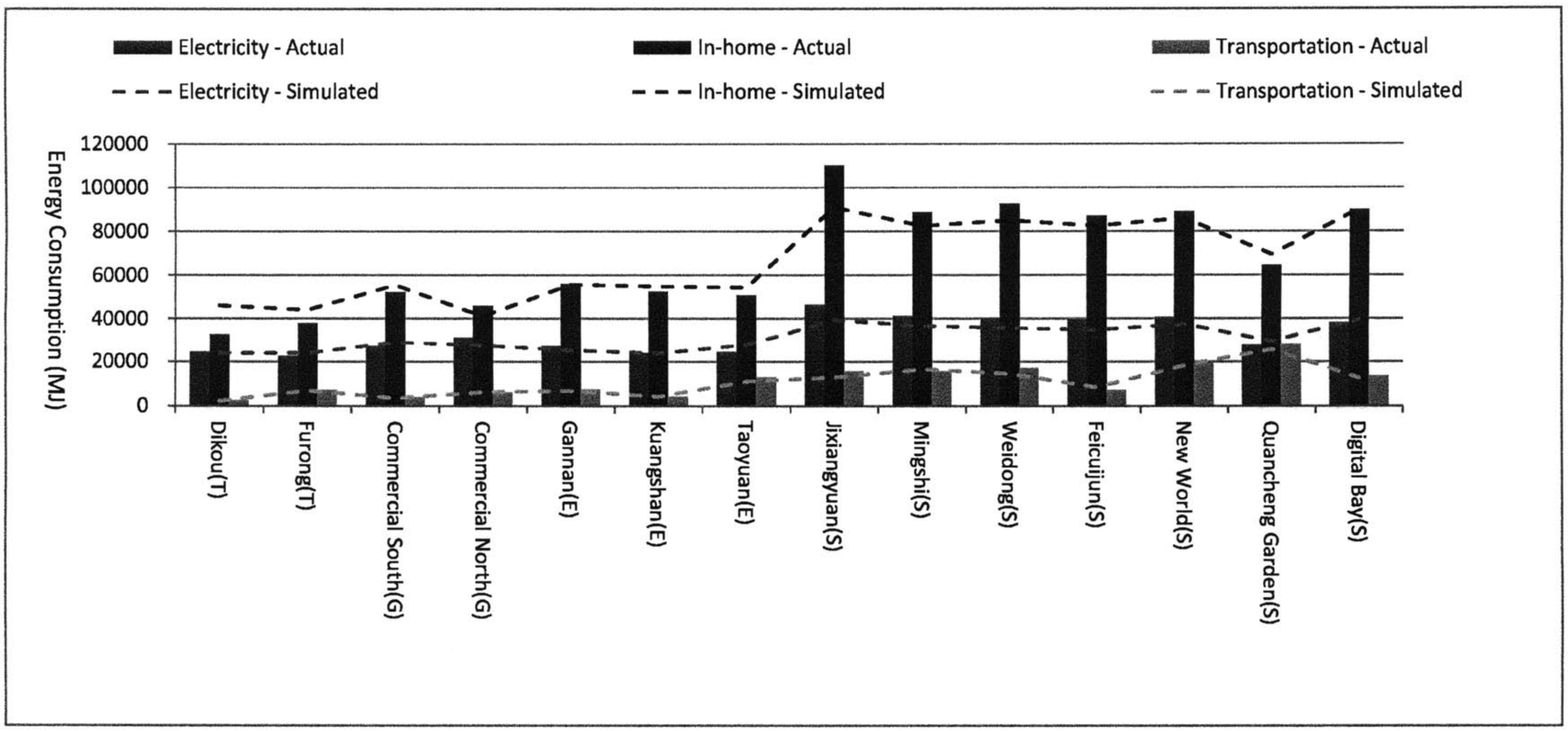

Figure 5.4 - Simulated vs. actual energy consumption (MJ) in the base year for 14 neighborhoods

(T-Traditional; G-Grid; E-Enclave; S-Superblock)

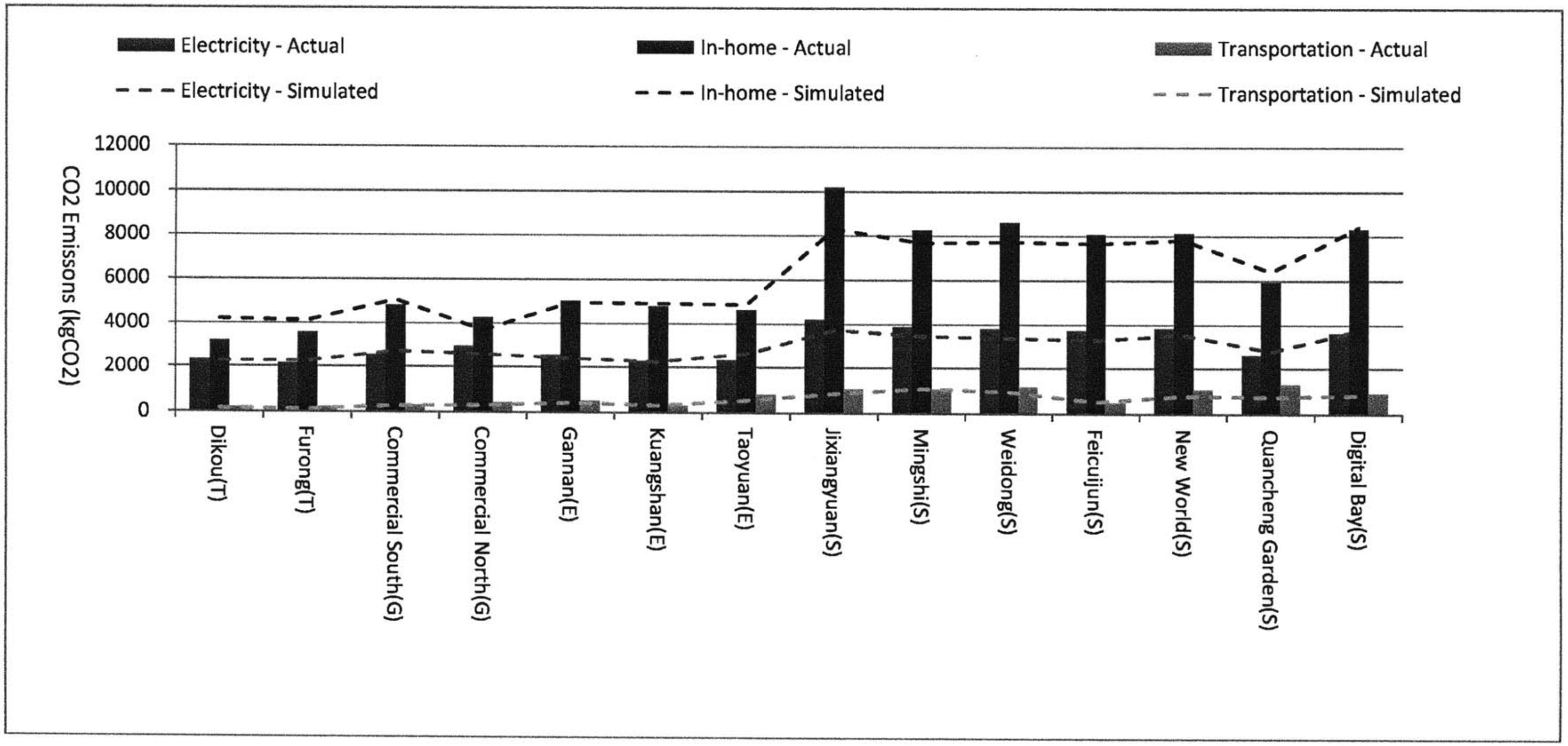

Figure 5.5 - Simulated vs. actual CO2 Emissions (kgCO2) in the base year for 14 neighborhoods

(T-Traditional; G-Grid; E-Enclave; S-Superblock)

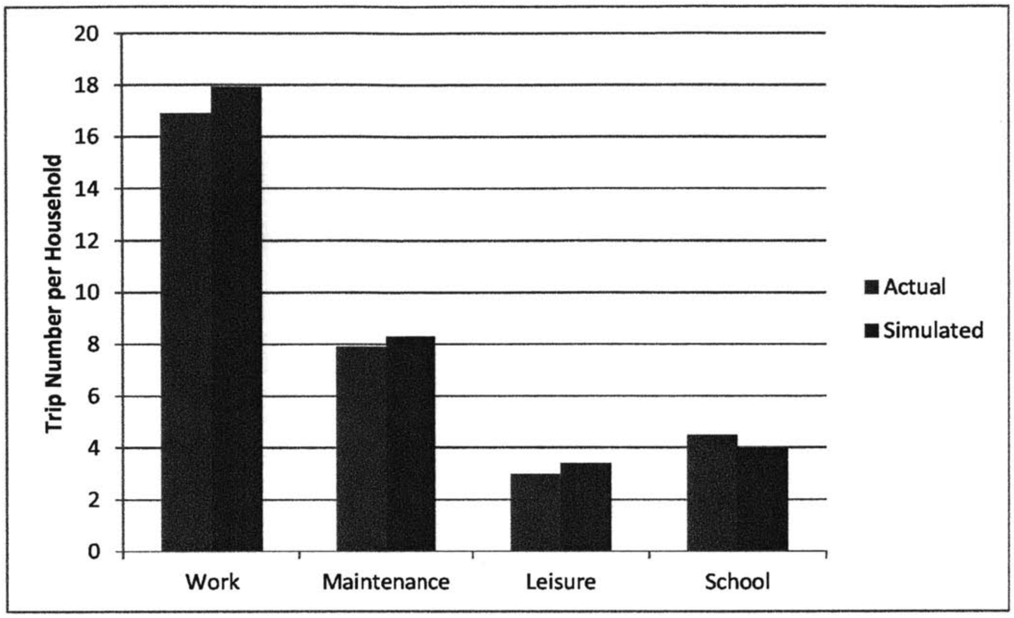

Figure 5.6 – Simulated vs. actual trip number per household in the base year

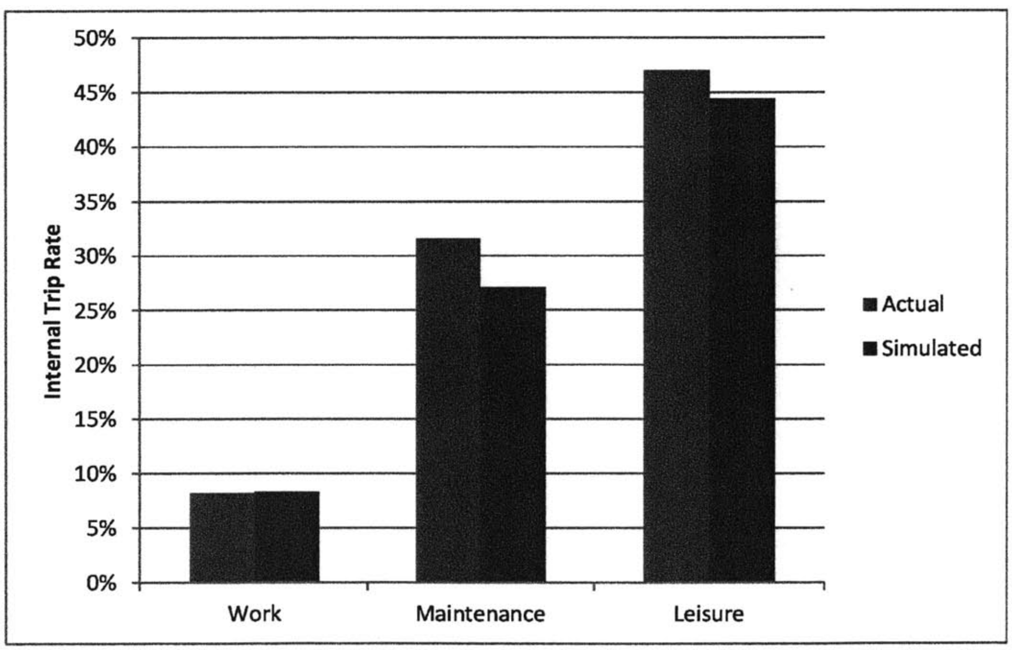

Figure 5.7 - Simulated vs. actual internal trip rate in the base year

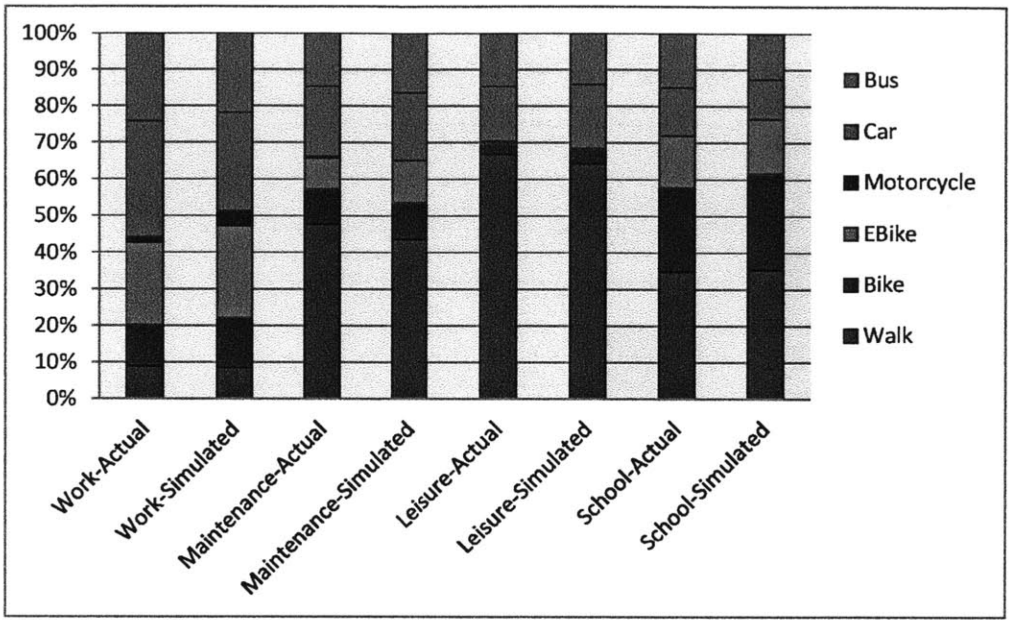

Figure 5.8 - Simulated vs. actual mode distribution for work, maintenance, leisure, and school trips in the base year

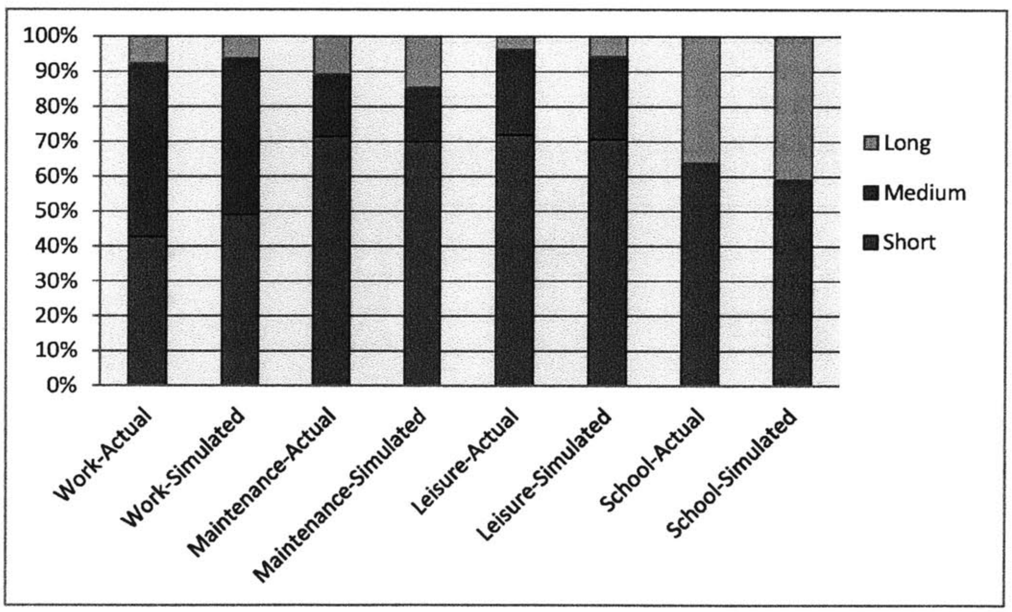

Figure 5.9 - Simulated vs. actual distance distribution for work, maintenance, leisure, and school trips in the base year

5.3 Forecasts

In this section, forecast uncertainty is first discussed and then three types of scenarios are developed to simulate the changes in energy consumption and CO2 emissions resulting from the evolution of socioeconomic and demographic (SED) characteristics, equipment stock, fuel efficiency, and neighborhood forms:

1) Baseline with only the evolution of SEDs and equipment stock
2) Adding yearly fuel efficiency improvement to the baseline forecasts
3) Adding neighborhood design interventions to the baseline forecasts

5.3.1 Uncertainty of simulation-based forecasts

Forecast uncertainty largely depends on the distributions of the output projections, not just the means. There are various sources of variability in the output that come from microsimulation. Considering the detailed processes within the microsimulation, I conclude that at least three sources of uncertainty exist – the Monte Carlo method, the sampling error, and the behavioral parameter estimates. The uncertainty from parameter estimates is common to all statistical forecasting approach as the distribution of the coefficient can be approximated with asymptotic normality theory. Other two sources will be further examined in following sections.

5.3.1.1 Uncertainty by Monte Carlo Method

Variance by Monte Carlo method refers to the fact that different runs of the model will produce different decisions for a given agent facing the same choices, even with identical model parameters. This type of uncertainty is due to the nature of the random number generating process in computer programs with varying seeds. In theory, this type of uncertainty is known as stochastic variation and it can be reduced to an acceptable range with sufficient runs. That is, if enough runs are repeated, the value assigned each time to the agent will converge to the theoretical probability distribution of the same variable. As such, the average of all those values from multiple runs would be a reasonable estimate of mean behavior of the agent. In this sense, the sensitivity analysis of exogenous impact can use mean values to illustrate the expected effect of changes like fuel efficiency improvement and urban design interventions. Classical variance measures such as standard deviations are suitable to capture the magnitude of this uncertainty.

5.3.1.2 Uncertainty by Sampling

Another important source of uncertainty also comes from the very nature of the microsimulation, as it utilizes a sampling base to represent the starting point from which to trace the state and behavior of the entire population. Policy makers are normally interested in the summary statistics aggregated from microsimulation and the difference between the simulated summary statistics of the sample and the actual values of the population is often referred to as the sampling error. Measuring uncertainty caused by sampling error is typically not feasible as the true population value is unknown in most cases. As a result, unlike for the Monte Carlo method, the sample average of summary statistics is not guaranteed to be a good estimate of the population mean.

5.3.1.3 Uncertainty in Application

Previous sections summarized three sources of uncertainty in the microsimulation. Other important sources of variation could come from the model structure itself, the values of exogenous variables, etc.. To deal with uncertainty, I focus on two aspects – variance reduction and variance measurement. For variance that can be reduced (normally caused by Monte Carlo process), I test for different number of runs and find that 1000 iterations will give a reasonable variance range for most output projections in this case. Meanwhile, for other existing variance sources, uncertainty measurement is estimated associated with mean output projections to provide a comprehensive understanding of forecasting values.

5.3.2 Baseline Scenario

I first develop a baseline forecast of energy consumption and CO2 emissions over 20 years, considering only changes in the underlying demographics and equipment ownership (Tables 5.2 and 5.3). The standard deviations are measured along with mean values and we can observe that the variance of predictions rises over time. As expected, energy consumption across all end-uses increases, with transportation leading the way, with an average increase of 4.5% per year, versus 0.6% for electricity and 0.4% for in-home. Similarly for CO2 emissions, the transportation sector has the largest rate of increase followed by in-home operations. These rates are consistent with the fact that household transportation energy use and emissions in Jinan is starting from a much lower base than in-home, relative to international precedents (e.g., Chen, 2012).

Year	Electricity(MJ)	In-Home(MJ)	Transportation(MJ)
1	30630±40	66780+60	8700±240
2	31960±50	68600±80	9930±260
3	32610±50	69460±80	10780±300
4	33000±60	69990±90	11380±300
5	33270±60	70340±100	11910±320
6	33480±60	70620±100	12360±320
7	33630±60	70810±100	12790±310
8	33770±70	70980±100	13100±300
9	33880±70	71110±100	13230±310
10	33980±70	71230±100	13510±320
11	34060±70	71330±110	13750±320
12	34120±70	71390±110	13920±310
13	34180±70	71460±110	14030±350
14	34230±70	71500±120	14140±340
15	34270±70	71550±120	14290±350
16	34310±70	71580±130	14380±350
17	34330±80	71590±130	14440±330
18	34340±80	71610±130	14520±350
19	34360±80	71620±140	14570±350
20	34360±80	71620±140	14640±350

Table 5.2 - Household energy use baseline predictions (ranges)

Year	Electricity (kg CO2)	In-Home (kg CO2)	Transportation (kg CO2)
1	2898±5	6091+7	578±74
2	3024±5	6250±7	1106±120
3	3084±5	6327±7	1350±139
4	3121±6	6372±7	1458±165
5	3147±6	6404±8	1477±162
6	3167±6	6427±9	1479±163
7	3182±6	6444±8	1504±162
8	3195±6	6459±8	1505±150
9	3205±7	6470±8	1515±155
10	3214±6	6480±8	1538±153
11	3222±6	6487±9	1544±157
12	3228±6	6492±9	1535±155
13	3234±6	6497±9	1531±138
14	3238±7	6501±10	1523±151
15	3242±7	6505±10	1537±136
16	3245±7	6507±10	1535±129
17	3247±7	6508±10	1552±134
18	3249±8	6510±11	1528±141
19	3250±8	6510±11	1537±136
20	3251±8	6510±11	1530±144

Table 5.3 - Household emission baseline predictions (ranges)

Examining in detail the transportation forecasts, we see, unsurprisingly the important role of the car in travel energy and emission growth (Figures 5.10 and 5.11). This can be traced back to the fact that only about 40% of households have at least one car in the base year (Table 4.3) while the rate of car ownership increases rapidly in the following years (Table 5.1). The second largest source of transport energy and emission production is public transit, with a much lower overall energy use and emissions than cars. Motorcycles are the third largest transport energy consumption source, but EBikes generates more emissions than motorcycles due to the difference between energy intensity factor and emission factor for the two modes (Tables 3.2 and 3.3). Across neighborhood typologies, the "Superblocks" has the highest travel energy and emissions, following by "Enclave" and "Grid", and finally the "Traditional".

We can further explore the behavior underlying the transportation forecasts. The overall simulation model produces indicators of the detailed behavioral outcomes of the sub-models, such as internal trip rate, trip mode and trip length choice, making it easier to relate policies, such as mode-oriented strategies, to ultimate outcomes of interest. For internal/external trips, a higher internal trip rate will reduce travel energy consumption and emissions by preventing longer motor vehicle-based trips outside the local development area. As seen in Figures 5.12-5.14, the models predict that the internal trip rate will not change much with the evolution of demographics and vehicle stocks. This is consistent with the coefficient estimates from the internal/external trip choice models, as most of the significant factors are neighborhood form variables (see in Tables 4.12, 4.13, and 4.14). For mode choice (Figures 5.15-5.18), a clear pattern is the increasing share of car trips for work, maintenance, and leisure travel, although walking remains the most common way of travel for maintenance and leisure purposes. School trips reveal a slight increase in the share of car use and a more balanced split among the available modes. For external trip distances (Figures 5.19-5.22), we observe somewhat stable overall shares among short, medium, and long trips across various purposes over time, except with a trend of longer travels for leisure purposes.

The big story here is the rocketing car use as the evolution in socioeconomics and demographics and the vehicle stock, which drives the rapid increase in transport energy over time as seen in Tables 5.2 and 5.3. The baseline predictions suggest that travel energy use will not balance itself over time; approximately constant internal trip rate and trip distance distribution is overwhelmed by more car use. Thus, in following sections, I will further examine two scenarios – improving fuel efficiency or adding neighborhood design interventions – to compare energy-use mitigation strategies.

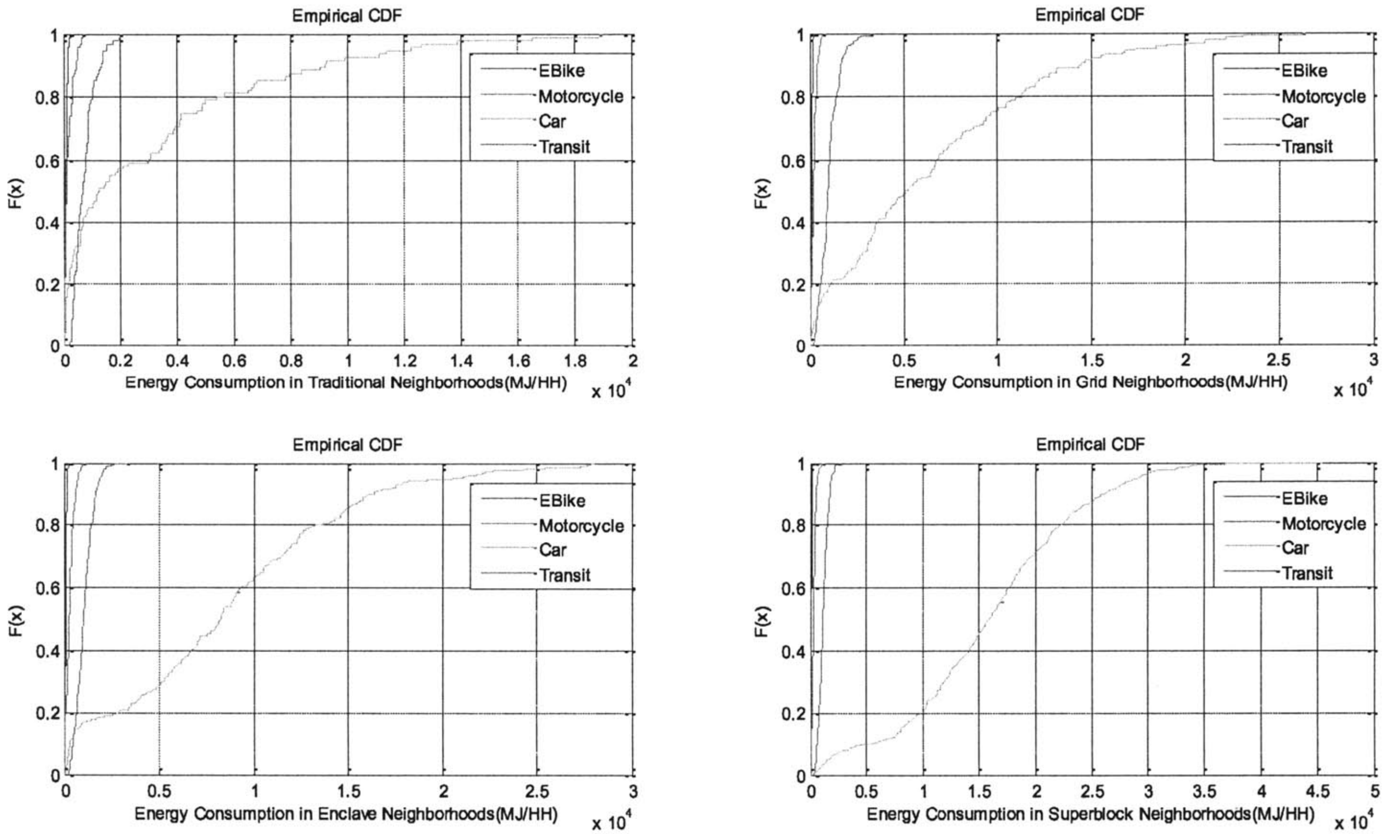

Figure 5.10 - Transportation energy use by mode and neighborhood typology over time (averaged over 20 years)

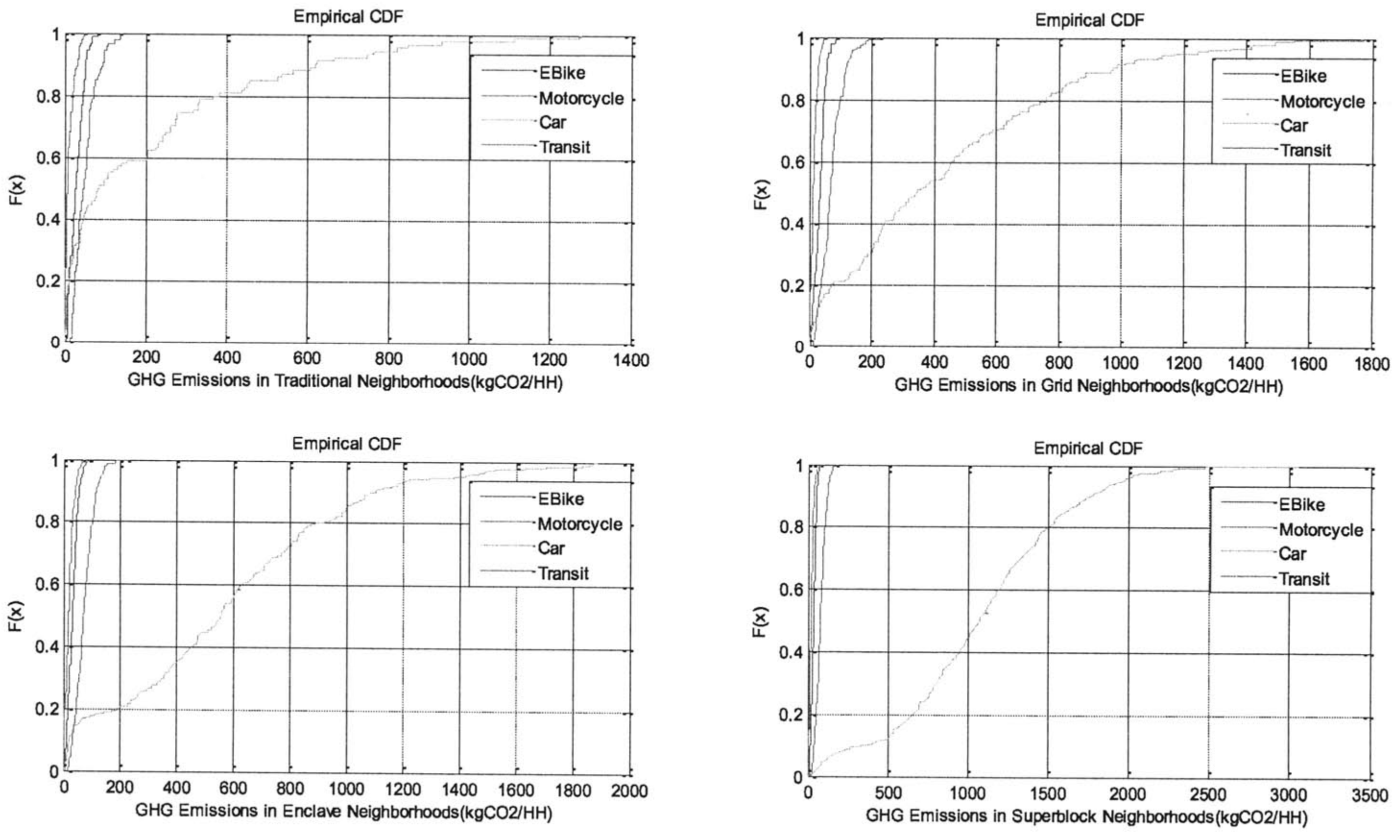

Figure 5.11- Transportation CO2 Emissions by mode and neighborhood typology over time (averaged over 20 years)

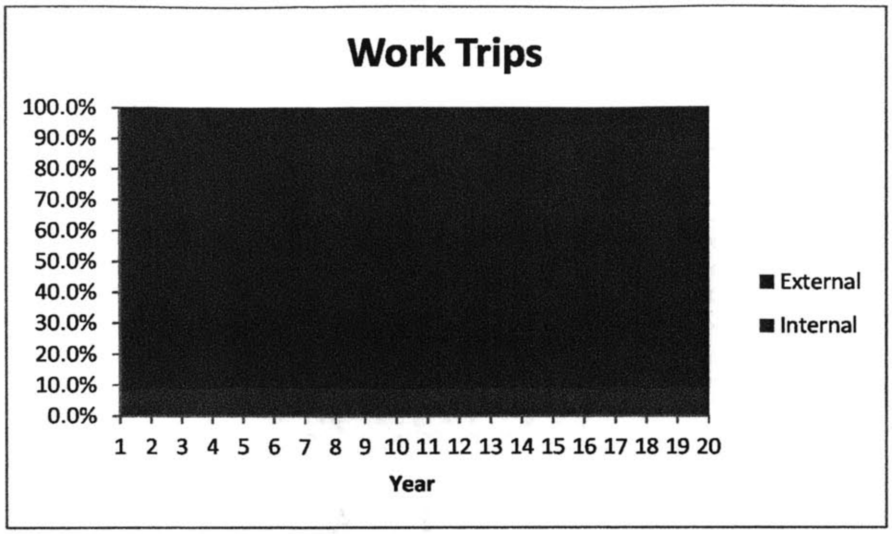

Figure 5.12 – Internal trip rate baseline predictions for work trips

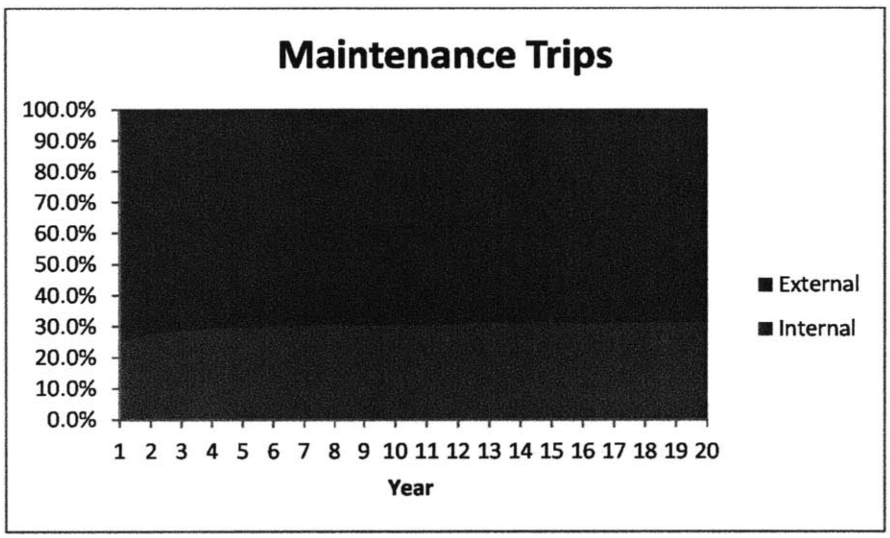

Figure 5.13 - Internal trip rate baseline predictions for maintenance trips

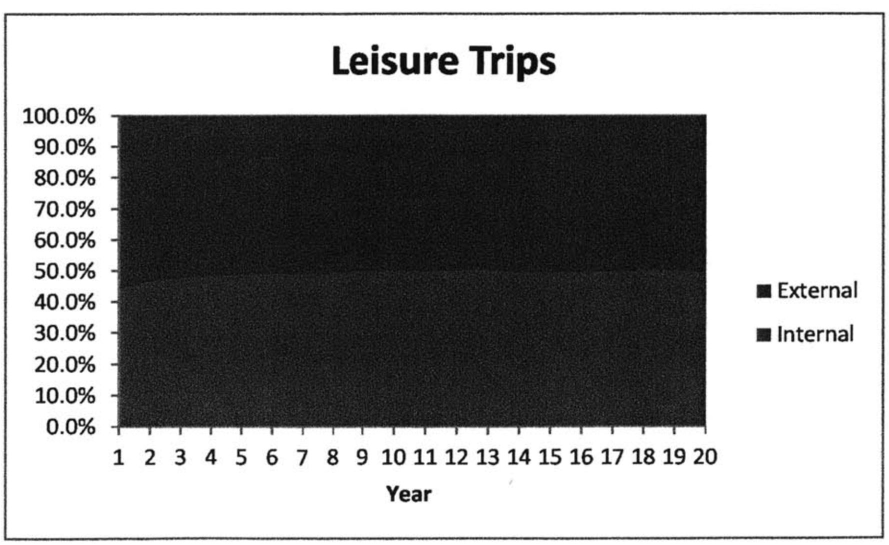

Figure 5.14 - Internal trip rate baseline predictions for leisure trips

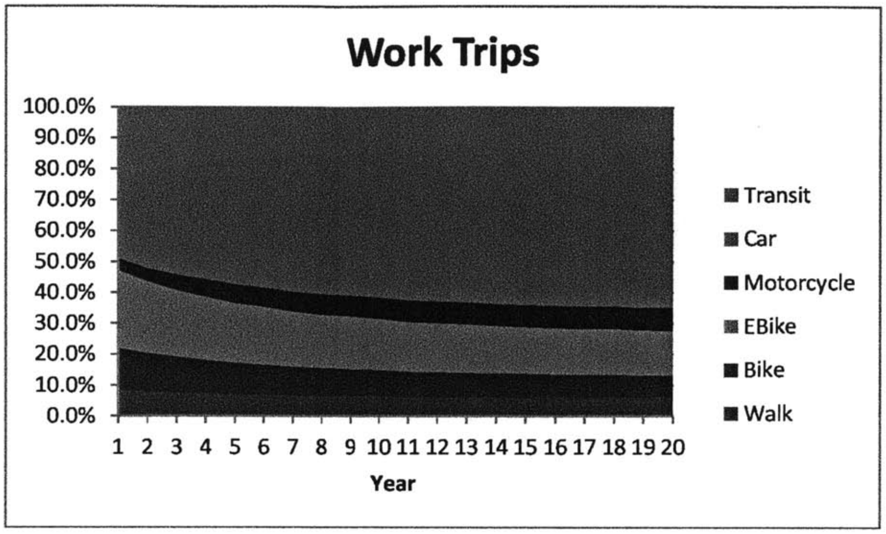

Figure 5.15 - Mode share baseline predictions for work trips

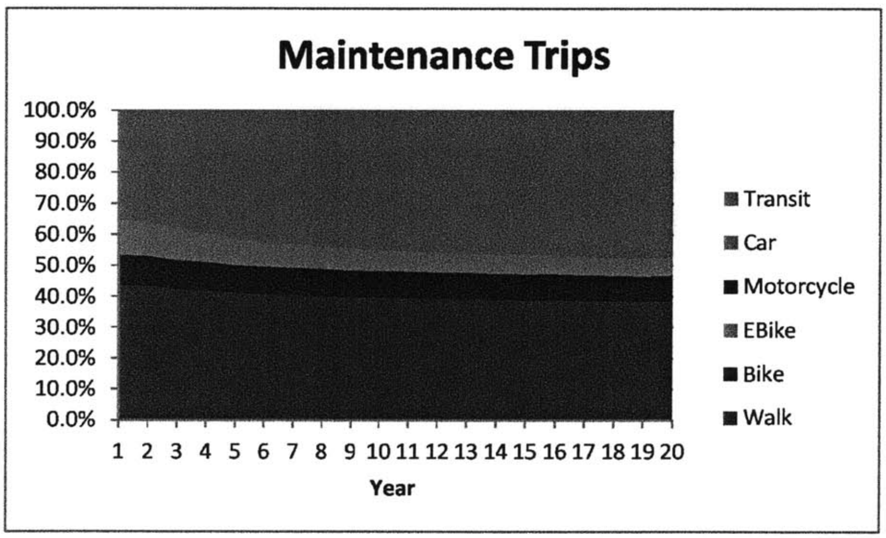

Figure 5.16 - Mode share baseline predictions for maintenance trips

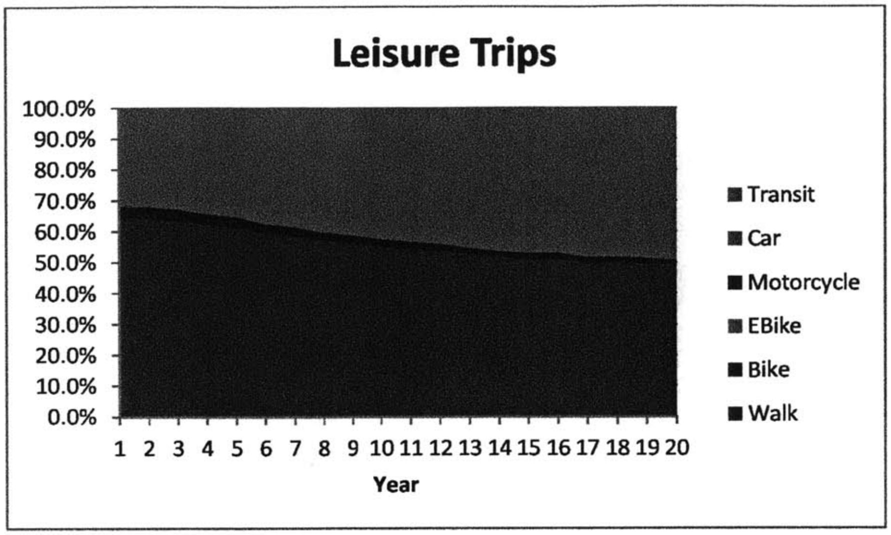

Figure 5.17 - Mode share baseline predictions for leisure trips

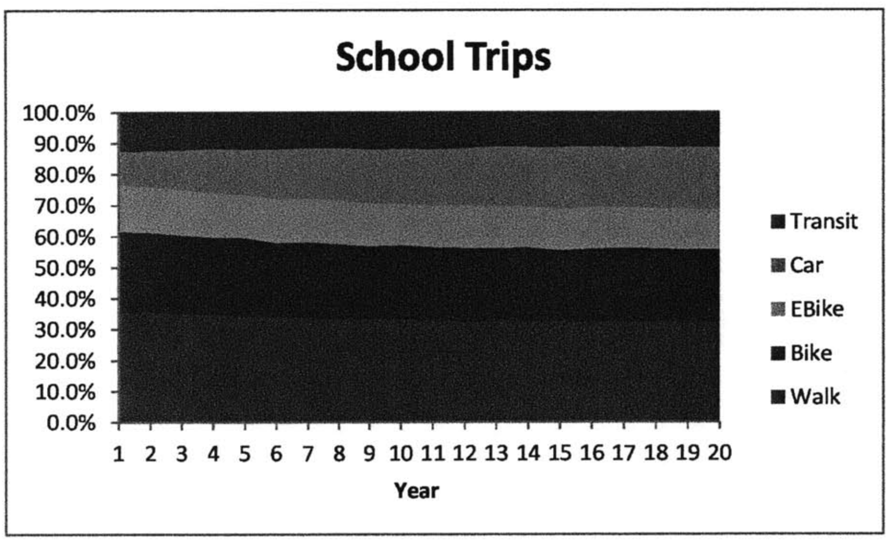

Figure 5.18 - Mode share baseline predictions for school trips

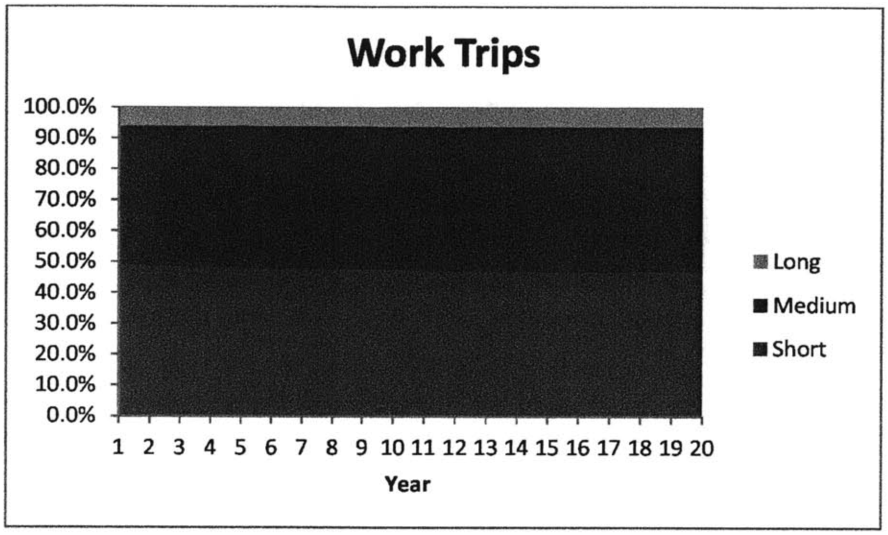

Figure 5.19 – Distance distribution baseline predictions for work trips

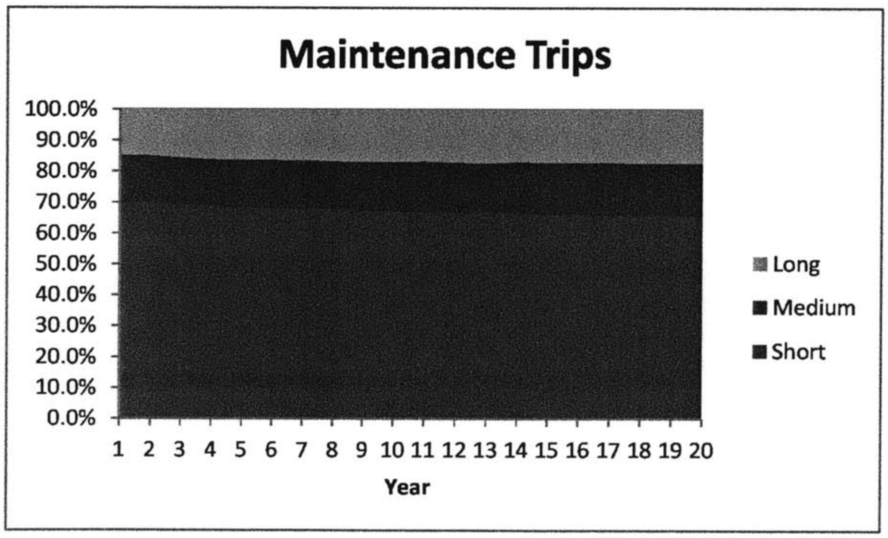

Figure 5.20 - Distance distribution baseline predictions for maintenance trips

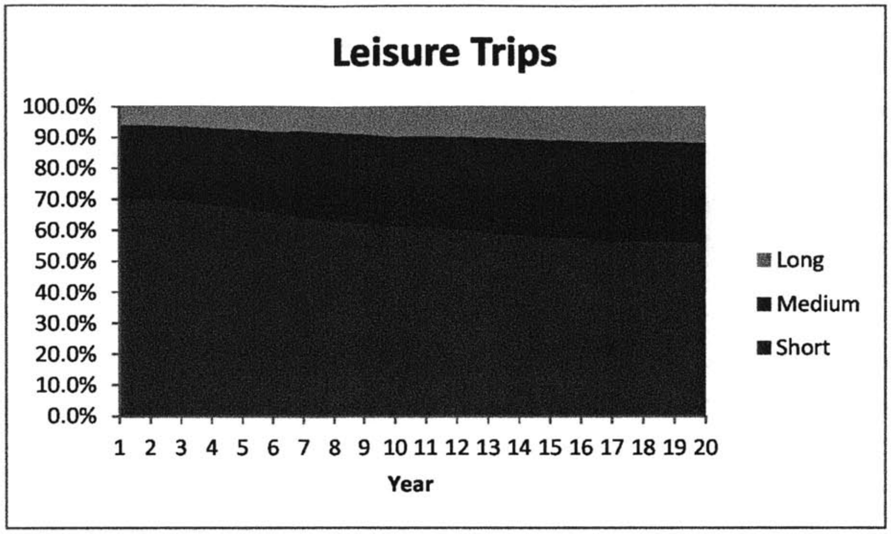

Figure 5.21 - Distance distribution baseline predictions for leisure trips

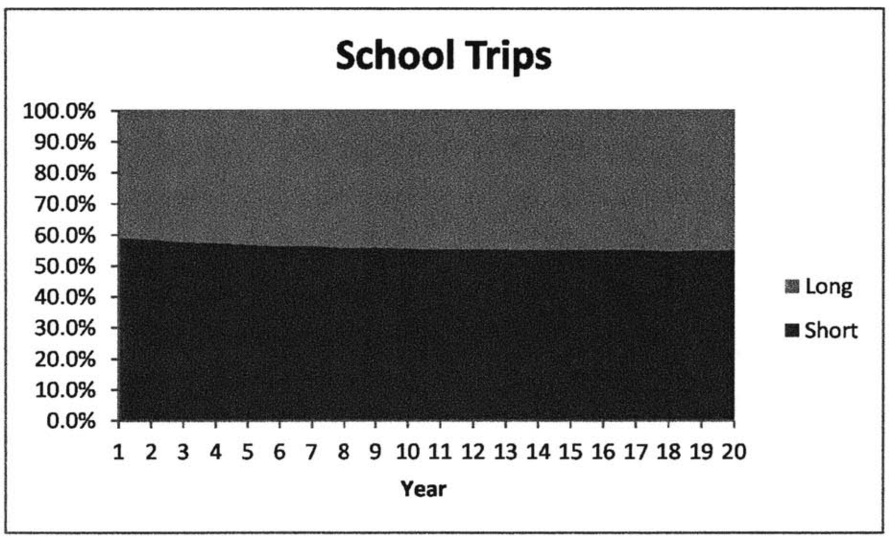

Figure 5.22 - Distance distribution baseline predictions for school trips

5.3.3 Fuel Efficiency Scenario

Fuel efficiency measures how far a vehicle can travel per unit of fuel consumed. Fuel efficiency improvements lead to more vehicle miles traveled (VMT) with the same amount of fuel, thus leading to energy savings. However, the impacts of the penetration of vehicle technologies are complex, due in part to the so-called "rebound effect" (Small and Van Dender, 2007). Herring (2006) summaries three types of rebound effects:

1) Direct rebound effect – increased use of vehicles stimulated by reduced travel cost due to greater fuel efficiency;
2) Indirect rebound effect – increased use of other goods and services due to the reduced price of vehicle travel;
3) General equilibrium effects – adjustment and equilibrium of supply and demand for both producers and consumers in all sectors.

In this research, the developed microsimulation model can only account for the direct rebound effect and thus simulate potential energy savings given the improvement in vehicle fuel efficiency. To be specific, with more fuel-efficient cars, the cost of car travel is reduced and the probability for choosing car is increased. This will be reflected in the household mode-distance choice model (see Figure 3.1). Meanwhile, the fuel consumption per VMT will decrease and the calculation methods embedded in transport energy estimation module will be adjusted accordingly.

I explore the potential impact of fuel efficiency improvements on energy savings by assuming a continuously increasing annual rate. More specifically, three sub-scenarios with annual efficiency improvement rates of 1.0%, 1.5%, and 2.0% are contrasted. The simulation results are presented in Table 5.4. A common pattern in all these cases is that energy consumption savings and emission reduction will be achieved despite the fact that car travel ratios increase for all purposes. The energy savings in year 10 are significantly higher than those in year 2. The magnitudes of consumption savings and emission reductions are about 0.5~1.5 percent in the beginning and 6~11 percent by year 10. This sets the benchmark for comparing energy-use mitigation strategies through urban design interventions.

Fuel Efficiency	Specific Year	Car Travel Ratio	Transport energy savings
↑1.0% annually	Year 2	↑0.2% Work Trips ↑0.2% Maintenance Trips ↑0.3% Leisure Trips ↑0.1%School Trips	0.6% of energy consumption (MJ) 0.7% of emissions (kgCO2)
	Year 10	↑0.6% Work Trips ↑0.5% Maintenance Trips ↑1.4% Leisure Trips ↑0.2% School Trips	5.6% of energy consumption (MJ) 5.4% of emissions (kgCO2)
↑1.5% annually	Year 2	↑0.2% Work Trips ↑0.3% Maintenance Trips ↑0.7% Leisure Trips ↑0.2%School Trips	0.6% of energy consumption (MJ) 0.8% of emissions (kgCO2)
	Year 10	↑1.2% Work Trips ↑0.6% Maintenance Trips ↑1.9% Leisure Trips ↑1.1%School Trips	7.9% of energy consumption (MJ) 6.6% of emissions (kgCO2)
↑2.0% annually	Year 2	↑0.3% Work Trips ↑0.9% Maintenance Trips ↑0.4% Leisure Trips ↑0.4%School Trips	1.1% of energy consumption (MJ) 1.3% of emissions (kgCO2)
	Year 10	↑2.2% Work Trips ↑0.5% Maintenance Trips ↑3.5% Leisure Trips ↑1.8%School Trips	10.9% of energy consumption (MJ) 9.1% of emissions (kgCO2)

Table 5.4 - Energy saving potentials with example change of fuel efficiency

5.3.4 Neighborhood Design Interventions Scenario

Given the various neighborhood form characteristics present across the underlying behavioral models, we can use the simulation tool to predict how changes in neighborhood characteristics would change household energy use trajectories. Such analysis could help inform neighborhood development towards lower energy consumption based on empirical evidence. To better associate energy saving potentials with neighborhood form variables, we perform the sensitivity analysis based on Superblock neighborhoods, as they are the most prevalent type of development being built across the contemporary Chinese urban landscape. The detailed results are present in Table 5.5.

For neighborhood density and massing, higher residential density is associated with less trip generation, more internal trips, and shorter external trip travel distance. Hence, an increase of 20 households per acre will reduce around 9% of transportation energy and CO_2 emissions in year 2 and year 10. Lower porosity, in conjunction with greater building volume, may reduce the in-home operational energy considering the winter wind cooling effects (2% energy savings with 10% decrease of porosity). Increasing the Southern Exposure Index by 10% could result in more than 7% of in-home energy savings and around 8% of emission reductions due to an increase in solar gain in winter. For neighborhood land use mix, the presence of street level shop shows some potential for mitigating transportation energy trajectories. To be specific, 20% more street level shops are estimated to generate around 5% in transportation energy savings. A larger number of roads with sidewalks would create more "walkable streets," predicted to reduce 3~4 percent of transportation energy use and emissions in the future. Building façade continuity is a measure of the continuousness of a streetscape which helps create a sense of enclosure and a definition of street space. A 10% increase in façade continuity could potentially lead to more than 10% of transportation energy savings since it creates street-oriented, pedestrian trips.

Compared with Scenario 2, we can see that the consumption savings and emission reductions produced by design interventions are equally impressive as fuel efficiency improvement. This bolsters the argument for the role of neighborhood design in the development of energy efficient cities.

Neighborhood Form	Example Value Change	Average Energy Saving for a particular year
Density and Massing		
Residential Density	↑20 households per acre	9.2% of transport consumption in year 2
		10.0% of transport emissions in year 2
		8.3% of transport consumption in year 10
		9.3% of transport emissions in year 10
Porosity	↓0.1 (ratio of volume)	2.0% of in-home consumption in year 2
		2.2% of in-home emissions in year 2
		1.9% of in-home consumption in year 10
		2.0% of in-home emissions in year 10
Passive Systems		
Southern Exposure Index	↑10%	7.2% of in-home consumption in year 2
		8.2% of in-home emissions in year 2
		7.1% of in-home consumption in year 10
		8.0% of in-home emissions in year 10
Function Mix and Land Use		
Street Level Shop	↑0.2	4.4% of transport consumption in year 2
		5.0% of transport emissions in year 2
		4.3% of transport consumption in year 10
		5.3% of transport emissions in year 10
Pedestrian Facility		
Roads with Sidewalks	↑0.2	2.7% of transport consumption in year 2
		3.3% of transport emissions in year 2
		3.4% of transport consumption in year 10
		4.0% of transport emissions in year 10
Building Façade		
Continuity	↑0.1	13.7% of transport consumption in year 2
		10.4% of transport emissions in year 2
		13.1% of transport consumption in year 10
		9.7% of transport emissions in year 10

Table 5.5 - Energy saving potentials with example change of neighborhood form

Chapter 6: Conclusions and Future Directions

We propose and implement an integrated model of both in-home and out-of-home energy consumption. This newly proposed model is an extension to the original models applied in the "Energy Proforma"©, an online tool for estimating neighborhood-level energy consumption in China. Rather than estimate household in-home and travel energy consumption separately and at a single point in time, our approach explicitly considers the trade-off among relevant household behaviors that might driver energy use and, furthermore, formally incorporates a temporal dimension to the analysis. Integrated multi-sector energy model has become a growing interest with improved data and econometric techniques. This research contributes to this modeling area by gaining additional insights into the dynamic linkage and transition of human behavior under complex decision and energy-use system.

The microsimulation model is based on a total of eight inter-related behavioral models, which estimate transport energy use with a sequence of trip-based forecasting techniques and in-home energy use with multivariate-regressions. Several neighborhood form measurements are first gathered from Jinan household & neighborhood survey, covering the aspects of density, diversity, design, accessibility and location (see also at Table 6.1). In various sub-models, relevant dimensions of neighborhood form and design are included as explanatory variables. These models are then combined with updating modules that trace the evolution of demographics, equipment stocks, and trade-off lifestyle patterns. These inter-linked models can then be used to estimate the long-term effects of different policy scenarios on household energy consumption and CO2 emissions.

Section 6.1 of this chapter summarizes the research findings from the model estimation and simulation processes. Section 6.2 discusses limitations of current model and section 6.3 points out directions for future research.

6.1 Research Findings & Implications

Among the eight underlying behavioral models, we find varying relationships between urban form and the activities that result in household energy use (Table 6.1). Combined into the simulation tool, the integrated models can be used in a range of ways, such as: providing ex-ante estimates of neighborhood-level household energy consumption; generating relevant behavioral indicators such as travel mode choice which can be related to policy objectives such as mode-oriented development; capturing long-term effects of neighborhood form and design while accounting for socioeconomic and demographic evolution.

In the simulation, three types of scenarios are developed to compare the changes of energy consumption and CO2 Emissions with respect to the evolution of demographic, equipment stock, fuel efficiency, and neighborhood forms. The major findings include:

1) Energy consumption and CO2 emission across all end-uses will increase over time. This baseline forecasts provides an overall picture of what is going to happen with the natural evolution of demographics and appliance/vehicle ownership. Transportation energy starts from a much lower base than in-home energy (12% of the total consumption and 9% of the total emission in base year) but with a much higher increasing rate (4.5% per year for transportation versus 0.4% for in-home).

2) Car ownership plays an important role in travel energy and CO2 emission growth. From the base year, only about 40% of the households have a least one car but this ratio reaches rapidly to 75% in year 10 and 85% in year 20, according to vehicle portfolio choice model specified in the simulation.

3) Compared across different modes, car travels generate most transport energy and emissions. Transit is the second largest energy production source but it has a much lower energy-use. Motorcycle and EBike play slightly different roles in travel energy and emission growth. Motorcycles are the third largest transport energy consumption source but EBikes creates more CO2 emissions than motorcycles.

4) Considering different neighborhood typologies, the "Superblock" produces the highest energy consumption and emission per household, following by the "Enclave" and the "Grid", and finally the "Traditional".

5) With household demographics and vehicle stock evolution, the internal trip rate and travel distance distribution will not change significantly over time. The mode share, however, experience a dramatic shift with an increasing number of car trips for work, maintenance, and leisure purposes. By tracing travel behavior at the level where decisions are actually taken, we can conclude that travel energy cannot balance itself in the near future due to the higher proportion of car travels.

6) Improving fuel efficiency is a useful way of reducing energy and emissions even with the

"rebound effect". By applying 1-2 percent of annual technology improvement rate, we can expect 0.5~1.5 percent of energy savings and emission reductions in year 2 and 6~11 percent in year 10.

7) Design intervention at the neighborhood scale is capable of mitigating short-term urban energy use and emissions and ensuring a long-term, lower-carbon urban development trajectory. For transportation, energy savings and emission reductions can be achieved by raising neighborhood density, adding more street level shops, enhancing pedestrian facility, and increasing building façade continuity. For in-home sector, reducing porosity and improving Southern Exposure Index are empirically helpful to lower the operational energy consumption and emission.

8) In terms of the magnitude, the neighborhood design intervention strategy is equally impressive as fuel technology penetration. This further emphasizes the role of urban form design in the development of clean energy cities.

Neighborhood Variables	Appliance	Vehicle	Trade-off Lifestyle	Electricity	In-home Energy	Trip Generation	Internal/ External	Mode-Distance
Density								
Residential Density		√	√	√	√	√	√	√
Building coverage			√	√	√			
Porosity					√			
Diversity								
Function Mix		√	√	√	√	√		√
Lumix_500m								√
Street level shop							√	√
Design								
Neighborhood size							√	√
Green coverage							√	
Continuity								√
Motor_width			√	√	√			
Accessibility								
Footprint							√	√
Entry_m								√
Parking provision		√	√	√	√	√	√	√
Walking facility		√	√	√	√	√	√	√
Road Density						√	√	
Southern exposure index				√	√			
Surface to volume ratio	√			√	√			
Cul_de_sac			√	√	√			
BRT						√	√	√
Location								
Distance to center		√	√	√	√	√	√	√
Regional accessibility			√	√	√	√		√

Table 6.1- Summary of significant neighborhood design variables for energy consumption

6.2 Research Limitations

Despite the advances implied in this work, a number of shortcomings remain.

1) The behavioral models are estimated on a rather small, likely biased, cross-sectional survey for only 14 neighborhoods in a single city in China. The household survey itself does not include the full range of household energy-consuming activities and relies on reported travel behavior and reported energy bills, both of which are certainly subject to errors. As such, the current results should be viewed as indicative and demonstrative of the technique, not necessarily authoritative regarding the magnitudes of expected effects.

2) Several home and building physical characteristics that help to explain in-home energy consumption and emissions are not surveyed, such as the home ventilation/orientation/ insulation and building envelop, etc.

3) Non-residential energy consumption is currently excluded from the modeling approach, which may influence the total neighborhood energy estimates in unknown ways.

4) This model takes a non-systems approach towards neighborhood level energy use. The simulation does not account for the fact that neighborhood change in one part of the city will likely affect the entire dynamics of the city and the inter-relations among the relevant agents.

5) Technology evolution for in-home appliances is ignored (e.g., the simulation does not account for changes in appliance energy efficiency), an assumption which should be relaxed in the future. Although the second scenario considers vehicle technology improvement, the assumption of constant annual increasing rate is too simplistic and requires real-world research and confirmation. Similarly, larger evolution of the city, and the interactions among neighborhoods is also ignored, which would, at minimum, likely impact travel energy use.

6) Vehicle and appliance replacement is ignored as it will become increasingly important when taking technology penetration into account.

7) The simulation assumes constant birth rate for households in the demographic evolution module, which could be more detailed with available data. Since the original survey only has age categories, the death rate stratified by age and gender can only be approximated.

8) The triangular distribution assumed for income change uses the average increasing rate comes from Jinan government report, which is an overall description of the whole city. The sample used in this case may be biased towards higher income households. As such, the actual average income increasing rate in survey might differ from that in the city.

9) No aggregate-level control of demographic information is provided for population evolution (cannot apply IPF process here). This could result in bias predictions of energy consumption with those input demographics. Besides, the in-/out- migration process is not incorporated.

10) The traditional mode-destination joint choice model is adapted as mode-distance nested model in this case. The classification of short, medium, and long trips is purely based on frequency analysis but not reflect the actual distribution of locations.

11) Dining trade-off lifestyle has a counter-intuitive impact on in-home energy and emissions. Perhaps households with a tendency to dine out have other unobserved characteristics that lead to more in-home energy consumption. This should be further examined with more detailed data or more advanced statistical techniques.

12) In fuel efficiency scenario, the model is only capable of capturing the direct "rebound effect". Additional study on indirect rebound effect and general equilibrium effects should be conducted to figure out the magnitude of impact on energy savings.

13) More generally, any effort to forecast the future, particularly in a highly dynamic context like urbanizing China, must be viewed with some skepticism. Such forecasts face behavioral uncertainties and exogenous uncertainties (e.g., new technologies, economic transformations) that are not currently considered in our approach. Point estimates of the future are wrong.

6.3 Future Directions

These shortcomings point to an ambitious future research agenda. Behaviorally, the move to an activity-based simulation model would be productive, but would require detailed data on in-home and out-of-home activities to enable the development of a model of activity trade-offs and complete energy consumption. Such data could possibly be collected via new technological devices (e.g., smartphones; see Cottrill et, al. 2013) perhaps in combination with in-home smart meters and more comprehensive and accurate energy use data (such as annual bills). Such an approach could lead to a more responsive decision support tool for urban planners, developers, and communities, and enable immediate feedback to consumers and thus realize the savings potentials due to energy-efficient neighborhood form. We hope to have provided a step in this direction.

References

Almeida, A. M., M. Ben-Akiva, F. C. Pereira, A. Ghauche, C. Guevara, S. Niza, and C. Zegras. 2009. A framework for integrated modelling of urban systems. 45th International Society of City and Regional Planners (ISOCARP) Congress, Porto, Portugal, 18–22 October 2009. http://www.isocarp.net/Data/case_studies/1623.pdf.

Aydinalp M, VI. Ugursal, A. Fung. 2002. Modeling of the appliance, lighting, and space cooling energy consumptions in the residential sector using neural networks. Applied Energy, 72(2), pp.87-110.

Bagley, M. N., P.L. Mokhtarian. 2002. The impact of residential neighbourhood type on travel behaviour: A structural equations modeling approach. Annals of Regional Science, 36, pp. 279-297.

Bailey, L., P.L. Mokhtarian, et al. 2008. The Broader Connection between Public Transportation, Energy Conservation and Greenhouse Gas Reduction. ICF International: Fairfax, VA.

Ballas, D., G. P. Clarke, I. Turton. 1999. Exploring microsimulation methodologies for the estimation of household attributes'. Paper presented at the 4th International Conference on GeoComputation, Fredericksburg, VA.

Ben-Akiva, M. and Lerman, S.R. 1985. Discrete Choice Analysis: Theory and Application to Travel Demand, Cambridge, Massachusetts: MIT Press.

Bhat, C. R., and F. S. Koppelman. 1999. Activity-Based Modeling of Travel Demand. International Series in Operations Research & Management Science, Volume 23, pp 35-61.

Bhat, C., and T. Waller. 2008. CEMDAP: A Second Generation Activity-Based Travel Modeling System for Metropolitan Areas. Presented at the 2008 TRB Innovations in Travel Modeling conference, Portland, Oregon.

Boarnet, M., R. Crane. 2001. The influence of land use on travel behavior: specification and estimation strategies. Transportation Research Part A: Policy and Practice, 35(9), pp. 823-845.

Bowman, J.L. and M. Ben-Akiva. 2001. Activity-based disaggregate travel demand model system with activity schedules. Transportation Research Part A, 35(1), pp. 1-28.

Caldwell, S.. 1996. "Health, Wealth, Pensions and Life Paths: The CORSIM Dynamic Microsimulation Model", in Harding A. (ed.) Microsimulation and Public Policy, Amsterdam: Elsevier.

Caldwell, S., R. Morrison. 2008. Validation of Longitudinal Dynamic Microsimulation Models: Experience with CORSIM and DYNACAN, in Mitton et al. (eds.) Microsimulation Modelling for Policy Analysis, Cambridge: Cambridge University Press.

Cai, Y. 2005. National and Provincial Life Tables Derived from China's 2000 Census Data. http://www.unc.edu/~caiyong/papers/provlt.pdf.

Capaso, A., W. Grattieri, R. Lamedica, A. Prudenzi. 1994. A bottom-up approach to residential load modeling. IEEE Transactions on Power Systems, 9(2), pp. 957-64.

Chang, J., D. Leung, C. Wu, Z. Yuan. 2003. A review on the energy production, consumption, and prospect of renewable energy in China. Renewable and Sustainable Energy Reviews, 7(5), pp. 453-68.

Chen, W.Z. 2008. Neighborhood scale and market-responsive urban design. Thesis submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy at the University of Hong Kong. September.

Chen, Y. 2012. Neighborhood Design and the Energy Efficiency of Urban Lifestyle in China: Treating Residence and Mobility as Lifestyle Bundle. Submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy in Urban and Regional Planning, MIT. submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy at the University of Hong Kong. September.

Cottrill, C., F. Pereira, F. Zhao, I. Dias, H.B. Lim, M. Ben-Akiva, C. Zegras. 2013. The Future Mobility Survey: Experiences in Developing a Smartphone-Based Travel Survey in Singapore. Transportation Research Record (forthcoming).

Dubin, J.A. D.L. McFadden. 1984. An Econometric Analysis of Residential Electric Appliance

Holdings and Consumption. Econometrica, 52(2), pp. 345-362.

Energy Information Administration. 2005. Energy Consumption Survey - Detailed Tables. U.S. Department of Energy
http://www.eia.doe.gov/emeu/recs/recs2005/c&e/detailedtables2005c&e.html

Ewing, R., R. Cervero. 2001. Travel and the built environment: a synthesis. Transportation Research Record: Journal of the Transportation Research Board, 1780, pp. 87-114.

Fung AS, M. Aydinalp, and VI. Ugursal. 1999. Econometric models for major residential energy end-uses. CREEDAC-1999-04-05 report. Halifax, NS.

Ewing R, and R. Cervero. 2010. Travel and the Built Environment. Journal of American Planning Association 76(3), pp. 265-294.

Farahbakhsh, H., V. Ugursal, A. Fung. 1998. A residential end-use energy consumption model for Canada. International Journal of Energy Research, 22(13), pp. 1133-1143.

Frenchman, D., C. Zegras, J.C. Brazier. 2013. Clean Energy Urban Design in China: The Energy Proforma© in Practice and Policy. Paper submitted to Peking University-Lincoln Institute for Land Policy Second International Workshop on Regional, Urban, and Spatial Economics in China.

Gao, W., M. Balmer, and E.J. Miller. 2010. Comparisons between MATSim and EMME/2 on the greater toronto and hamilton area network. Transportation Research Records, Journal of the Transportation Research Board, 2197, pp. 118–128.

Ghauche, A.. 2010. Integrated Transportation and Energy Activity-Based Model. Master Thesis, Department of Civil and Environmental Engineering, MIT.

Golob, T. F. 2003. Structural equation modeling for travel behavior research. Transportation Research Part B, 37(1), pp. 1-25.

Goudie, D. 2002. Zonal method for urban travel surveys: sustainability and sample distance from the CBD. Journal of Transport Geography, 10(4), pp. 287-301.

Hao H., H. Wang, and R. Yi. 2010. Hybrid modeling of China's vehicle ownership and projection through 2050. Energy, 36, pp. 1351–61.

Herring, H.. 2006. Energy efficiency - a critical view, Energy, 31(1), pp. 10-20.

Huang, Y., J. Broderick. 2000. A bottom-up engineering estimate of the aggregate heating and cooling loads of the entire US building stock. Lawrence Berkeley National Laboratory, Report LBNL-46303.

Jaccard, M., A. Baille. 1996. CO2 emission reduction costs in the residential sector: behavioral parameters in a bottom-up simulation model. Energy Journal ,17(4), pp. 107-134.

Jang, T. Y., 2005. Count data models for trip generation. Journal of Transportation Engineering 131 (6), pp. 444–450.

Jiang Y. 2010. Does Energy Follow Urban Form? An Examination of Neighborhoods and Transport Energy Use in Jinan, China. Master in City Planning and Master of Science in Transportation thesis, Massachusetts Institute of Technology, Cambridge, MA.

Kadian, R., R. Dahiya, H. Garg. 2007. Energy-related emissions and mitigation opportunities from the household sector in Delhi. Energy Policy, 35 (12), pp. 6195-6211.

Keirstead, J. and A. Sivakumar, A. 2012. Using Activity-Based Modeling to Simulate Urban Resource Demands at High Spatial and Temporal Resolutions. Journal of Industrial Ecology, 16, pp. 889–900.

Kumar, S., K. Kockelman. 2008. Tracking the Size, Location and Interactions of Businesses : Micro-simulation of firm Behavior in Austin , Texas. Proceedings of the 87th Annual Meeting of the Transportation Research Board, Washington D.C.

Larsen, BM., R. Nesbakken. 2004. Household electricity end-use consumption: results from econometric and engineering models. Energy Economics, 26(2), pp. 179-200.

Lemp, J.D., L. McWethy, and K. Kockelman. 2007. From Aggregate Methods to Microsimulation: Assessing the Benefits of Microscopic Activity-Based Models of Travel Demand. Transportation

Research Record, Journal of the Transportation Research Board, 1994, pp. 80-88.

Liu, Z. and A. Salzberg, 2012. Developing Low-Carbon Cities in China: Local Governance, Municipal Finance, and Land-Use Planning – The Key Underlying Drivers. In Sustainable Low-Carbon City Development in China (A. Baumler, Ijjasz-Vasquez, E., Mehndiratta, S., eds.). World Bank, pp. 97-127.

MacGregor, W., F. Hamdullahpur, V. Ugursal. 1993. Space heating using small-scale fluidized beds: a technoeconomic evaluation. International Journal of Energy Research, 17(6), pp. 445-466.

Martínez, F. J., P.P. Donoso. 2001. MUSSA: a land use equilibrium model with location externalities, planning regulations and pricing policies, in Proceedings of the 7th International Conference on Computers in Urban Planning and Urban Management (CUPUM 2001), Hawaii, USA.

McKinsey & Company. 2009. China's green revolution: Prioritizing technologies to achieve energy and environmental sustainability.

McNeil, M. A. and V.E. Letschert. 2005. Forecasting Electricity Demand in Developing Countries: A Study of Household Income and Appliance Ownership. Submission to ECEEE Summer Study, June 2005.

Miller, E. J., M.J. Roorda. 2003. A prototype model of household activity/travel scheduling. Transportation Research Record, Journal of the Transportation Research Board, 1831, pp. 114-121.

Miller, E.J., J.D. Hunt, J.E. Abraham and P.A. Salvini. 2004. Microsimulating Urban Systems. Computers, Environment and Urban Systems special issue, Geosimulation: Object-Based Modeling of Urban Phenomena, 28, pp. 9-44.

Miller, E. J., B. Farooq, F. Chingcuanco, and D. Wang. 2011. Historical validation of integrated transport – Land use model system. Transportation Research Record, Journal of the Transportation Research Board, 2255, pp. 91-99.

MIT and Tsinghua University. 2010. Making the Clean Energy City in China. Year 1 Report submitted to the Energy Foundation of China. Massachusetts Institute of Technology.

MIT. 2012. Making the Clean Energy City (CEC) in China. Year 2 Report submitted to the Energy Foundation of China. Massachusetts Institute of Technology.

Mitton, L., H. Sutherland, M. Weeks (Eds). 2000. Microsimulation Modelling for Policy Analysis: Challenges and Innovations, Cambridge University Press, Cambridge.

Mohammadian, A., E.J. Miller. 2003. Dynamic modeling of household automobile transactions. Transportation Research Record, Journal of the Transportation Research Board, 1831, pp. 98–105.

Moeckel R., K. Spiekermann, C. Schürmann, and M. Wegener. 2003. Microsimulation of urban land use. Paper presented at the 9th Conference on Computers in Urban Planning and Urban Management, Sendai.

Mokhtarian P. and X. Cao. 2008. Examining the impacts of residential self-selection on travel behavior: A focus on methodologies. Transportation Research B 42, pp. 204-228.

Naess, P. 2010. Residential Location, Travel, and Energy Use in the Hangzhou Metropolitan Area. The Journal of Transport and Land Use, 3(3), pp. 27-59.

Newbold, K. B., D. M. Scott, J.E.L. Spinney, P. Kanaroglou, and A. Paez. 2005. Travel behavior within Canada's older population: a cohort analysis. Journal of Transport Geography, 13(4), pp. 340-351.

O'Donoghue, C.. 2001. Dynamic Microsimulation: A Methodological Survey. Brazilian Electronic Economic Journal. 4(2).

Orcutt, G.. 1957. A new type of socio-economic system. Review of Economics and Statistics, 58, pp. 773-797.

Pan, H., Q. Shen, M. Zhang. 2009. Influence of Urban Form on Travel Behaviour in Four Neighbourhoods of Shanghai. Urban Studies, 46(2), pp. 275-294.

Parekh, A. 2005. Development of archetypes of building characteristics libraries for simplified energy use evaluation of houses. IBPSA, ninth international conference, Montreal, Canada.

Pritchard, D., E.J. Miller. 2009. Advances in agent population synthesis and application in an integrated land use/transportation model. In 88th Annual meeting of the transportation research board, Washington, D.C..

Research Center for Sustainable Development (RCSD). 2007. Understanding China's Energy Policy. Chinese Academy of Social Sciences.

Santin, O.G., L. Itard, and H. Visscher. 2009. The Effect of Occupancy and Building Characteristics on Energy Use for Space and Water Heating in Dutch Residential Stock. Energy and Buildings, 41, pp. 1223-1232.

Small, K.A. and C. Winston. 1999. The Demand for Transportation: Models and Applications. Chapter 2 in Essays in Transportation Economics and Policy: A Handbook in Honor of John R. Meyer (J. Gómez-Ibáñez, W. Tye, C. Winston, Eds), Brookings Institution Press, Washington, DC.

Small, K.A., K. Van Dender. 2007. Fuel efficiency and motor vehicle travel: the declining rebound effect. Energy Journal. 28(1), pp. 25-51.

Spielauer, M.. 2010. What is social science microsimulation?. Social Science Computer Review, 29(1), pp. 9-20.

Suganthi, L., A. Samuel. 2012. Energy models for demand forecasting - A review. Renewable and Sustainable Energy Reviews, 16, pp. 1223-1240.

Swan, L. and V. I. Ugursal. 2009. Modeling of End-use Energy Consumption in the Residential Sector: a Review of Modeling Techniques. Renewable and SustainableEnergy Reviews, 13, pp. 1819-1835.

Tirumalachetty, S.. 2009. Microsimulation of household and firm behaviors: Anticipation of greenhouse gas emissions for Austin, Texas. Master's Thesis. Department of Civil Engineering, The University of Texas at Austin.

Tirumalachetty, S., K. Kockelman, and S. Kumar. 2009. Micro-simulation models of urban regions: Anticipating greenhouse gas emissions from transport and housing in Austin, Texas. In 88th Annual meeting of the transportation research board transportation research record, Washington, USA.

Train K. 2003. Discrete Choice Methods with Simulation, Cambridge University Press.

Ullman, J. B.. 2001. Structural equation modeling and confirmatory factor analysis. In B. G. Tabachnick & L. S. Fidell (Eds.), Using multivariate statistics (pp. 653–771). Boston: Allyn & Bacon.

Vassileva, I., F. Wallin, and E. Dahlquist. 2011. "Analytical comparison between electricity consumption and behavioral characteristics of Swedish households in rented apartments". Applied Energy, 90(1), pp. 182-188.

Vovsha, P., E. Petersen, and R. Donnelly. 2002. Micro-simulation in Travel Demand Modeling: Lessons Learned from the New York Best Practice Model. In Transportation Research Record: Journal of the Transportation Research Board, 1805, pp. 68-77.

Wang, D. 2012. Household Operational Energy Consumption in Urban China: A Multilevel Analysis on Jinan. Masters Thesis, Department of Urban Studies and Planning, MIT.

Wang, X., N. Berrah, X. Peng, L. Sugar, H. Du. 2012. Low-Carbon Cities in China: Characteristics, Roadmap, and Indicators. In Sustainable Low-Carbon City Development in China (A. Baumler, Ijjasz-Vasquez, E., Mehndiratta, S., eds.). World Bank, pp. 63-95.

Woetzel, J., L. Mendonca, J. Devan, S. Negri, Y. Hu, J. Devan, L. Jordan, X. Li, A. Maasry, G. Tsen, F. Yu. 2009. Preparing for China's Urban Billion. McKinsey Global Institute.

World Bank. 2013. World Development Indicators. data.worldbank.org.

Yao R., B. Li, and K. Steemers. 2005. Energy policy and standard for built environment in China. Renew Energy, 30, pp. 1973–88.

Zaidi, A., K. Rake. 2001. Dynamic Microsimulation Models: A Review and Some Lessons for SAGE, SAGE Discussion Paper no.2, Simulating Social Policy in an Ageing Society (SAGE)

London School of Economics.
http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.96.1328&rep=rep1&type=pdf)

Zhang, J. 2008. Operational Energy Consumption and GHG Emissions in Residential Sector in Urban China: An Empirical Study in Jinan. Thesis for Master in City Planning, Massachusetts Institute of Technology.

Zhang, S. X. Yang, Y. Jiang, Q. Wei. 2010. Comparative analysis of energy use in China building sector: current status, existing problems and solutions. Front. Energy Power Eng. China, 4(1), pp. 2-21.

Zhou, N. D. Fridley, M. McNeil, N. Zheng, V. Letschert, J. Ka, Y. Saheb. 2011. Analysis of potential energy saving and CO2 emission reduction of home appliances and commercial equipments in China. Energy Policy, 39(8), pp. 4541-4550.

Zhou, N., M. A. McNeil, and M. Levine. 2009. Energy for 500 million Homes: Drivers and Outlook for Residential Energy Consumption in China. Lawrence Berkeley National Laboratory.

Appendix - Jinan Urban Residents' Residential and Passenger Transport Energy Survey in 2010

Date:____________ Time:____________ ***Questionnaire #***____________

Neighborhood:__________________ Surveyor:________________ Recorder:________________

Building #_____Entry #______at the_______th floor (total floor__________) Apt#__________

Housing Area: Construction Area __________________sq. m _______(#)bedrooms and ______(#)living rooms

(A) Your Household

Q1. There are ______family members in your household, among which ______ of them are employed.

Household Type: ☐ Single ☐ Couple ☐ Couple with Kid ☐ Parents with Married Children ☐ Grandparents and Kid ☐ 3 Generations

Q2. Your household has been living in this neighbourhood for____________years and____________months

Q3. You are currently: ☐Renting ☐Homeowner ☐Homeowner (still paying mortgage)

Q4. Fill out personal information and commuting activities (journey to/from work or school) of each household member

Occupation: *a.Teacher/Professor b.Student c.Worker d.Government official e.Company employee f.service/self-employed g.Peasant h.Unemployed i.Retired j. other*

Monthly Income: *a.below 600 b.600~1,000 c.1,000~2,000 d.2,000—5,000 e.5,000~10,000 f.>10,000*

Mode: *a.walk b.bicycle c.electric bike/scooter d.motorcycle e.taxi f.private car g.company car h.bus i.company shuttle j.BRT*

Occupancy: *no need to fill if mode is bus, shuttle or BRT. If the driver is sending or picking up the passenger, the driver is not counted.*

Destination: *put down the name of your destination, or point it out on a neighborhood map*

HH member		*Age*	*Sex*	*Occupation*	*Monthly Income*	*Personal Weekly Commuting Activities*					
						Frequency	*Mode*	*Distance (km)*	*Time Taken (min)*	*Occupancy (person per vehicle)*	*Destination*
Yourself											
Others	*2*										
	3										
	4										
	5										

Q5. Household Non-commuting activities

Trip Purpose		*Household weekly non-commuting activities*				
		Frequency	*Mode*	*Distance (km)*	*Time Taken (min)*	*Destination*
Shopping	*Farmers' Market*					
	Convenient Store					
	Supermarkets					
	Department Store					
	Other					
Using Public Facilities	*Park*					
	Post Office					
	Bank					
	Pharmacy					
	Hospital					
	Open space, gym					
Visiting Friends and Relatives						
*Other:*______________						

Q6. _______ **(#) of your household members have drivers' license,** _______**(#) currently hold transit passes.**

Q7. Number of Private Cars________**, number of company cars you have access to**______. *(If zero, jump to Q8)*

Main Purpose of Owning a Car:

☐commute ☐pick up kids ☐shopping ☐leisure and travel ☐household urgencies ☐other _____

a) This vehicle is________ years old, annual mileage driven_______, fuel economy_______liter/100km

b) Parking space (☐own|☐rent):

☐neighborhood underground parking ☐neighborhood parking lot

☐parking outside the neighbourhood ☐not specified space (street, sidewalk)

Q8. If your family does not have a car, do you plan to buy one? (multiple choice)

☐Yes, main purpose is:

☐commute ☐pick up kids ☐shopping ☐leisure and travel ☐household urgencies ☐other _____

☐No, because:

☐no need of one ☐the vehicle is too expensive ☐gas and maintenance is too expensive ☐congestion

☐lack of parking ☐not environmentally friendly ☐other ________

Q9. Your household has________**(#) motorcycles;** ________**(#) electric-bicycles; and** ________**(#) bicycles.**

Q10. Any of your household members have habits of dining out? ☐**Yes** ☐**No**

a) He/she/they dine out ______(#) meals each week, average expenditure__________yuan each time.

Q11. Any of your household members live elsewhere (not home) because of work/school/travel/other reasons?

☐**Yes** ☐**No** a) Each year there are ______(#) person*days when they are not home.

Q12. In 2009, your household electricity bill is about __________**yuan (or kwh) on average per month.**

Spring/fall______yuan (or kwh); Summer______yuan (or kwh); winter______yuan (or kwh)

Q13. Gas Source: ☐Natural Gas (pipeline) ☐Coal Gas (pipeline) ☐LPG (gas pitcher_____kg)

Monthly Consumption__________M^3/pitchers (or________yuan)

Q14. For cooking your household uses:

☐ electricity ☐ gas(pipeline) ☐ LPG (gas pitcher___ kg) _____pitchers(or________yuan) /month ☐ other

_____

Q15. For heating your household uses:

☐Neighborhood centralized heating, heating bill: __________yuan/season

☐Honeycomb-shaped briquet, average usage amount: __________ton/season

☐Electric heating facility (air conditioning, electric heater) ☐Other(specify): ____________

Q16. Type of Water Heater: ☐Electric Heater ☐Gas Heater ☐Solar Power Heater ☐Other____________

Q17. For air cooling in the summer, your household uses: ☐Air conditioner ☐Electric fan (jump to Q19)

# of air conditioners: _______power: ________p; **Type:** ☐split-type ac ☐in-home central ac ☐building central ac

Q18. Your household's ac-using habits in the summer: (multiple choice)

☐use when people feel hot at home ☐use all the time to keep temperature constant (no matter people are at home or not)

☐turn AC off when people leave the room ☐do not turn AC off when people leave the room

☐turn AC off and open window when sleeping ☐keep AC on when sleeping

Q19. In the summer your household usually sets the AC temperature at:

☐lower than 25°C ☐25°C ☐26°C ☐27°C ☐28°C or higher

Q20. There are _______ (#) south-facing rooms in your home.

Q21. Window ventilation of your rooms: (tick the corresponding cells)

	Living room	Dining room	Kitchen	Bathroom 1	Bathroom 2
Open window					
Window towards patio/courtyard					
No window					

(B) Yourself

Q22. Rank the factors when you choose your neighborhoods (number the first five factors); and satisfaction level towards your current neighborhood: 1 = Unsatisfied, 3 = neutral, 5 = Satisfied

Items		Importance Ranking	Satisfaction level				
Housing price			1	2	3	4	5
Neighborhood Safety			1	2	3	4	5
Names of developer and property management company			1	2	3	4	5
Building and room layout			1	2	3	4	5
Congestion near the entrance or around the neighborhood			1	2	3	4	5
Neighborhood Quality	Within-neighborhood facilities		1	2	3	4	5
	Green space in neighborhood		1	2	3	4	5
	Parking space in neighborhood		1	2	3	4	5
	Walking environment around the neighborhood		1	2	3	4	5
	Water quality and air quality of the neighborhood		1	2	3	4	5
Neighborhood Location	Distance to working place		1	2	3	4	5
	Distance to school		1	2	3	4	5
	Distance to daily shopping		1	2	3	4	5
	Distance to hospitals		1	2	3	4	5
	Distance to public facilities		1	2	3	4	5
	Distance to city center		1	2	3	4	5
	Distance to main roads		1	2	3	4	5
	Distance to bus(BRT) stations		1	2	3	4	5
	Distance to relatives and friends		1	2	3	4	5

Q23. Among the following facilities, you think it's best to be able to walk to: (multiple choices)

☐bus station ☐parking lot ☐daycare/kindergarten ☐elementary school ☐clinic ☐pharmacy ☐bank ☐ post office ☐elderly activity center ☐entertainment and gym ☐farmers' market ☐convenient store ☐restaurant

☐barber shop ☐laundry ☐supermarket ☐department store

Q24. For each statement, express your level of agreement. 1 = strongly disagree, 3 = neutral, 5 = strongly agree

01. I like to buy plenty of daily food and necessities at once in big supermarkets	1	2	3	4	5
02. Driving is a sign of prestige	1	2	3	4	5
03. It is convenient to take buses	1	2	3	4	5
04. I like riding bicycles	1	2	3	4	5
05. Time spent on travel is a waste to me	1	2	3	4	5
06. I'd like to live in bigger house	1	2	3	4	5
07. I like traveling	1	2	3	4	5
08. Plastic shopping bags in supermarkets should be free	1	2	3	4	5
09. High-rank officials do not take buses or ride bicycles to go out	1	2	3	4	5
10. Rich men do not take buses or ride bicycles to go out	1	2	3	4	5
11. I don't mind spending more money to achieve better quality of life	1	2	3	4	5
12. I exercise regularly	1	2	3	4	5
13. I reuse things like plastic bottles or bags	1	2	3	4	5
14. More powerful home appliances are better, if electricity bill is not considered	1	2	3	4	5
15. I pay attention to deals and promotions, and sometimes I buy second-hand stuff	1	2	3	4	5