Does Energy Follow Urban Form?
An Examination of Neighborhoods and Transport Energy Use in Jinan, China

By

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Master of Engineering in Urban Planning and Design, Tsinghua University, 2007
Bachelor of Architecture, Tsinghua University, 2005

Submitted to the Department of Urban Studies and Planning and the Department of Civil and Environmental Engineering in partial fulfillment of the requirements for the degrees of

Master in City Planning
and
Master of Science in Transportation
at the
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Abstract

This thesis explores the impacts of neighborhood form and location on household transportation energy use in the context of Jinan, China.

From a theoretical perspective, energy use is a derived outcome of activities, and households choose their travel patterns to maximize net utilities subject to constraints of time, budget and means. Neighborhood features presumably could 1) in the short-term directly influence households' choices of their travel patterns by changing incurred trip costs (disutilities) and realization benefits (positive utilities) among alternatives; 2) in the long-term indirectly influence patterns by affecting households' attitudes and their choices of vehicle ownership, both taken into account in the short-term utility maximization process. However, due to other complicating interactions among different aspects of travel patterns and other factors (e.g., housing choice), we cannot *a priori* determine what the impact of neighborhood on household travel energy use will be.

This research takes an empirical approach to examining the relationship between the neighborhood and household travel energy use in Jinan, China, using 9 neighborhoods representing four different urban form typologies commonly found in Chinese cities: "traditional", "grid", "enclave", and "superblock." Data on neighborhood forms and households are obtained from visual survey, GIS digitalization and a household survey. Household transport energy uses (and greenhouse gas emissions) are derived from self-reported household weekly travel diaries. Descriptive analysis, multivariate regression analysis (i.e., OLS, TOBIT), and advanced two-step instrumental models (i.e., LOGIT+OLS/TOBIT) are employed.

Results show that, all else equal, households living in the "superblock" neighborhoods consume more transportation energy than those living in the other neighborhood types, as they tend to own more cars and travel longer distance. The proximity to transit corridors and greater distance from the city center also apparently increase household transport energy use, although both impacts are somewhat minor, partially due to offsetting effects on car ownership. A number of effects of household socioeconomics, demographics and attitudes on transport energy use and car ownership are also identified.

Overall, the analysis suggests that to help chart a more energy-efficient Chinese urban future, policymakers and urban designers should examine past neighborhood designs in China to find alternatives to the "superblock", focus on strategic infill development, possibly encourage e-bike use as substitute to larger motorized vehicles, improve the efficiency of public transport, and examine preference-shaping possibilities to influence more energy efficient lifestyles.

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At MIT, I feel fortunate to have Chris Zegras as my thesis advisor. He has been a great mentor in transforming me from an urban designer towards a transportation expert and disciplined researcher. Every piece of this thesis was influenced by him. I also thank Jinhua Zhao, my thesis reader, for playing a critical role beyond a "reader" in my thesis. Frequent meetings with both of them have solved many puzzles I faced during my research design, statistical analysis and thesis writing.

I am grateful to have Professor Dennis Frenchman, as my academic advisor. He introduced me to MIT and offered tremendous help over the past three years. He truly cared about my needs and interests, and open-mindedly supported me to explore fields of transportation and energy in addition to urban planning and design.

I thank Yang Chen for her long-standing support from the beginning of the project. As a close research partner, she made tremendous efforts on cleaning data, performing part of the GIS analysis, and discussing methodological issues with me. I also thank Mi Diao and Weifeng Li for their conversations with me on modeling techniques and assistance with some ad-hoc GIS problems. I thank Cristian Angelo Guevara for offering advice on my instrument models.

On the China side, I thank Dongquan He, who kindly accepted me as an intern at the Energy Foundation-Beijing Office in summer 2008. My first-hand experience on exciting local projects and communication with international experts (e.g., Paulo Custodio) during that time triggered my deep interest in land use-transportation connection from an energy perspective. I hope my coming career with him after graduation will lead to more achievements in practice and benefit Chinese cities.

I would like to acknowledge faculty and students from Shandong University, Beijing Normal University and Tsinghua University as local partners in this project. Particularly, I thank Prof. Zhang Ruhua and Ms. Zuo Weiwei in Jinan for guiding a high quality household survey and data entering; and Prof Zhang Lixin and Mr. Zhang Tao in Beijing for their leading efforts on the GIS database building for my studied neighborhoods.

Most importantly, I thank my parents for their love, endless support and encouragement. Till now, I have received so much from them in my life while giving little back. This thesis is dedicated to them.

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1 INTRODUCTION

This thesis examines whether neighborhood form typology, size and location could affect households' transportation energy use; and if so, to what extent. The research is based on analysis of 9 neighborhoods in Jinan, the capital city of Shandong Province in China.

Section 1.1 presents three emerging trends in China that motivate this research; section 1.2 introduces broader research context of the thesis, as embedded in a broader "Making the Clean Energy City in China" collaborative research project; section 1.3 and 1.4 presents the main research objectives and research questions, respectively; section 1.5 describes the research approach including the choice of Jinan as the case study; section 1.6 concludes with the thesis structure.

1.1 Motivation

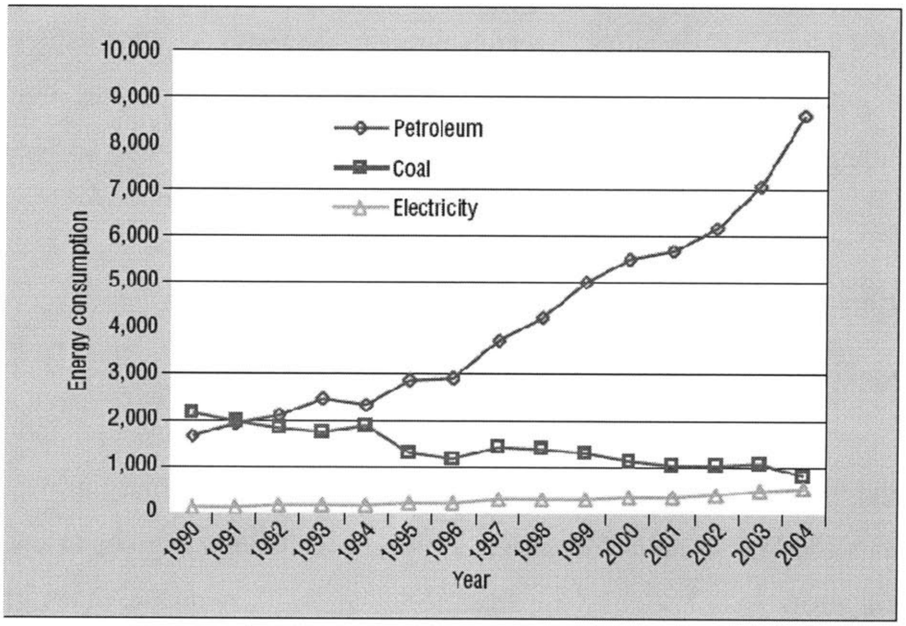
1.1.1 Rocketing Transport Energy Use in China: A Challenge

The transportation sector accounts for 22% of primary energy use and 27% of CO_2 emissions in the world as of 2004, and is expected to be the most rapidly growing source over the next 30 years (de Ia Rue du Can & Price, 2008). In the developing countries, transportation energy use will grow at 2.7% per year from 2006 to 2030, a rate 8 times higher than the projected rate for OECD countries, and the use of fuels in the non-OECD transportation sector as a whole will nearly double over the period (International Energy Agency, 2009)

In China, the trend is more pronounced. Thanks to ongoing economic growth, urbanization and changing consumer lifestyles, oil consumption by Chinese road transport has increased by 9% per year between 1995 and 2005 (see Figure 1-1), currently consuming about 30% of the total national oil consumption (He, *et al.*, 2005). In the next decades, demand is projected to continue to increase at an annual rate of 6% under current trend, triggering a quadrupling increase in oil consumption in 2030 and accounting for more than two-thirds of the overall increase in national oil demand (He, *et al.*, 2005; International Energy Agency, 2007)

This rocketing transport energy use adds uncertainty to China's future growth, because the country has relatively limited petroleum resources compared to other energy sources like coal. Measured on a per-capita basis, the petroleum reserves in China presented 4.3% of the world average in 2000 (Chen & Wang, 2007). As China becomes more mobile, the transportation sector's petroleum consumption poses important energy security problems. In addition, the rapid increase in greenhouse gas (GHG) emissions from the transport energy use creates big challenges for China, the largest carbon emitter in the world as of 2007, in working to mitigate climate change risk.

Figure 1-1 Transportation Energy Sources and Consumption in China (1990-2004) (in 10K tons of standard coal equivalent)



Source: Chen & Wang(2007), p. 11

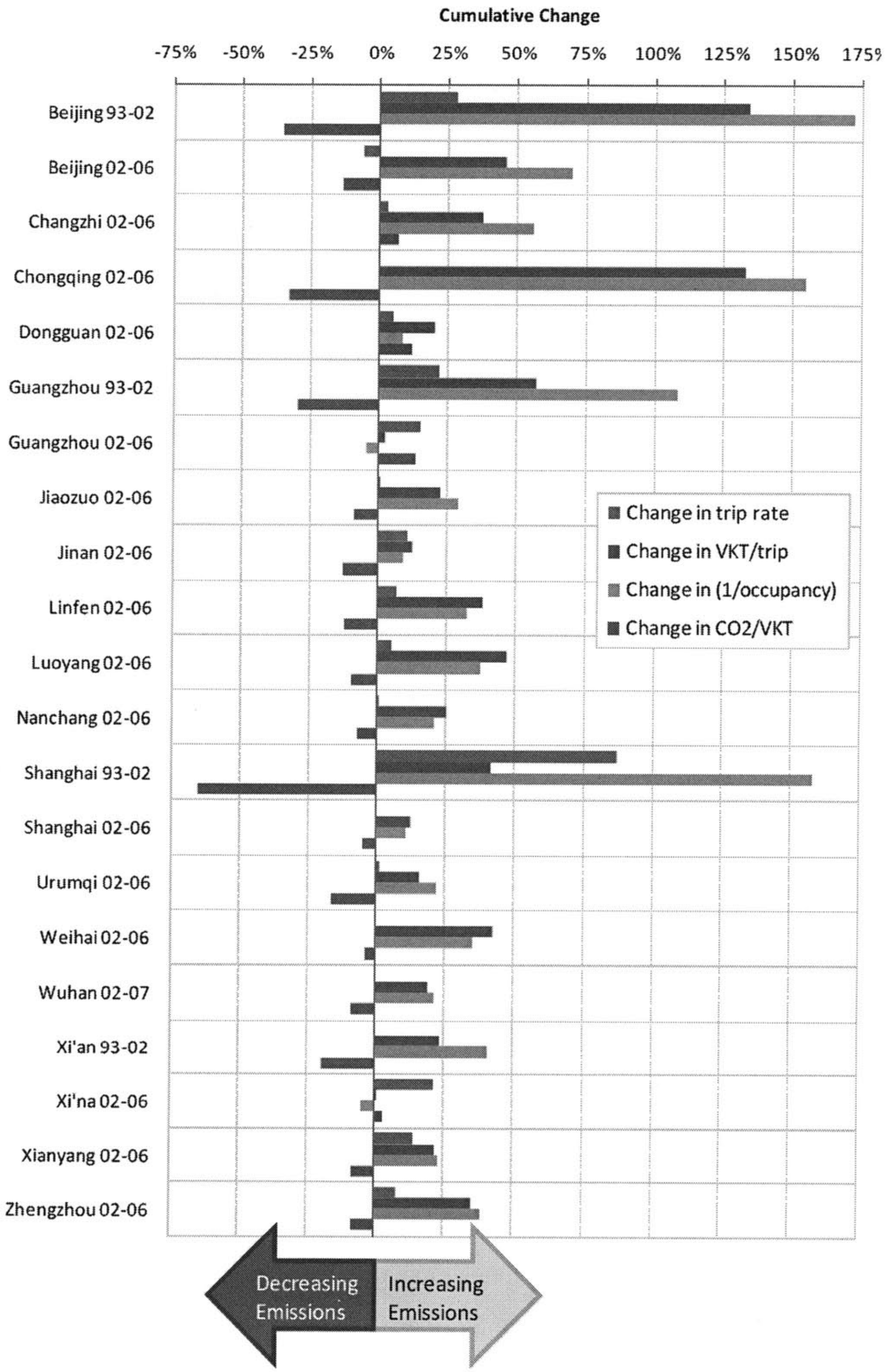
1.1.2 Supply-Side Mitigation Strategies in China: An Inadequacy

The Chinese government has recognized the challenge in the transport sector and committed to make changes mainly through introducing alternative fuels and regulating vehicle fuel economy. For example, since 2002, China has been promoting E10 (10% bio ethanol and 90% gasoline blend by volume) as an alternative transport fuel; China is now the third largest fuel-ethanol producer in the world (Yan & Crookes, 2009). In addition, China has adopted the Euro-4 tailpipe emissions standard in major cities to restrict exhaust emissions of new vehicles sold in the market. Very recently, the Chinese government and the private sector have emphasized electric car technology development (Bradsher, 2009).

Unfortunately, recent empirical studies in Chinese cities suggest that gains in vehicle technology or fuel improvements in the past have been overwhelmed by underlying changes in travel behavior and life-style, leading to rapid overall increases in energy use and GHG emissions (Darido, *et al.*, 2010), as shown in Figure 1-2. China is currently the world's largest automobile market, and the vehicle fleet population is projected to grow by some 230 million between 2006 and 2030, to reach almost 270 million (International Energy Agency, 2007). While the alternative fuel and vehicle economy efforts are necessary and important given that so much of the vehicle fleet is "yet to come", the relatively slow turn-over of the vehicle fleet and ever-changing technology may significantly delay the incorporation of a large amount of "greener" cars operating on China's roads.

In the face of similar situations faced by other countries, an increasing consensus among international scholars seems to be emerging that a single technological fix will not resolve the complex transportation energy use and greenhouse gas (GHG) problem; efforts from different fields are warranted (Guan, *et al.*, 2008; Mui, *et al.*, 2007; Pacala & Socolow, 2004; Wright & Fulton, 2005; Zeng, *et al.*, 2008). As Ewing, *et al.* (2008) note, the objective of reducing transportation energy or GHG emissions "can be viewed as a three-legged stool, with one leg related to vehicle fuel efficiency, a second to the carbon content of the fuel itself, and a third to the amount of driving or vehicle miles traveled (VMT) (p.1)." Those authors further note, in the U.S. context, that relevant policy initiatives "have pinned their hopes almost exclusively on shoring up the first two legs of the stool, through the development of more efficient vehicles (such as hybrid cars) and lower-carbon fuels (such as biodiesel fuel)" and that "a stool cannot stand on only two legs" (Ewing, *et al.*, 2008; p.1). A somewhat similar situation seems to exist in China, where the energy and climate initiatives in the transport sector have primarily been supply-oriented. Thus, to make sure the stool does not "fall over" and to solve the deteriorating energy problem in China, an increasing focus must explicitly target the demand side, or the third leg of the stool, to manage transportation energy use.

Figure 1-2 Change in Major Urban Transport Drivers in 14 Chinese Cities



Source: Darido, *et al.* (2009), p.6

Notes: Changes in trip rate, VKT/ trip and 1/occupancy are demand-side travel behavior changes; change in CO_2/VKT indicates supply-sidechange resulting fromfuel/automobile technology improvement and standards;
VKT = vehicle kilometers traveled

1.1.3 Urban Form and Design to Reduce Travel Demand in China: A Potential

In the US and Europe, many have argued that urban growth management can be an effective way to shape people's travel behavior towards less energy-consuming patterns. On the other hand, skeptics argue that urban development's impact on travel demand and energy use can be limited not only because it is difficult to achieve in practice, due to relatively weak policy leverage from local governments, but also because cities in developed countries are already largely built up with an auto-oriented structure, with an auto culture already dominating society (Pickrell, 1999). By this argument, from a cost-effectiveness point of view, taxing fuel would be a much simpler, faster, cheaper, and more effective policy instrument than rearranging metropolitan areas and/or major investments in transit (Gordon & Richardson, 1989).

China, however, is different. China is still experiencing rapid urbanization, a trend likely to continue for decades. A projected 350 million or more Chinese will move to the city in the next 15 years and the urbanization rate will increase to 60% by 2025, from 46% in 2010; at that time, there will be 221 Chinese cities with more than one million people (McKinsey & Company, 2009). If travel demand can indeed be reduced through intervention in the urban built environment, there is much larger scale-up potential for China than in developed countries to intervene in the form of urban development in order to purposefully influence travel behaviors and outcomes in the latter half of her urbanization process.

In addition, compared with many developed countries, Chinese city governments have relatively strong control over local urban development patterns through their institutional settings and public ownership to urban land. The recent heavy investment in urban infrastructures (e.g., subway lines, bus rapid transit systems, etc.) as a component of the national stimulus package has made urban growth patterns (e.g., transit oriented development) advocated by many in the west look feasible and promising in future China.

Unfortunately this opportunity for China has not been quite recognized. Instead, on the one hand, auto-oriented neighborhood development (e.g., the so-called "superblock" development) dominates current urban expansion and construction (Cervero & Day, 2008; Monson, 2008); on the other hand, there have been very few empirical studies supporting alternative urban growth patterns in China from the energy perspective. Although the neighborhood serves at the spatial unit of intervention, planning, and institutional organization, transferring western policies and design standards directly to China without careful adaption is viewed as risky and problematic by local leadership given the much different social, cultural and institutional context. For example, the existing neighborhood density in China already greatly exceeds any density level considered in US development today. Even if the transit-oriented development (TOD) concept, for example, is favorable, what kind of TOD we should pursue is still an urgent question. This cannot be answered without empirical investigation in the local context.

1.2 Thesis Context: "Making the Clean Energy City in China"

This research is a component of the "Making the Clean Energy City in China" project, sponsored by the China Sustainable Energy Program of the Energy Foundation-Beijing Office. The overall project aims to create new physical models of urban development as well as new analytical models to understand potential paths towards, and impacts of, alternative urban growth patterns from an energy efficiency perspective. The collaborative project involves a number of institutions in China and the USA, including:

- The Transportation Planning & Design Research Center, Shandong University
- The School of Geography and Remote Sensing, Beijing Normal University
- The School of Architecture, Tsinghua University
- The School of Environmental Science, Tsinghua University
- The Lawrence Berkeley Laboratory
- The School of Architecture and Planning, MIT

One of the tasks of the project focuses on deepening our knowledge of the "state of the context"- the relationships between urban design and energy consumption in the Chinese city. This work includes: (1) general data collection on the city, including energy consumption, building types, etc.; (2) the development of typologies of urban development in the city, utilizing GIS and other available data; (3) selection of a limited number of comparison sites that represent some of the typologies identified in (2); (4) implementation of a survey of households in the selected comparison sites, to collect data on energy use, travel behavior, etc.; (5) utilization of statistical methods and models to quantify the apparent relationship between urban design and energy consumption in the city. This thesis contributes directly to the sub-task (5), focusing specifically on household transport energy use and GHG emissions, while a brief description of previous tasks is also provided in Chapter 4 and Chapter 5.

1.3 Research Objectives

The main objective of this research is to improve our understanding of the link between urban development at the neighborhood scale and household passenger transport energy use in China. Specifically, we aim to quantify the energy reduction potentials from alternative neighborhood locations and patterns based on empirical evidence.

1.4 Research Questions

The research objectives above can be grouped into two corresponding categories of research questions.

Question 1: Neighborhood location features

Do neighborhoods near the city center or adjacent to transit corridors result in less household transportation energy consumption? Should we encourage infill development and concentrate urban development along transit corridors to reduce energy use?

Question 2: Neighborhood design features

What are the representative neighborhood forms in today China? Controlling for socioeconomics, demographics and household attitudes, to what extent does transport energy use vary across those different neighborhood forms? Should we build cities in future as the way we build now in China (i.e., the "superblock"-like development), or should we look for alternatives from an energy efficiency perspective?

1.5 Research Approach

In an attempt to answer the above questions, in this thesis I employ a research approach that can be characterized as: an empirical study with a micro-level urban form focus, using statistical techniques guided by activity-based econometrics.

First, empirical data were collected on both micro-level neighborhood features (location, form, size) and households' characteristics in Jinan, China. The city of Jinan was chosen because 1) it represents middle-size Chinese cities (as opposed to Beijing and Shanghai) cities which are drivers of China's increasing energy demand yet which have been rarely studied in the literature; 2) the city has recently implemented bus-rapid-transit (BRT) corridors, allowing examination of the transit-corridor effect on household transportation energy use; and 3) survey data in Jinan were available from local partners of the collaborative research project funded by the Energy

Foundation China. The survey data were collected from 2629 households in 9 different neighborhoods which were, ex-ante via visual surveys and geographic information system (GIS) analysis, determined to represent four distinct typologies (i.e., “traditional”, “grid”, “enclave” and “superblock”).

Second, an activity-based econometric behavior framework was developed to guide the analysis of household travel energy use. Techniques used include: descriptive statistics, single-stage multivariate regression models (i.e., OLS, TOBIT), and two-stage instrument models (i.e., LOGIT + OLS/TOBIT) incorporating household vehicle ownership choice models with instruments. Due to the nature of the data and the complexity of the research questions, the statistical techniques deployed attempt to control for various influencing factors and statistical challenges (e.g., endogeneity) and make it possible to strengthen the inferences. For more details, see section 5.6.

1.6 Thesis Structure

The thesis is organized as follows (see Figure 1-3).

In Chapter 2, I summarize key neighborhood design principals advocated by urban designers and others to change travel behavior towards lower travel energy use. I then review empirical findings and methodologies employed in selected studies of district and neighborhood form-energy use relationships. Finally, I discuss specific issues regarding research operationalization and data constraints in the Chinese context.

In Chapter 3, I introduce the theoretical behavioral framework for understanding the relationship between neighborhood urban form and household travel behavior and energy use. The framework draws from existing travel demand theory, especially utility theory, specifically combining the cost-based approach and activity-based approach to understand how neighborhood characteristics and other factors may influence household transportation energy consumption. Finally, I conduct a series of comprehensive and detailed analyses to illustrate the complicated implications of some advocated neighborhood interventions on household travel behavior and energy use.

Chapter 4 describes the Jinan city context, the ongoing bus-rapid-transit (BRT) corridor development, and the representative neighborhood forms in the city.

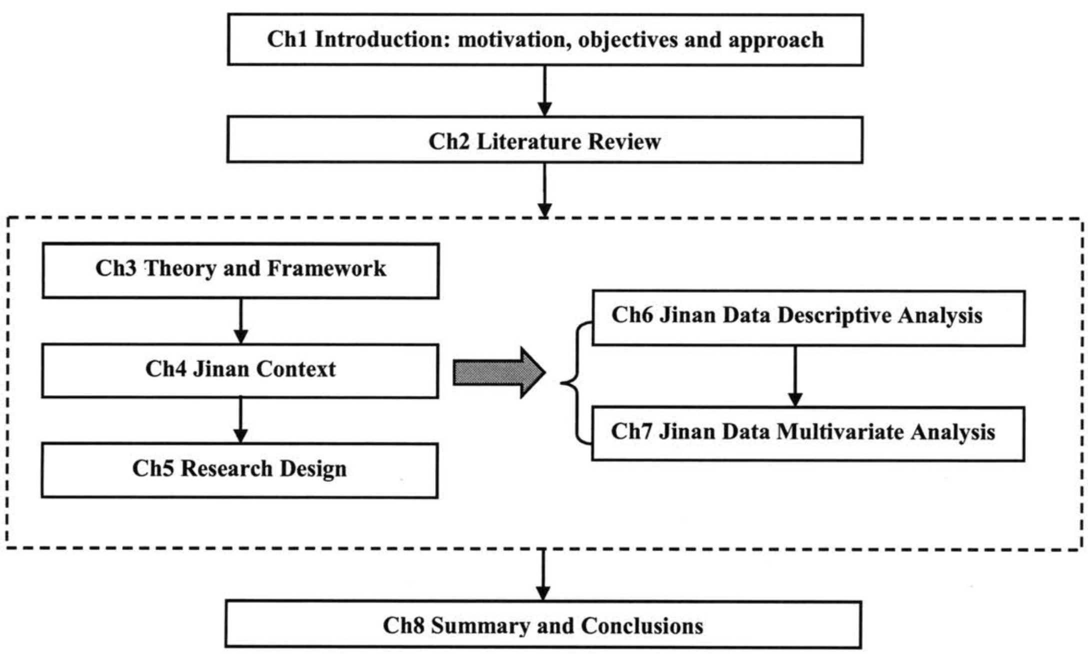
Chapter 5 introduces the detailed research design in this thesis in terms of the neighborhood sampling approach, household data collection, and the general econometric techniques employed and related issues.

In Chapter 6, I perform descriptive analysis based on the neighborhood form and household data. Specifically, I conduct cluster analysis on the 9 neighborhoods using derived form measures. I also compare household attribute, travel patterns and associated energy use and emission across the four neighborhood types.

Chapter 7 presents the quantitative analysis of the relationship between urban form and household energy consumption. Specifically, I present a number of econometric models examining the relationship between neighborhood typology, size, location features and household transportation energy use. Two-stage instrumental models are employed to identify that relationship meanwhile controlling for confounding effects from household attributes and others. Marginal effects of neighborhood features on household transport energy use are estimated.

In Chapter 8, I summarize the policy and planning implication of the findings, discuss research limitations, and suggest directions for future research.

Figure 1-3 Thesis Structure



2 LITERATURE REVIEW

Chapter 1 discussed the urgent need for, and potentials to, incorporate better spatial planning and design, particularly at the micro/neighborhood development scale, into mitigation strategies on urban transportation energy use and GHG emissions in the context of China's urbanization and motorization. While such a concept is new to China, similar claims have been made by urban planners (e.g., the "New Urbanists") in developed countries for a long time.

In the field of empirical research (as opposed to simulation studies) at the neighborhood scale, there have been two main groups of efforts: 1) *direct* assessments on the relationship between neighborhood design and explicitly measured household transportation energy use or emissions; and 2) *indirect* assessments via examining whether and how neighborhood features can influence people's travel behaviors, especially car driving and transit use. Does such relationship indeed exist? Unfortunately, research results accumulated to date support both sides of the argument; a debate over the effectiveness of neighborhood design strategies continues among urban designers and transportation planners.

This chapter reviews the literature to examine why this has been the case and how the situation is changing, and the implications for future empirical research in China. The chapter is organized in four sections. In section 2.1, we begin with a background section summarizing key neighborhood design principles advocated by urban designers to achieve travel energy and emissions reductions. In section 2.2, I discuss analytical approaches that have been employed in empirical studies in developed countries, the results from those studies, and lessons we can draw. In section 2.3, I scan relevant empirical precedents in China, accompanied by comments on their research findings and methodological limitations in the China context from an energy perspective. Finally, section 2.4 provides a summary.

2.1 Neighborhood Features for Transport Energy Reduction: Advocates from Designers

The evolution of concepts for creating walking/transit-friendly neighborhoods, which imply reducing car use and, presumably, energy consumption, can be traced back to the inception of urban planning profession. In the late 1800s, the British urban planner Ebenezer Howard proposed the "Garden City" model for British cities. The idea was to establish self-sufficient communities linked by rail transit, with each community of approximately 6,000 acres housing no more than 30,000 people and providing most services within walk distance (Howard, 1902). In 1929, the American planner Clarence Perry advocated the "Neighborhood Unit" model with the concept of housing 6,000-10,000 inhabitants and centering elementary schools in the community with major roads bounded, so that children could safely walk to school without crossing them (Perry, 1929). Both models were partly implemented in practice evidenced by, for example, the Radburn (New Jersey, USA) development in the late 1920s (Lee & Ahn, 2003). From the transport energy use perspective, Howard's and Perry's neighborhood design models seem inherently associated with lower travel energy consumption, since they were devised with the intention of promoting a community-based lifestyle by providing good walking accessibility within the neighborhood. .

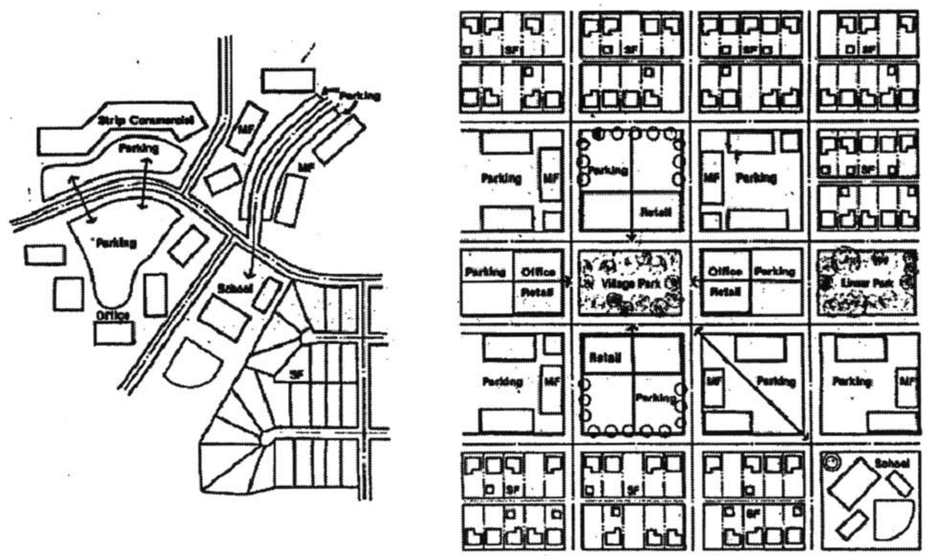
During the post-World War II era, however, suburban development, characterized by single-use, low-density residential buildings and auto-oriented street configurations, dominated the urban growth pattern and automobile use boomed in the United States (Zegras, 2005). Aiming at breaking this urban growth pattern and mitigating its negative impacts on the society and environment, a number of architects, urban designers, and advocates have brought a series of alternative concepts, as will be discussed below.

Within this general school of thought, New Urbanism has become perhaps the most popular planning idea since the 1980s and 1990s. Espoused by architects Peter Calthorpe and Andres Duany, the "New Urbanist" model is characterized by features including medium-density, mixed-use, human-scale and pedestrian-focused design, to discourage car use and encourage walking and transit (Katz, *et al.*, 1994).

In a similar vein, Traditional Neighborhood Development (TND) is another comprehensive planning model with similar characteristics (Figure 2-1): a grid-like street network; higher-density residential uses surrounding retail, recreational, and governmental uses; better accessibility to retail and transit; and pedestrian-friendly neighborhoods (Aurbach, 2005; Duany & Plater-Zyberk, 1992; Katz, *et al.*, 1994). Planners have claimed that the TND neighborhoods can utilize shorter trip lengths, promote better traffic flow, reduce the number of vehicle trips

(Horsley Witten Group, 2007), and therefore presumably perform well in terms of transportation energy efficiency and pollution reduction.

Figure 2-1 A Comparison of "Conventional" Suburban Development and "Traditional" Neighborhood Development



A. Conventional Suburban Development Development

B. Traditional Neighborhood

Source: Boarnet & Crane (2001), p.42

In some sense building on the New Urbanism and TND, transit oriented development (TOD) generally refers to higher-density development which sets pedestrian priority and locates within easy walking distance of a major public transit station. It has been argued that TOD can contribute to energy efficiency and emission reduction in that it can increase transit use and reduce automobile trips and vehicle miles traveled (VMT) (Evans Iv & Pratt, 2003). For example, the California Air Resource Board used a hypothetical simulation approach (as opposed to empirical analysis) and estimated that TOD would produce a 20 to 30 percent reduction in household VMT as compared with non-TOD households, resulting in a corresponding reduction in greenhouse gas emissions of 2.5 to 3.7 tons per household per year (Arrington, *et al.*, 2002).

Table 2-1 Post-World War II Neighborhood Design Principles Claimed to Reduce Transport Energy Consumption or Automobile Use

	Density	Diversity	Design	Location
New Urbanism[a]	▪ Medium-density	▪ Mixed-use	▪ Pedestrian focus	▪ Transit-friendly
Traditional neighborhood development (TND)[b]	▪ Compact development	▪ Variety of housing types and land uses	▪ Provide a network of paths, streets and lanes suitable for pedestrians and vehicles	▪ Present and future modes of transit
Transit Oriented Development (TOD)[c]	▪ Higher-density development	▪ Mix land uses	▪ Pedestrian priority	▪ Within easy walking distance of a major public transit station or stop(s)

a. Katz, et al. (1994)
b. Aurbach (2005)
c. Evans Iv & Pratt (2003)
Note: Design principles for non-transport energy reduction are not listed.

Table 2-1 summarizes the neighborhood concepts and standards underlying the new urbanism, TND, and TOD. While the names are different, all three concepts converge to similar basic design principles, namely to have relatively high density, mixed land uses, a pedestrian/bicycle friendly environment, and a "smart" location close to transit services. Designers expect that neighborhood developments with such features will promote alternatives to driving and thus reduce demand for car-mobility and its associated energy use and emissions.

Various design-oriented tools have emerged which attempt to rate neighborhood-level developments, following the school of thought summarized in Table 2-1. For example, the LEED-ND certification program (Leadership in Energy & Environmental Design for Neighborhood Development) was launched in 2006. The program creators (the US Green Building Council, the Natural Resources Defense Council, the US Environmental Protection Agency, and the Congress for the New Urbanism) stated that the LEED-ND program will facilitate neighborhood development practices that can achieve less automobile dependence (US Green Building Council, 2007).

2.2 Empirical Precedents in the Developed Countries

Although urban designers seem to share similar neighborhood design strategies for reducing car use and energy consumption, there might be "a mismatch between what we know about travel behavior and what we need to know to evaluate the transportation goals of urban designers" (Boarnet & Crane, 2001; p.11). In the past decades, numerous studies have been conducted in the developed countries using empirical data to test whether those claims from urban designers are true or not, and to what degree. Unfortunately, and maybe surprisingly, studies accumulated to date appear to show that identifying a direct connection between the built environment and people's travel behavior (and the associated energy use and emissions) remains elusive (Boarnet & Crane, 2001; Guo, *et al.*, 2007; Pan, *et al.*, 2009).

2.2.1 Empirical-analytical Methods

Comparative analysis, multivariate-regression analysis and advanced methods are among the most widely used approaches applied in the field of empirical research. The more advanced the method, the more data-hungry and sophisticated the modeling techniques become.

a) Comparative Analysis

Comparative analysis simply compares observable facts of travel behavior or energy consumption patterns in different neighborhood settings, directly showing what is happening at a particular place at a particular time. This approach was more favored in the early stage of empirical research in the field (Cervero & Gorham, 1995; Dagang & Loudon, 1995; Friedman, *et al.*, 1994), although it was also applied in some recent studies (VandeWeghe & Kennedy, 2007). In terms of the scale of data, the urban form data were often collected at the neighborhood level. Identification of neighborhoods could be: 1) pre-determined by existing data sources (census tract, traffic analysis zone, census block group, etc.); 2) standardized via assigning a buffer area (e.g., a 400m by 400m grid) for each household sample; or 3) based on relative homogeneity among a range of form attributes. The first two are more of operational convenience. Examples of the third approach are shown in Table 2-2, which involves somehow arbitrary neighborhood definition. In terms of the travel energy/emission/behavior data, information from individuals or households was aggregated to the neighborhood level before cross-comparison.

Table 2-2 Neighborhood Typologies and Characteristics in US Travel Behavior Studies

Source	Auto-Oriented Neighborhood	Transit-Oriented Neighborhood
Sasaki Associates (1993)	Started construction after 1910 auto-oriented from outset single land use branching street system	started construction before 1910 transit-oriented in initial stages mix of land uses interconnected system of streets
Friedman et al. (1994)	Developed since the early 1950s Segregated land uses well-defined hierarchy of roads access concentrated at a few points little transit service	developed prior to WWII mixed-use commercial district neighborhoods close to commercial uses interconnecting street grid
Cervero and Gorham (1995)	laid out and built after 1945 laid out without regard to transit primarily random street pattern lower density	laid out and built before 1945 initially built along a transit line primarily gridded street pattern higher density
Handy (1995)	Irregular curvilinear street networks strip commercial commercial areas outside walking distance	regular rectilinear street networks main street commercial commercial areas within walking distance

Source: Ewing & Cervero (2001), p. 88

There are two main drawbacks of this method. First, comparative analysis tends to use aggregated travel data for direct comparison (comparing household by household is impossible), which makes the isolation of effects from any underlying disaggregate factors and the exploration of the urban form- travel pattern dynamics difficult (Handy, 1996). Second, findings using this approach are often challenged of the failure in effectively filtering out non-neighborhood factors (e.g., income) which also are believed to be crucial in affecting travel behavior patterns, associated energy use and emissions.

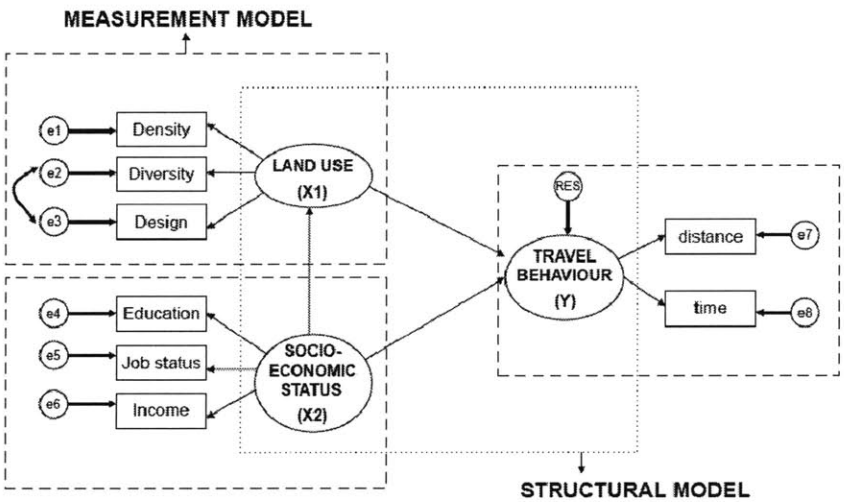
b) Multivariate-regression Analysis

Relevant multivariate-regression analyses typically involve ordinary least square (OLS), logitistic regression (LOGIT), TOBIT and/or other modeling techniques, in which confounding factors such as household socioeconomics and demographics are brought directly into the analysis for statistical control. Disaggregated neighborhood form elements represented in the models are sometimes grouped into three dimensions: density, diversity, and design (Ewing & Cervero, 2001). Although the multivariate-regression approach is effective in controlling for potentially confounding effects (e.g., due to socioeconomics and demographics), the approach still poses challenges in establishing causality, due to the data type (e.g., lack of data on attitudes) and analytical approach (e.g., cross-sectional) typically employed. This problem has become widely referred to as the "self-selection" problem (e.g., see Mokhtarian and Cao, 2008).

c) Advanced Methods

More advanced methods and data have been applied to the urban form-travel behavior analysis field in recent years, mostly to address the "self-selection" problem and thereby attempt to strengthen claims that the built environment actual *causes* measurable differences in travel behavior. Instrumental variable models, sample selection models, joint discrete choice models, structural equations models, and/or models using longitudinal data are among the relevant advanced models. For detailed discussions, comparisons and evaluations of these modeling techniques, readers can refer to Mokhtarian & Cao (2008).

Figure 2-2 An Example of a Structure Equations Model



Source: Van Acker, et al. (2007), p. 342

2.2.2 Results

Some studies directly assess the links between neighborhood characteristics and transport energy use or emissions. Section a), below, reviews these in some detail and Table 2-3 summarizes them. Other studies more indirectly assess such a link by looking at elements of energy-related travel behavior[1] (e.g., travel distance or VMT, frequency, mode choice, etc.). Section b), below, reviews some of those studies and literature reviews that exist (Ewing & Cervero, 2001; Handy, 2006; Zegras, 2005) and Table 2-4 summarizes them.

a) Energy/ emissions specific studies

Cheslow & Neels (1980) provided one of the first studies to explicitly investigate neighborhood form and location effects on travel energy use. They conducted multivariate regressions based on aggregate travel data from eight metropolitan areas in the United States. Energy use by urban passenger transportation was found to be lower with some development patterns than with others. Specifically, it was estimated that a tripling of neighborhood densities would reduce fuel use by 24% due to declining auto trip rates and travel distances (Cheslow & Neels, 1980).

Naess & Sandberg (1996) collected journey-to-work travel information of 485 employees from six companies in the Greater Oslo region, Norway. Multivariate regression analysis based on those disaggregated individual travel data was performed. The authors found that employees working in peripheral, low-density areas use considerably more energy in commuting than those working in central, high-density areas. Statistically, controlling for car ownership and income (but not density), an additional energy use of 73 percent, or 1640kWh was estimated for an outer-area worker in his/her commuting trips annually (Naess & Sandberg, 1996).

[1] Travel behavior studies that focus exclusively on physical activities (e.g., walking, biking) are not included in the literature review since their energy consumption is considered negligible in this context, although we recognize there exists a possible link between physical activities and fuel-based travel patterns.

Table 2-3 Empirical Evidence from Transport Energy Use/ Emissions Specific Studies

Impacts on	Higher Density	Higher Diversity	Better Design	Smarter Location	TOD-Overall	Methodology	Context	Source
Less travel energy use	✓			✓		Regression/ Aggregate	8 metro areas, US	Cheslow & Neels (1980)
Less travel energy for commuting trips	✓			✓		Regression/ Disaggregate	Greater Oslo, Norway	Naess & Sandberg (1996)
Less vehicle emission (NOx, VOC, CO)	✓		✓			Regression/ Disaggregate	Puget Sound, US	Frank, *et al.* (2000)
Less household transport energy use	×				×	Regression/ Disaggregate	Greater Oslo, Norway	Holden & Norland (2005)
Less annual eco-footprint on commute	✓			✓		Regression/ Aggregate	Barcelona, Spain	Muniz & Galindo (2005)
Less per capita full-lifecycle transportation-related GHG emissions and energy use for auto, transit and light trucks)	✓			✓		Comparative/ Aggregate	Toronto, Canada	Norman, *et al.* (2006)
Less per capita GHG emissions from transport operations for auto and transit	✓			✓		Comparative/ Aggregate	Toronto, Canada	VandeWeghe & Kennedy (2007)
Less household total auto emissions (CO, NOx, HC)	×	×	×	✓		Regression/ Disaggregate	Charlotte, US	Yasukochi (2007)
Less vehicle emissions (CO_2)	✓					Regression/ Disaggregate	Nationwide, US	Emrath & Liu (2008)
Less motorized energy	✓	✓	✓	✓		Regression/ Disaggregate	Atlanta, US	Frank, *et al.* (2009)
Less energy burned from walking	×	✓	×	×				

Notes:

"Smarter location"- close to the city center (CBD) or a major transit station

"TOD"- transit-oriented development or a compact neighborhood development pattern

Frank, *et al.* (2000) explored the relationship between census-tract-measured urban form and automobile emissions (nitrogen oxides, volatile organic compounds, and carbon monoxide) within the Puget Sound region, US. Disaggregated household emission data were estimated from detailed local travel survey data using emission rates from MOBILE5a and separate engine start rates. Multivariate regression analysis was also adopted for controlling effects of income, vehicle ownership, and household size. Results showed that household density, work tract employment density, and, in the case of nitrogen oxides, street connectivity (census block density) were significantly and inversely correlated with vehicle emissions (Frank, *et al.*, 2000).

Holden & Norland (2005) conducted surveys in eight residential areas in the Greater Oslo Region, Norway, the same area that Naess & Sandberg (1996) previously studied. The research performed similar multivariate regression analysis while using disaggregated household data. They found that the total household energy use decreases as density reaches a certain point, yet at higher density levels the total energy use increases. This effect is different from the workplace density effect identified in Naess & Sandberg (1996). The more recent research also found an interesting interaction between households' everyday travel and leisure-time travel: for example, residents living in high-density areas compensated for the energy savings from everyday travel by having more leisure-time travel by plane (Holden & Norland, 2005).

Muniz & Galindo (2005) measured ecological footprints of commuting in the Barcelona Metropolitan Region (BMR), Spain for its 163 municipalities, considering the energy used in traction, vehicle manufacturing, the construction and maintenance of transport infrastructures, and the land occupied by those infrastructures in each municipality. Multivariate regression analysis using aggregated ecological footprint data was performed to control for average household income and job ratio (per capita employment) at the municipality level. Net population density was found to be negatively associated with ecological footprints. Conversely, distance to center and distance to transport axis were found to have significant positive effects. In general, urban form factors explained more of the variability of ecological footprints among municipalities than socioeconomics did (Muniz & Galindo, 2005).

Norman, *et al.* (2006) assessed energy use and GHG emissions (including transportation operations from light duty vehicles and public transit) associated with high and low residential development in the City of Toronto, Canada, using input-output life-cycle assessment "EIO-LCA" model. Through a comparative analysis at this aggregated scale, it was found that per capita transportation energy use and GHG emissions associated with low-density development was 3.7 times higher than the high density development; and the difference were mainly from automobile use accounted for more than 90% of total transportation energy use (Norman, *et al.*, 2006).

VandeWeghe & Kennedy (2007) also focused on the City of Toronto, comparing GHG emissions (including auto and transit operations) among 832 census tracts, a more refined, yet still aggregate, scale than that in Norman, *et al.* (2006). They also followed a comparative approach, and found that the top ten tracts in terms of GHG emission were all located in low-density tracts on the outskirts, with their high emissions largely due to private auto use (VandeWeghe & Kennedy, 2007). In both analysis of Norman, *et al.* (2006) and VandeWeghe & Kennedy (2007), no socioeconomics or demographics were controlled for.

Yasukochi (2007) estimated a series of multivariate-regression models to analyze the affect of neighborhood design (measured at the census block group) using disaggregated household total automobile emission data (CO, NOx, HC) in the Charlotte, North Carolina metropolitan area. The study found that the most important land use variables in the models were median distance of houses within the block group to the central business district as well as local/regional accessibility. Other land use variables were either statistically insignificant or very weak in terms of their marginal effects (Yasukochi, 2007).

Emrath & Liu (2008) analyzed the effects of subdivision compactness and location on transportation CO_2 emissions in the United States. In estimating disaggregated household travel emissions, the study used VMT, the efficiency of the vehicles owned, and the efficiency of the speed with which vehicles are driven, all information extracted or derived from 2001 US National Household Travel Survey. Multivariate regression models were further applied and showed that controlling for household attributes, CO_2 emissions were lower in denser developments primarily due to reductions of VMT, even though vehicles were driven at less efficient speeds (Emrath & Liu, 2008).

Frank, *et al.* (2009) studied the effect of regional accessibility and local walkability on the personal energy consumption pattern of in the Atlanta region, USA. The disaggregated energy consumption for both motorized travel and walking were derived from household 2-day travel diaries of 10,148 residents. Neighborhood forms were measured in GIS based on a 200-m grid around each participant's home location. Multivariate regression analysis was employed for controlling demographic factors. Results showed that increase of transit accessibility, residential density and intersection density could all significantly reduce motorized energy of residents but meanwhile energy for walking was increased. The land use mix, interestingly, reduced energy for motorized travel and walking at the same time. Authors speculated that because a mixed land use pattern places destinations closer together, it reduces travel demand for both walking and driving (Frank, *et al.*, 2009).

b) Travel behavior specific studies

Table 2-4 summarizes findings from relevant studies in the field. Those discussed below include only a part of the full literature. Conclusions appearing in the table but not in the discussion were drawn from existing literature reviews (Ewing & Cervero, 2001; Handy, 2006; Zegras, 2005).

Holtzclaw (1994) claimed his study as "a first attempt to measure reduction in automobile usage and personal transportation costs that result from different characteristics of a neighborhood (p.1)". He focused on 28 communities in California, measuring neighborhood forms and average household annual VMT at the community level. He then used multivariate regression on this aggregate dataset, finding that controlling for household income and size only, the residential density were effective for reducing per household annual VMT, whereas the effects of neighborhood shopping and pedestrian accessibility were not statistically significant (Holtzclaw, 1994).

Handy & Clifton (2001) studied the effect of local shopping area on people's shopping travel behavior. Disaggregated travel data were collected from residents in six neighborhoods in Austin, Taxes, US. Results of their multivariate regression models suggested that that local shopping was not effective in reducing automobile dependence (Handy & Clifton, 2001).

Table 2-4 Empirical Evidence from Travel Behavior Specific Studies

Impacts on	Higher Density	Higher Diversity	Better Design	Smart Location	TOD -Overall	Methodology	Context	Source
Less driving	√	×	×			Regression/ Aggregate	California, US	Holtzclaw (1994)
Fewer trips					√	Comparative/ Aggregate	San Francisco, US	Friedman, *et al.* (1994)
More transit use					√	Comparative/ Aggregate	San Francisco, US	Cervero & Gorham (1995)
Higher transit share	√				√	Regression / Aggregate		
Fewer total trips/ More transit use					√	Comparative/ Aggregate	California, US	McNally & Kulkarni (1997)
Fewer trips			√			Regression/ Disaggregate (attitudes included)	San Francisco, US	Kitamura, *et al.* (1997)
Less auto share/ Higher transit share	√	√	√	√				
Less driving to shopping		×				Regression/ Disaggregate	Austin, US	Handy & Clifton (2001)
Fewer VMT	×	×	×	×	×	Advanced (SEM)/ Disaggregate	San Francisco, US	Bagley & Mokhtarian (2002)
Less auto trip time for commuting					×	Regression/ Aggregate	Milan, Italy	Camagni, *et al.* (2002)
Less transit trip time for commuting					√			
Fewer trips/ Lower auto share					×	Regression/ Disaggregate (longitudinal data)	Seattle, US	Krizek (2003)
Fewer VMT					√			
Less driving	×	×	×	×	×	Regression/ Disaggregate	San Francisco, US	Guo, et al. (2007)
Less driving					×	Advanced (SEM)/ Disaggregate	Flemish, Belgium	Van Acker, et al. (2007)
Less driving, more transit use for nonwork travel		√			√	Regression/ Disaggregate	Northern California. US	Cao, *et al.* (2007)

Notes:

"Smarter location"- close to the city center (CBD) or a major transit station

"TOD"- transit-oriented development or a compact neighborhood development pattern

"VMT"- vehicle miles traveled

"HH"- household

"SEM"- structural equations models

Kitamura, *et al.* (1997) examined the effects of land use characteristics on travel behavior for five diverse San Francisco Bay Area (USA) neighborhoods using disaggregated household travel survey data. Multivariate regression models were conducted incorporating socioeconomics and attitudinal factors also. Results confirmed that residential density, public transit accessibility, mixed land use, and the presence of sidewalks mattered in trip frequency and modal split; that said, however, household attitudes were more strongly associated, suggesting that "land use policies promoting higher densities and mixtures may not alter travel demand materially unless residents' attitudes are also changed (p.156)" (Kitamura, *et al.*, 1997). This study raised an important "self-selection" problem, which inspired more research efforts on addressing it.

Bagley & Mokhtarian (2002) examined travel behavior of residents in the same five neighborhoods in San Francisco using disaggregated household travel data. To address the self-selection problem, they adopted more advanced method of structural equations models incorporating attitudinal and lifestyle variables. Results from their models confirmed Kitamura, *et al.* (1997)'s finding that household attitude and lifestyle had the greatest impact on travel demand among all factors. Conversely, results showed that neighborhood type and form characteristics had no influence on travel behavior, strongly suggesting a correlation, rather than a *causal* relationship, between the two (Bagley & Mokhtarian, 2002).

Krizek (2003) used longitudinal household travel data in the Puget Sound region, Seattle and conducted a multivariate regression analysis to examine the relationship between changes in neighborhood form (measured at the 150-meter grid cell) and changes in household travel behavior. The results found that controlling for changes in lifestyle, the relocation of households to a neighborhood with more accessibility could effectively reduce their VMT, but it is has no significant effects on their trip generation or mode split (Krizek, 2003).

Guo, *et al.* (2007) explored impacts from neighborhood factors on the interaction of motorized versus non-motorized trip frequencies in the context of the San Francisco Bay area. Multivariable regression analysis using bivariate ordered probit models were conducted based on disaggregate household travel data. Controlling for socio-demographics, temporal indicators and weather, results of models suggested that few built environment factors led to the substitution of motorized travel by non-motorized travel. Instead, some factors (e.g., bikeway density, street network connectivity) tend to increase non-motorized travel supplementing individuals' existing motorized trips (Guo, *et al.*, 2007). From the energy perspective, these findings suggest no neighborhood's effect on reducing automobile energy consumption. One shortcoming to this study is that household attitude was not controlled, thus facing the "self-selection" challenge.

Cao, *et al.* (2007) studied the relationship between the residential environment and non-work travel frequencies by auto, transit, and walk/bicycle modes in Northern California. They addressed the "self-selection" issue by using quasi-longitudinal data from 547 movers and assuming their residential preferences and travel attitudes remained constant. Through structural equations model, they found more promising effects of neighborhood characteristics than those found in previous studies after controlling for the "self-selection". Specifically, mixed land uses and the availability of transit service was effective in discouraging auto travel and facilitating the use of transit (Cao, *et al.*, 2007).

Similar travel behavior empirical studies can be found in European developed countries as well. For example, Camagni, *et al.* (2002) examined the effect of urban development patterns (i.e., infilling, extension, linear development, sprawl, and large-scale projects) on workers' mobility in the metropolitan area of Milan, Italy. Using multivariate regression models with aggregated travel time data at the municipality level, they found that commuting times for private transport seemed uncorrelated to urban development patterns after controlling for socio-economics. On the contrary, the more dispersed and less structured the development tended to increase trip time for transit but lower the share of it in the mobility market (Camagni, *et al.*, 2002).

Van Acker, *et al.* (2007) developed a structure equations model using disaggregated household travel data in the context of Flemish region, Belgium. Results from their models showed that the effect of land use is "restricted", whereas socio-economic characteristics (e.g., social status, household responsibility) influenced travel behavior (e.g., distance, time, trips) to a greater extent (Van Acker, *et al.*, 2007).

2.2.3 Comments

In this section, comments on findings, theory, methodology problems, outcome variables, and urban form variables in the western literature are provided. Challenges of inferring western evidences to China are also discussed.

First, empirical results are dependent upon local contexts and analytical approaches. As shown in Table 2-4, neighborhood form and location may play significant roles in affecting travel behavior and energy use under some local and research settings, whereas they do no matter under others. The magnitude of relationship between neighborhood and travel can also vary. Therefore, we should be cautious of generalizing conclusions from a specific study.

A second comment relates to the ultimate travel outcomes measured in the travel behavior-focused studies. Many studies focus on a single aspect of the travel pattern (e.g., travel distance for certain trip purposes, mode choice, trip frequency, car-only energy use, etc.), thus giving incomplete insights of what the impact of neighborhoods might be on overall transport energy use. A narrow scope (e.g., single individual) and time window (e.g., a single trip or a single day), when applied to the study of energy use patterns, can bias the estimates, since a household's travel pattern may include random or systematic day-to-day and member-to-member variations. For example, full-time working couples may only go shopping together on weekends. Effectively capturing full household travel and energy use and related interactions would require a survey period of one week, or more.

A more fundamental problem of generalizing conclusions from the western literature to places like China has to do with a much different set of neighborhood forms in urban China. China has a longer urban development history compared to most developed countries. Cities and neighborhoods in China have continuously evolved and undergone several major societal and institutional transformations. In cities like Beijing, Xi'an and Jinan, the variety of neighborhood forms existing today (e.g., courtyards, work-unit compounds, superblock) represent development patterns from different historical periods. Such urban typologies do not specifically exist in developed countries, thus urban form indicators which have been widely used in the west may be not appropriate or sufficient for characterizing Chinese neighborhood forms.

Finally, and perhaps the most fundamentally, there has been a general lack of a complete theory (e.g., behavioral theory) or framework to explicitly illustrate the "neighborhood form-travel" mechanism. Theory is essential in any context because it "provides the basis for conceptual models, consisting of the behavior of interest and the factors that explain that behavior, the ways in which these variables are defined, and the assumed relationships between them" (Handy, 2006a, p. 1). Without a generic theory, empirical research and data collection is at risk of being poorly guided.

Given the above considerations, concepts and conclusions with respect to energy efficient neighborhoods drawn from the developed countries' experience may not be directly applicable to China. In the next section, we will review studies that directly target Chinese cities.

2.3 Relevant Empirical Precedents in China

2.3.1 Hypothetical Concepts

As the transportation and energy issues become more important to China, the attempt to explore the transport energy and emission reduction benefits from neighborhood-scale urban development intervention has recently emerged. Sadownik & Jaccard (2001) proposed the concept of community energy management (CEM) with recommended measures including facilitating bicycle use, improving quality of public transportation, encouraging more mixed land uses and higher density development (Sadownik & Jaccard, 2001). Zhang (2007) proposed a Chinese-version TOD (transit-oriented-development) concept with 5Ds: differentiated density, dockized district, delicate design, diverse destination, and distributed dividends (Zhang, 2007). Zegras, *et al.* (2009) proposed the concept of transport efficient development (TED), which is quite similar to TOD, in the Chinese context in a framework to quantify the transportation carbon emission reduction potentials of alternative neighborhood developments under the clean development mechanism (CDM) (Zegras, *et al.*, 2009). All ideas above share similar basic principles that have been advocated in the developed countries before.

2.3.2 Empirical Studies

In addition to adapting ideas for low-energy Chinese neighborhood development, researchers have more recently begun empirical examinations of the link between existing neighborhood forms and travel behavior in China. Unfortunately, few empirical assessments have directly examined the relationship between neighborhood form and transport energy use or emissions in China.

Cervero & Day (2008) studied the impacts of residents' relocation to four neighborhoods on Shanghai's outskirts (see Table 2-5) on their job accessibility, commuting mode choice, and commuting durations, based on quasi-longitudinal disaggregated individual travel data. Multivariate regression models (binary logistic models) were specified and estimated to predict mode changes. Relocating to a suburban area near a metro-rail station was found to encourage commuters' switching from non-motorized and bus transit to rail. In addition, this neighborhood location effect had far stronger influences than neighborhood form features (e.g., street designs, land-use patterns) (Cervero & Day, 2008).

Table 2-5 Neighborhood Types and Characteristics in Shanghai (a)

Neighborhood Type	Characteristics	Neighborhood Case
Non-metro with single use	No metro service, conventional bus service; Limited retail shopping and only a few shopping stores	(Jiangqiao)
Non-metro with mix use	No metro service, conventional bus service; Mixed use	(Sanlin)
Metro with mix use (proxy for transit-oriented neighborhood)	Rail-served; Job-housing isolated; Primarily market-based residential housing; High densities, local retail mixed-use, and good cycling infrastructure	(Mailong) (Xinzhuang)

Source: summarized from Cervero & Day (2008)

Pan, *et al.* (2009) studied people's travel behavior in another four Shanghai neighborhoods, which fall into three hypothesized neighborhood typologies (i.e., traditional, planned, and gated; see Table 2-6). Using the same multivariate regression analysis with also disaggregated travel survey data, authors found that pedestrian/cycle friendly neighborhood form helps to reduce auto dependence and shortens residents' travel distances (Pan, *et al.*, 2009).

Table 2-6 Neighborhood Types and Characteristics in Shanghai (b)

Neighborhood Type	Characteristics	Case
Traditional (1930s-1940s)	2-3 storey homes densely laid out along small alleys; Walking/cycling-friendly environment	(Lu wan)
Planned neighborhood/ Workers' new village (1970s-1980s)	Neighborhood unit (Perry' concept); Mostly mid-rise (5-7 stories) row houses or towers; Average block size: 400m*500m; School, retail, service facilities are provided according to the national planning codes that specify service radii or population thresholds for these facilities	(Kang Jian) (Zhong Yuan)
Gated (after late 1980s)	Commodity housing; Job-housing spatially isolated	(Ba Bai Ban)

Source: summarized from Pan, et al. (2009)

Wang & Chai (2009) focused on Beijing, China, and investigated the difference in commuting behaviors between residents living in the work-unit compound (so-called *danwei,* a special neighborhood type with good housing-job balancing as a legacy of the old Chinese command economy) and those living in private market housing development. The survey included 736 employed heads of households among eight urban districts in Beijing following the probability proportion to size (PPS) sampling strategy. Through structural equations model (SEM) analysis on the disaggregated travel data, the authors concluded that living in *danwei* neighborhoods was associated with shorter commuting trips and higher usage of non-motorized transport mode (Wang & Chai, 2009).

Li, *et al.* (2010) investigated and compared the influences of sub-district form features in Beijing and Chengdu on private car ownership. Multivariate regression models (i.e., binary logistic models) were conducted using disaggregated household data. Results indicated that sub-district population density had a significant negative effect on household private car ownership in both cities. Interestingly, a location effect opposite to that typical to the western context was found in both cities: households living close to the urban centers are more likely to own cars. In addition, the effects of education level on car ownership are different in two cities, as are the effects of household size. These suggests that conclusions may not be fully transferable among different local contexts in China (Li, *et al.*, 2010).

Finally, Naess (2010) presented perhaps the most relevant precedent in the literature so far, in that he explicitly examined the relationship between residential location and travel energy use in Hangzhou, China. Multivariate regression analysis was employed, using disaggregated motorized travel energy data that were derived from travel survey data of 3154 individuals. To address the residential "self-selection" problem in his analysis, the author collected information of respondents' dwelling preferences and included proxy variables of them in the model as statistical control. Results confirmed that all else equal, distance of residence from the city center in Hangzhou has a strong impact on increasing personal travel energy (Naess, 2010). Unfortunately, neighborhood form effects were not investigated in this research.

2.3.3 Comments

Results from the above empirical research efforts in China give us more confidence in the directionality of the travel behavior change from neighborhood design alternatives. Indeed, most studies in China so far suggest an effect of the built environment on travel behavior and automobile ownership exists. However, from a travel energy/emission perspective, several limitations from prior studies still remain.

First, similar to western travel behavior analysis literature, none of past empirical analysis in China provides a full picture of the implications of neighborhood form on transport energy consumptions. Most research has taken a piecemeal approach by examining relationships between certain neighborhood features and certain aspects of travel behavior (e.g., travel distance by car, vehicle ownership, etc.). This leaves uncertainty in inferring the overall impact on transport energy consumption. For example, neighborhoods with higher density are found to attract more transit users, but this impact may even increase transport energy use if additional transit users shift from walking or biking. Likewise, scholars confirm that certain neighborhood types may reduce car trip frequencies, but this cannot guarantee the overall energy savings since less frequent car trips can be accompanied with longer travel distances which will again increase energy use.

Second, studies in China to date have focused mainly on the mega-metropolitan areas (i.e., Beijing and Shanghai), and thus the generalizability of conclusions could be questioned. One exception is the Li, *et al.*'s (2010) article, in which the authors studied Chengdu in addition to Beijing for a cross-comparison using same analytical approaches. Interestingly, results suggest that several effects of urban form on automobile ownership are indeed different between the two cities. The other exception is the Naess' (2010) paper, which studied Hangzhou with an exclusive focus on residential location, not the form. Given these, many effects in the context of mid-size cities are yet to be confirmed. Since growth in mid-size cities is one of the main drivers of Chinese urbanization, additional empirical study on mid-size cities about the urban form-travel energy use or emissions is desirable.

Third, studies in China have put more efforts on the behavior side and less on the form, partly due to the availability problem of refined urban form data. In China, accurate micro-scale GIS data for a city are rarely open to public and sometimes they even do not exist at all. Also, the urban form data can easily become outdated since cities in China transform rapidly. As a result, there is still a lack of systematic and quantitative understanding and describing of various Chinese neighborhood forms.

2.4 Summary

In the realm of neighborhood form-travel behavior/energy/emission empirical analysis, more than 30 years' literature in the developed countries as well as emerging studies in China presents rich and valuable resources for doing similar research in future China. Several lessons can be derived, as summarized below.

- *Theory is always important.* There has been a lack of sophisticated and complete theory (e.g., behavioral theory) or framework to explicitly illustrate the "neighborhood form-travel-energy (emission)" mechanism. Without a generic theory, empirical research and data collection is at risk of being poorly guided.

- *Results are contradictory and can vary across local contexts and methodologies used.* Even in western academia today, questions remain about the quantifiable influence of the built environment on travel behavior; research in the area continues.
- *Methodological challenges remain.* Disaggregate analysis is preferable to aggregate analysis, but the former also requires much effort in data collection and processing. Comparative analyses pose difficulties in filtering out basic confounding factors such as household socioeconomics and demographics. Cross-sectional multivariate regression analysis leaves unanswered questions regarding the causal mechanisms involved, and results of this approach are often challenged by the "self-selection effect" argument. Advanced models (e.g., instrumental models) can partly address the "self-selection" problem, but they have not yet been used to model travel energy use or emissions, to the best of my knowledge.
- *Challenges of identifying and describing neighborhood forms in China may exist.* Form measures widely used in the west may not fit China's context. Neighborhood boundary definitions in western studies are often due to the convenience of data availability (e.g., TAZ, census block). This convenience may not exist in China given that city-wide urban form data are rarely available or reliable under rapid urbanization.
- *It is important to depict the full picture of travel pattern when estimating travel energy outcomes.* Energy use or GHG emissions are affected by all the characteristics of travel pattern (mode, distance, frequency, speed, occupancy, etc.). However, many travel behavior studies look at the influence of built environment on only one or two aspects of travel patterns, such as trips by certain modes with certain purposes. This is not sufficient to offer a full picture of the built environment's impact on travel energy use.

Many of the concerns raised above will be addressed throughout the following chapters in this thesis. To address the "theory" challenge, Chapter 3 elaborates a generic theory that can explain the relationship between the built environment and transport energy use from a neighborhood perspective. The rest of challenges mentioned above will be reflected in the methodological approach to this research, as will be discussed in Chapter 5.

3 THEORETICAL PERSPECTIVES ON HOUSEHOLD TRAVEL ENERGY DEMAND

In Chapter 2, we conclude that despite strong advocacy for compact, mix-used and walkable neighborhoods as a way to reduce transportation energy use and emissions and otherwise help achieve "sustainable" transport, the empirical evidence in the west has not been able to fully support the claims. However, people do agree on one thing. That is, such effectiveness, if it exists, can only come from the success of the built environment in changing household's travel behaviors. In other words, making adjustments to the built environment does not, in itself, constitute direct transportation energy reductions. Rather, it presumably facilitates a variety of travel energy conservation activities for households, including: (1) trip chaining (net trip frequency effect), (2) shorter total travel distances by all modes, e.g. less automobile driving (distance effect), (3) a shift to less energy-intensive modes, e.g., from car to transit or to non-motorized modes (mode shift effect), and (4) lower motor vehicle ownership (greener choice set effect). Each of these, independently or in some combination could translate into final transportation energy savings. Along these lines, travel demand theory with an explicit microeconomic behavioral framework provides perhaps the most straightforward way to analyze travel pattern effects and to provide a useful explanation of the mechanisms by which neighborhood form might indirectly influence household transport energy consumption.

This chapter includes three sections. In section 3.1, I introduce the travel demand theory (utility maximizing theory) and propose a conceptual framework integrating the cost-based approach and the activity-based approach, both of which have been used by transportation analysts to assess the link between the built environment and travel behavior. In section 3.2, I conduct a series of detailed qualitative illustrations of the influence of widely claimed urban design principles on travel behavior and associated energy use. Section 3.3 gives additional comments on previous theoretical discussions. Section 3.4 presents a summary of the chapter.

3.1 A Conceptual Framework

3.1.1 Travel Demand Theory

Household travel energy consumption or emissions is, by definition, a byproduct of travel. Indeed, individuals or households make decisions based primarily on their travel activity patterns, rather than the associated energy use or emission outcomes. Therefore, from a theoretical perspective, to investigate what drives household travel energy use or emissions we have to look at how people make choices among different travel behavior patterns available to them.

a) Utility maximizing theory

The utility maximizing theory has been the core of travel demand theory in the realm of disaggregated travel behavior studies since at least the early 1970s, thanks to the foundational work of McFadden and others (Ben-Akiva & Lerman, 1985; McFadden & Domencich, 1975; Train, 1986). The theory is grounded in microeconomic consumer behavior theory, basically assuming that individuals or households are utility-maximizing agents who choose, from among relevant alternatives, that which maximizes their utility subject to budget constraints, with their demand for different goods depending on prices of all goods, income, and tastes.

With respect to household travel analysis, we would expect household members to choose certain travel patterns to maximize their utility by weighing the comparative travel times, costs, and other attributes of available competing modes, destinations, times of day, etc.. Characteristics of the travelers (e.g., income, age) themselves also influence the final selection.

b) Activity-based theory

The activity-based analytical theory formally emerged shortly after the adoption of a utility-maximizing framework in travel behavior studies in 1970s, with two important assumptions extending from the utility-maximizing theory.

First, the demand for travel was recognized explicitly as a derived demand for activities (Jones, 1979; McFadden, 1974). Put another way, people shape their travel patterns not to minimize the travel cost, but rather to maximize the net utility. Here, the net utility is defined as the benefit obtained at destinations minus the cost of reaching them.

Second, people make decisions based on the whole of their expected activity patterns, rather than on specific trips alone. Budget constraints in terms of space, time and money are involved in the decision making process as well (Hägerstrand, 1970; Schäfer, 2000). Along this line, if land use changes reduce an individual's travel time, that individual might invest that saved time in additional non-home activities. This would result in increased total travel and energy use.

Although there has been almost half a century of development of t travel demand theory, the explicit role of the built environment in these theories only arose more recently. The most important contributions come from Crane (1996, 2001) and Maat, *et al.* (2005), as will be discussed below.

3.1.2 Cost-based Framework

Crane (1996, 2001) explicitly incorporated built environment into the above-mentioned travel demand theory by arguing that "land-use and urban design proposals, if they influence travel behavior, do so by changing the price of travel" (Boarnet & Crane, 2001, p. 103).

Crane illustrated how the built environment can change the relative trip costs of available modes. For example, higher densities might reduce travel times (thus costs) between origins and destinations; grid street patterns may lower trip costs for both car and walking modes in comparison to conventional suburban street designs; safer and more pleasing walking/biking environment can decrease relative "psychic" costs associated with those modes. Crane further argued that the relative attractiveness of driving versus walking depends on the relative change in the cost of each due to the built environment changes. For example, a grid-pattern street design will have an ambiguous impact on mode choice unless the time and money cost of non-automobile modes are reduced sufficiently more than car travel (Crane, 1996).

Crane's approach also reflected traveler time and budget constraints. For example, if an individual is able to save travel cost (e.g., time and money) from better designed built environment, he may decide to invest those savings in more trips to achieve higher benefits, and this decision in return will increase the travel activities and associated energy consumption; ambiguous ultimate effects can be expected (Boarnet & Crane, 2001; Crane, 1996).

There is one shortcoming associated with Crane's framework. As Zegras (2004) and Maat, *et al.* (2005) point out, Crane emphasized the influence of built environment on travel costs, but largely overlooked the important role of the built environment in also changing destination benefits. The latter is an important component of the activity-based framework, as will be discussed in the next section.

3.1.3 Activity-based Framework

To include the built environment's role in an explicit activity-based behavioral framework, Maat, *et al.* (2005) illustrated how the built environment can influence both travel costs (disutility) and potential activity realization benefit at destinations (positive utility).

More specifically, on the one hand, built environment changes (e.g., higher density) may reduce an individual's travel time to obtain the same amount of activity benefit. On the other hand, built environment changes may also increase the attractiveness of destinations at further locations. If there are no budget or time constraints, and if the incurred additional cost to reach a further location is less than the additional benefit derived from reaching it, the individual or household might take longer trips to the more preferred destination, thereby allowing the derivation of additional, latent, utility (Maat, *et al.*, 2005).

Take a shopping trip, for example. According to the activity-based framework, positive utility comes from the attractiveness of the shop (e.g., choice and quality of products, etc.) whereas the disutility comes from the cost of getting there. To maximize their *net* utility, individuals or households may opt for a more distant destination in order to get higher quality, greater choice, and/or cheaper products (Maat, *et al.*, 2005).

Not surprisingly, this consideration adds another level of ambiguity in predicting the ultimate built environment effects on travel patterns and associated energy use. In the next section, I will illustrate such ambiguity with a detailed focus on the effects of neighborhood form and location.

3.1.4 An Updated Framework

The frameworks of Crane (1996) and Maat, *et al.* (2005) do not explicitly differentiate between macro-scale urban form effects versus micro-scale neighborhood effects in travel behavior. Nor do they include the travel energy/emission component, which is a primary focus in my research. Therefore, building on Crane and Maat, *et al.*, I update a conceptual model for purposefully capturing the neighborhood form-travel energy use/emission relationship.

As shown in Figure 3-1, neighborhood design and location, plus individual/household socio-demographics, attitudes, and vehicle ownership are all considered to influence transport energy use by impacting travel activity patterns (composed of frequencies, travel distances, mode choice, and speed). Speed has been rarely mentioned explicitly in the travel studies, but it is important because it can affect fixed destinations for households (e.g., job location, parents' home location, etc.), which may be relevant since both origin and destination characteristics can enter the utility equation in the travel decision making process.[2]

Another important note regarding the utility maximization process is that neighborhood form and location have an influence on both the activity realization benefit and the travel disutility, given constraints on resources such as time and budget. This distinguishes the updated framework from the cost-based framework of Crane (1996). Furthermore, as a number of neighborhood influenced travel-related activities (e.g., shopping) can be shifted among days of the week, concerns about total household energy use and emissions suggest our timeframe of analysis should, at minimum, be weekly based at minimum, a timeframe which Maat, *et al.* (2005) do not consider explicitly in their framework. I argue that an examining an entire week allows us to observe, in theory, interactions among decisions about a variety of travel activities (e.g., commuting trips on weekdays versus shopping trips on weekends), thus providing the minimum acceptable time window for considering effects on household's lifestyle and travel activity patterns.

In addition to the travel pattern choice, I include in the extended framework two relatively longer-term choices: the residential choice and the vehicle ownership choice. Recall the discussions about self-selection issues in Chapter 2: people may choose residential locations based on their socioeconomics and demographics, vehicle ownership, as well as their lifestyles, attitudes and travel-mode preferences. Certain attitudes and preferences can also be shaped from living in certain forms of neighborhood (Mokhtarian & Cao, 2008), which suggests a possible *indirect* effect of neighborhood form on transport energy via the neighborhood- attitude- (vehicle choice)- vehicle use chain. Therefore, we need to acknowledge the potential mutual influences between neighborhood features and household characteristics.

Finally, both neighborhood and household characteristics affect vehicle ownership, and vehicle possession and use, in return, could shape households' travel preferences in the long run. Vehicle ownership has an immediate effect on determining the available choice set when

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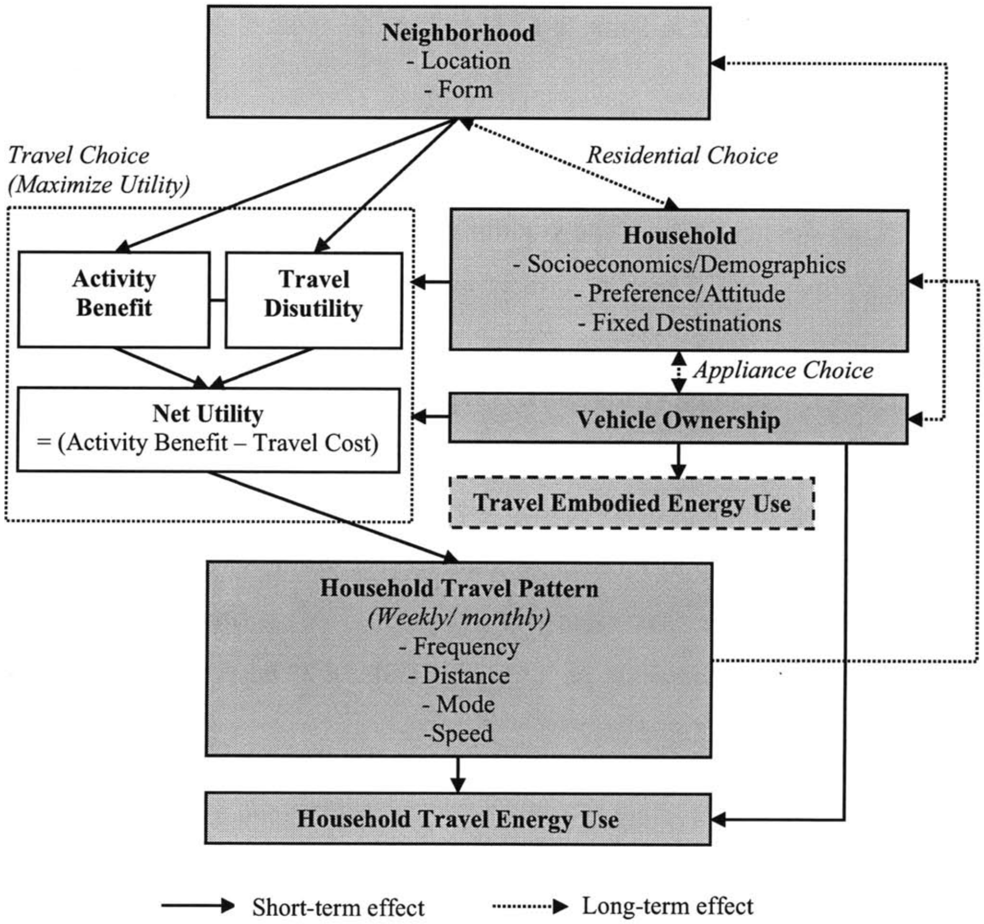
[2] Speed, of course, can also influence energy use and emissions, due to impacts on internal combustion engine performance.

household members make short-term travel pattern choices, which then translate into energy consumption. Besides this *indirect* effect on energy use, the vehicle ownership choice is relevant also in the sense that 1) the vehicle type (combined with speed) *directly* affects energy efficiency of distance traveled by a certain means; and 2) the vehicles themselves *directly* contain embodied energy, an important component for life-cycle energy consumption estimation. Although these two *direct* effects will not be explicitly examined in my empirical research due to data limitations, I include them in my framework to depict a full picture of neighborhood-travel energy mechanism.[3]

[3] Note that the embodied energy of infrastructures (e.g, roads and rails) that household travel energy demands also require are not included in the framework, although an extension to include such effects would be fairly straightforward (i.e., attributing relative infrastructure "responsibility" to demands generated).

Figure 3-1 Conceptual Framework of the Set of Factors Influencing Household Transportation Energy Consumption at the Neighborhood Scale



3.2 The Generic Impacts of Neighborhood Features on Travel Energy Use

In this section, I use the framework described above to investigate, stylistically, the short-term impacts of several popular neighborhood design concepts (which might reduce travel distances, auto speeds, and distance to transit) on different aspects of household's travel pattern (trip frequency, distance, mode) and the associated ultimate energy requirement. It is worth noting that to simplify the complexity of discussions, the analysis in this section do not account for the potential longer term effects which are also included in the framework- such as: the changes in net utility by each mode that the neighborhood interventions imply may in the medium term change vehicle ownership tendencies, which in return affect travel pattern and energy use; or, a walkable neighborhoods might attract more non-auto preferring households, further decreasing future travel energy demand.

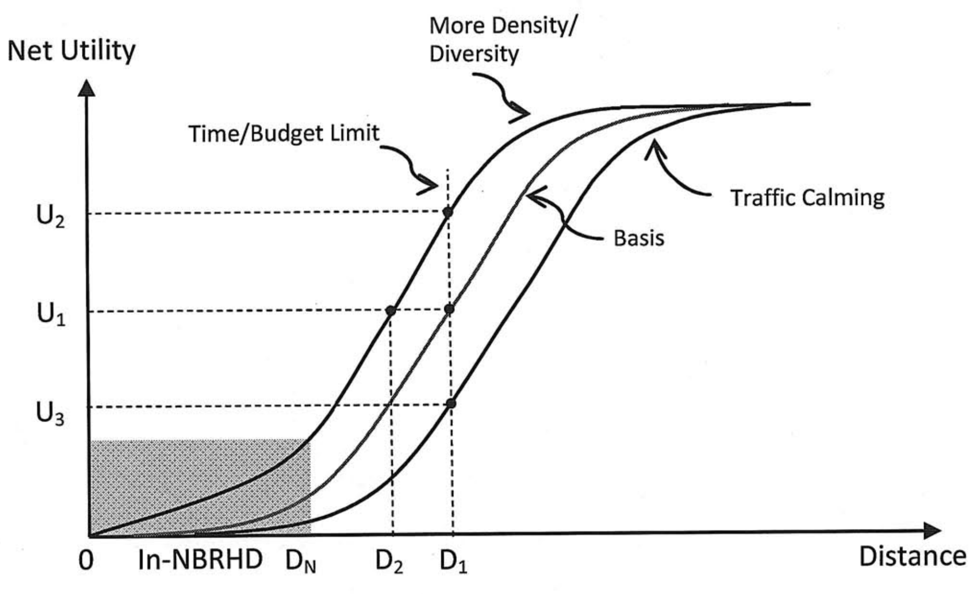
The graphical illustration is inspired by the work of Boarnet & Crane (2001) and Matt, *et al.* (2005), but with an exclusive emphasis on the effect of micro-level neighborhood characteristics. The summary of effects is shown in Table 3-1.

3.2.1 Neighborhood Design: Higher Density, Diversity & Traffic Calming

a) <u>Effects on travel frequency and distance</u>

Figure 3-2 shows the net utility effects with respect to changes in modally travel frequency and distances (e.g., by car). The net utility includes all benefits people can gain from participating in activities within a certain distance from home and the travel costs of realizing those activities. The red rectangle (In-NBRHD) represents the potential curve-shifting area due to an intervention within the neighborhood boundary (D_N). The utility-distance curve is assumed to be S-shaped, reflecting initial actions needed for initiating car use (walking to the car, starting the engine, etc.), increasing opportunities as one travels further afterwards, and the law of diminishing returns towards the maximum trip distance. Given a time/budget constraint at D_1, households could achieve the maximum net utility U_1 under the "basis" scenario.

Figure 3-2 Stylized Effects of Density, Diversity and Design Changes on Travel Frequency and Distance (e.g., by Car)



Source: Derived and extended from Maat, et al. (2005)

Now assume we introduce a higher density or more diverse land uses in the neighborhood. Either design concept produces shorter distances between potential destinations, as represented in the "More Density/Diversity" curve, which then impacts potential net utility levels. Higher non-residential density increases the scale of attractiveness in terms of possible destinations. For example, if increased non-residential density means a local shopping street instead of a single small grocery store, a household can satisfy a greater number of shopping needs. Adding land use mix could allow households to meet certain kinds of additional needs (not previously existing in the neighborhood under the "basis" scenario) with shorter driving distances. Also, diverse land uses may allow households to combine previously separate trips into a trip chain, thus lowering the trip frequency as well. Overall, if a household chooses the same net utility level as under the "basis" scenario (U_1), then the household's travel distance will decline from D_1 to D_2. However, this is not the end of the story. According to the activity-based theory, such a behavior change ($D_1 \rightarrow D_2$) will free up some time and travel expense budget, leading to the question: how will the household's activity pattern respond to these savings? A household may spend the saved time and budget on activities at the same destination (D_2) or at home (0). This will ultimately reduce the travel distance ($D_1 \rightarrow D_2$). However, the household could also use the saved time and budget for making more trips to the same location (D_2) or taking longer trips to a further location (e.g., D_1) that increase net utility ($U_1 \rightarrow U_2$). In this case, the urban design shift represented by the "reduced distance" curve translates ultimately into increased household net utility vis-à-vis the "base case," but with no change in travel energy use or emissions.

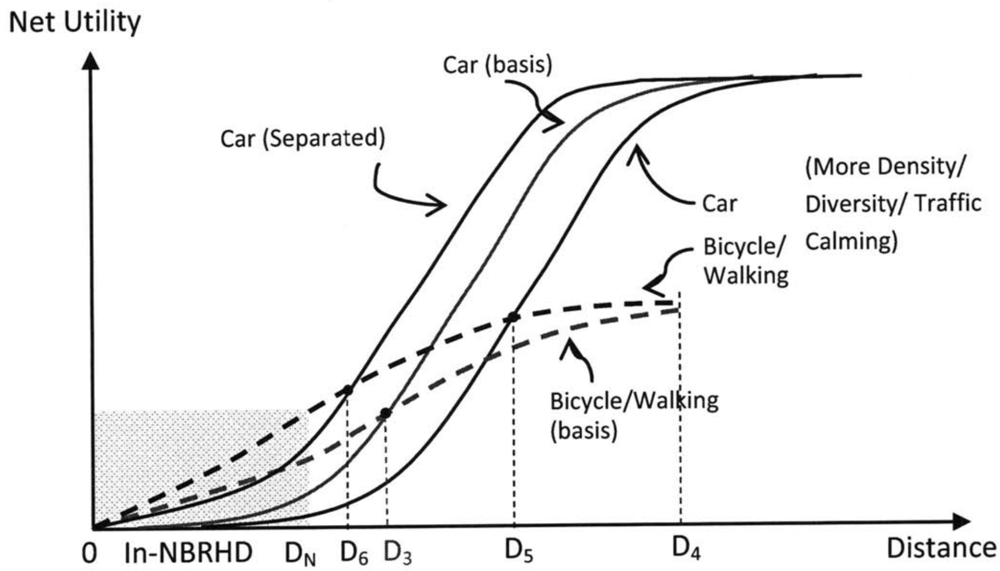
Consider now the implications of a design feature: traffic calming. Traffic calming measures will generally slow motorized travel speeds (especially for cars and buses), adding travel costs to the within-neighborhood segment of motorized trips. Note, that higher densities may have a similar impact on speeds due to congestion effects and, say, longer searching time for a parking in the neighborhood. Both can be depicted as the "traffic calming" curve in Figure 3-2. In this case, for the same distance (D_1), a household obtains lower net utility (U_3), because more time was consumed to traverse the distance. However, the household may not be able to take that longer trip, not to mention longer or more trips. Without additional time available, a slower trip means a shorter distance would be expected; and thus, energy is saved.

b) Effects on mode choice

Now we turn to an analysis of effects on different travel modes.

Figure 3-3 shows different trends in net utility changes across different modes (car driving and non-motorized travel [NMT]) as the travel distance increases. Travel distance implies different relative costs of each mode, due to speed differences. Pedestrians/bikers have hardly any initial actions compared to car driving; therefore, a lower NMT travel cost presents a higher net utility than car for short trips (assuming same net utility for a certain distance by either mode). As trip distances increase, car driving becomes more attractive due to its speed advantage. For very long trips (over D_4), the NMT travel may even be impossible because of the limitations of physical exertion. Under the "basis" scenario for auto and NMT, the same net utility level is achieved at D_3.

Figure 3-3 Stylized Effects of Density, Diversity and Design Changes on Mode Choice



Source: Derived and extended from Maat, *et al.* (2005)

As discussed above, traffic calming and compact development features can reduce car travel speed within the neighborhood (D_N). These reduced car travel speeds can have two-fold impacts. On the one hand, it will increase the car travel cost, shown as the "Car (More Density/ Diversity/ Traffic Calming)" curve; on the other hand, it can create safer and more pleasing NMT conditions, thus decreasing NMT travel cost and increasing net utility for same trip distance, shown as the "Bicycle/Walking (More Density/ Diversity/ Traffic Calming)" curve. Under these conditions, NMT remains as an attractive alternative up until at the point at D_5. In other words, people may shift from car to NMT for trips up to distance D_5. All else equal, this mode change will save travel energy.

It is also worth demonstrating the ambiguous consequences of designing a separated internal road network for cars and NMT in neighborhoods. Many designers strongly endorse this concept and think it can result in a shift from driving to walking/biking given a safer NMT environment. However, as illustrated by Figure 3-3, the fundamental factor is the relative cost for different modes. While separated NMT paths, as represented by the "Bicycle/Walking (More Density/ Diversity/ Traffic Calming)" curve, can certainly increase the safety and attractiveness of walking or biking, such interventions, all else equal, will reduce the cost of car travel, since now people can drive on exclusive roadways more freely and faster without potential conflicts with NMT. If the relative gain for the car mode is greater than that for walking and biking, as illustrated by the "Car (Separated)" curve, it is plausible to observe a NMT-to-car shift for trips with distances between D_6 and D_3, which would lead to an ultimate increase in travel energy consumption, all else hold constant.

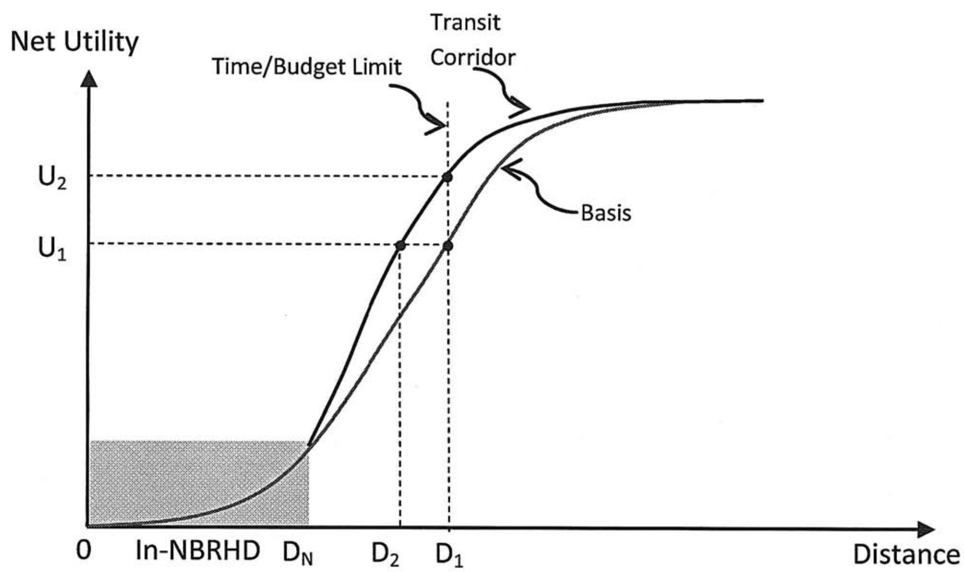
3.2.2 Neighborhood Location: Proximity to a Transit Corridor

Neighborhood location, such as proximity to a transit corridor, strongly impacts beyond-neighborhood destination utilities and cost patterns with respect to trip distance. A transit corridor often contains two main features. On the transportation system side, the corridor accommodates faster movement for transit, but may do the same or even more for car flows (again, similar to the NMT case discussed above, by reducing transit-car conflict on the streets; furthermore, such corridors may also simply improve the overall motorized transportation system speeds), thereby lowering the travel time cost for all motorized modes. On the land use side, intensified development along transit corridors presents greater destination reach-out benefits for households living close to it.

a) Effects on travel frequency and distance

Proximity to a transit corridor has two-fold impacts, both depicted by the "Transit Corridor" curve in Figure 3-4. On the cost side, adding more transit service can give households a faster option (e.g., through reduced waiting time for transit with higher frequency) for reaching an out-of-neighborhood location than previously. In other words, in moving from the "basis" to the "transit corridor" situation, a household can increase its net utility at D_1 from U_1 to U_2, due to travel time savings. The intensive development along the corridor automatically increases the activity-realization utility within the same distance beyond the neighborhood. Even without a transit corridor, per se, the more bus routes provided, the bigger the expected transit service area, and the larger the household's activity choices with the same distance travelled by transit. In both cases, the "net utility-distance" curve shifts inward. In other words, to obtain the same net utility U_1, now the household only needs to travel as far as D_2. In both cases, a reduction in travel distance can be expected. However, by the activity-based theory, the story does not end there. Households can invest the savings from transit proximity in more and longer trips, to maximize total net utility. The latter would, all else equal, involve more travel energy use.

Figure 3-4 Stylized Effect of the Proximity to a Transit Corridor on Travel Distance

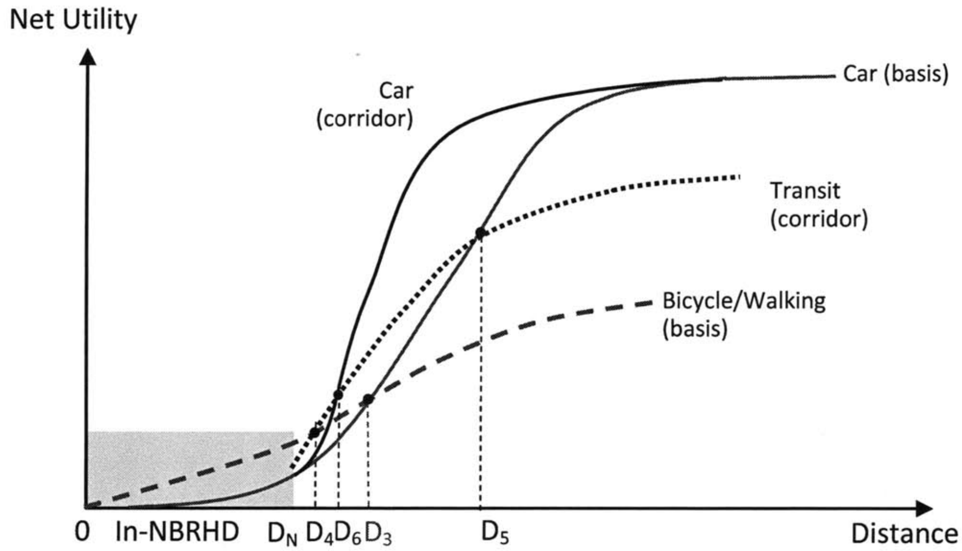


Source: Derived and extended from Maat, *et al.* (2005)

b) <u>Effects on mode choice</u>

In the "basis scenario", we assume no transit, with only car and NMT (bicycle/walking) available for all households. For short trips with distance less than D_3, NMT is the preferred mode. For trips of distance D_3 or more, the household prefers to drive car. Now in the transit corridor scenario, we add a transit curve. Note that the curve starts at the neighborhood boundary with a lower net utility point than NMT. This represents the assumption that the transit station is on the edge of the neighborhood and the access mode for households to transit is NMT. The gap between net utility of transit and NMT at D_N reflects the utility loss for households waiting for the transit service without gaining any utility at the station. Net utility then increases faster for transit than NMT due to a higher speed for transit. The "corridor" scenario can also change the curve for car mode, as shown in the graph. This is because most road-based transit corridors are not exclusive to transit and the resulting wide lanes (sometimes viaducts) and traffic management make car travel easier and faster.

Figure 3-5 Stylized Effects of the Proximity to a Transit Corridor on Mode Choice



Source: Derived and extended from Maat, *et al.* (2005)

As shown in Figure 3-5, there are three important potential mode changes induced by a transit corridor. First, for households with automobiles, we might expect a mode shift from car to transit for trips of distance between D_3 and D_5. This will result in less transport energy consumed, all else equal. However, if the transit corridor also improves car use conditions, then car use may be more attractive than transit use, resulting in increased energy use. Second, for people who do not own a car, a mode shift from NMT to transit can also happen for trips of distance between D_4 and D_3. This could also result in an increase in transport energy use, since transit vehicles also require energy. The ultimate energy requirement is uncertain, depending on which effect dominates. For neighborhoods that have a majority of households without cars, the second energy increasing impact could be greater than the impact of a car-to-transit mode shift. For an auto-oriented neighborhood adjacent to a transit corridor which also improves car use conditions, the energy consumption may also increase due to the relative advantage of car use and the relative energy intensity of auto travel relative to transit.

3.3 Additional Comments

Table 3-1 presents a summary of the above exercises, illustrating the stylized effects of neighborhood features on travel behavior. As one can expect based on the previous discussions, no conclusive energy reduction outcomes can be deduced from popular neighborhood design principles, except for the "traffic calming" concept.

Table 3-1 Qualitative Effects of Different Neighborhood Features on Travel and Energy Use

	Neighborhood Features				
	Higher density (reduce distance & speed)	Land use mix (reduce distance)	Traffic calming (reduce speed)	Transit proximity (reduce distance)	All
Car trips	+/-	+/-	-	+/-	+/-
Car trip distance	+/-	+/-	-	+/-	+/-
Car shift to transit/ NMT	-	n.a.	-	-	+/-
NMT shift to Transit	n.a.	n.a.	n.a.	+	+/-
Overall energy use	+/-	+/-	-	+/-	+/-

Source: Extended from Boarnet & Crane (2001); p.72

Although the summary focuses exclusively on the *direct* relationship between neighborhood (form and location) and travel behavior (travel distance, mode choice, frequency), first we need to recognize that such behavior is also affected by a bundle of other factors (e.g., household characteristics) and long-term mechanisms (e.g., residence choice, vehicle ownership). Our approach in this section is rather from a short-term comparative static perspective.

Second, the relevance of neighborhood characteristics in travel-pattern decisions may vary depending upon trip purposes. For commuting trips, neighborhood effect on mode choice is likely to dominate the effect on the travel frequency and distance. The reason is that the destination of a workplace is much less flexible that for a non-workplace (e.g., a store); an increase of job density in a neighborhood may not be able to reduce commuting distance since there is not an easy match between the type of job and the person's skill and that individual has to work at the same firm anyway. That said, it can still effect partially on commuting cost (i.e., time), which affects frequency decisions. For example, the BRT corridor may significantly shorten commuting time (via higher speed facility) and people may decide to return home for a rest in the middle of day. On the other hand, higher job density (e.g., in the service sector) may suggest more commercial/recreational opportunities in the neighborhood, which could have a significant impact on the trips for non-work purposes.

Third, the energy use outcome is also affected by travel speed. The "traffic calming" concept aims at lower car travel speed with more acceleration and braking, an effect that would make the vehicle operated less efficiently in terms of fuels use and emissions. This could cause some "leakage" of the energy reduction effectiveness, such that the shorter distances become less fuel efficient, creating no net reductions in energy use and emissions.

3.4 Summary

Travel demand theories, such as the utility maximizing theory and the activity-based theory, provide the basis for developing a conceptual model to show the mechanisms underlying the neighborhood-travel energy relationship. Drawing from these theories and existing frameworks developed by Crane (1996, 2001) and Matt, *et al.* (2005), I developed an updated framework comprised of the travel pattern choice as well as longer-term choices on vehicle ownership and residential location. Household socioeconomics and demographics affect all three choices. Neighborhood form and location affect both the activity realization benefits and the associated travel costs. Three choices are intertwined with mutual influences among factors, making it difficult to isolate the specific causal relationship between the neighborhood, travel patterns, and the associated energy use or emissions.

In the second section, I followed Maat, *et al.* (2005)'s graphical illustrations, and used a series of diagrams to demonstrate the ultimate ambiguity of neighborhood (form and location) effects on travel behaviors such as frequency, distance and mode choice. Although the discussion was limited to the short-term travel pattern decisions (i.e., I did not consider the broader picture of long-term residence and vehicle ownership choices), the core message is clear: the neighborhood-travel behavior relationship is already a complex one. Further complicated by the interaction with longer-term vehicle ownership and housing choices, no conclusive energy reduction outcomes can be theoretically deduced, ex ante, from the neighborhood design principles widely advocated by urban designers (except for the "traffic calming" concept).

4 RESEARCH CONTEXT

This research effort focuses on the relationship between neighborhood characteristics and household transport energy consumption in Chinese cities. Jinan, a mid-size city undergoing rapid urbanization and motorization shared by many Chinese cities, provides a good context for exploring this relationship. The availability of support from a local academic institution in Jinan through the Energy Foundation China Office (sponsor of this project) made the empirical research logistically convenient. Furthermore, the city government's intent of integrating ongoing bus-rapid-transit corridor construction with transit-oriented development gives this research immediate policy relevance.

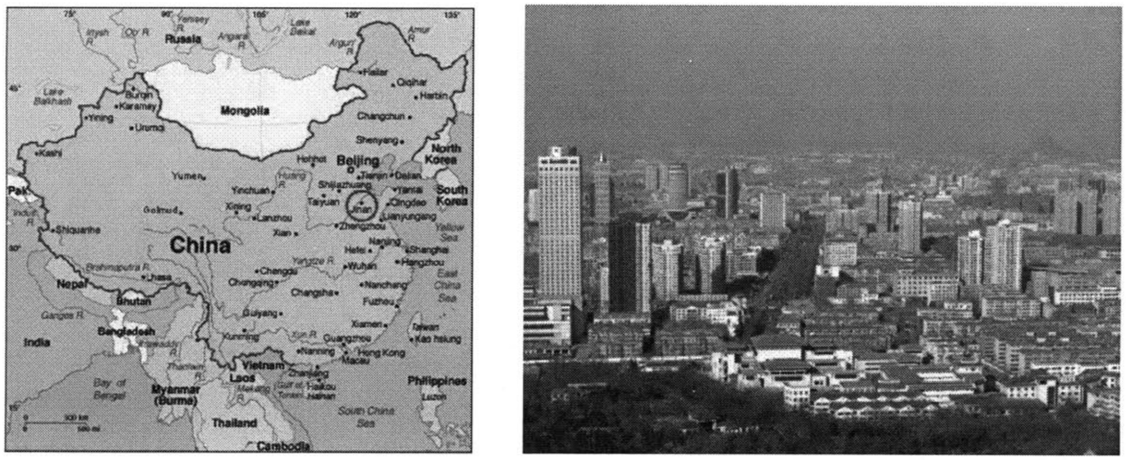
This chapter presents the overall empirical setting, including the Jinan city context (section 4.1), the bus rapid transit (BRT) corridor development (section 4.2), and the neighborhood typologies identified in the city (section 4.3). Section 4.4 provides a summary.

4.1 Jinan City

Jinan is the capital city of Shandong Province in China with a registered urban population of about 3.5 million as of 2008 (Statistics Bureau of Shandong Province, 2009). Lying on the lower reaches of the Yellow River (see Figure 4-1, left) and positioned on the east coast of China, Jinan is one of China's most famous historical and cultural cities with rich natural spring water resources and a long history dating over 4,000 years.

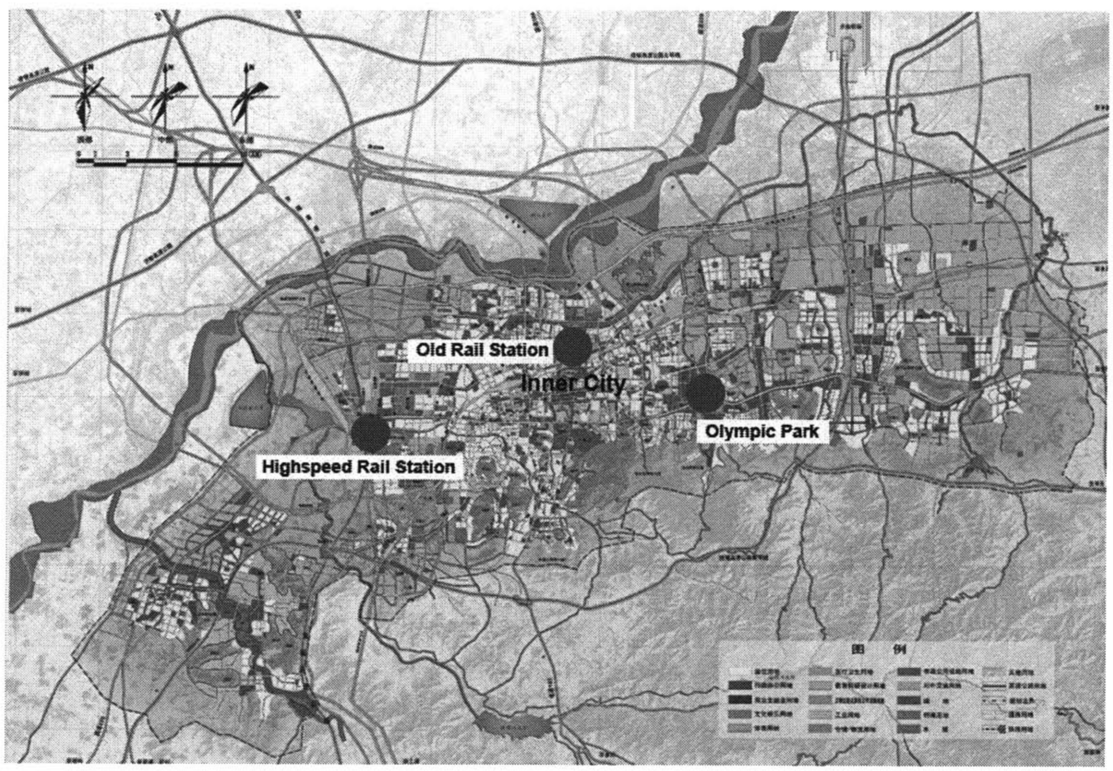
Jinan has been experiencing rapid urbanization and urban growth since the 1980s, a trend likely to continue for decades. In 1986, the city built-area in Jinan was only 117 square kilometers; by the end of year 2007, the total urban area has expanded to 295 square kilometers (Statistics Bureau of Shandong Province, 2007). According to the recent city master plan, the city's built-up area is projected to expand to 410 square kilometers by 2020, mainly towards the east (the Olympic park and administration district) and the west (the high-speed rail station area) (see Figure 4-2); an additional 1 million people are expected to move into the Jinan city area during the next decade (Jinan Urban Planning Bureau, 2005).

Figure 4-1 Jinan City in Shandong, China



Source: (left) Adapted from (Warriortours.com, 2010)

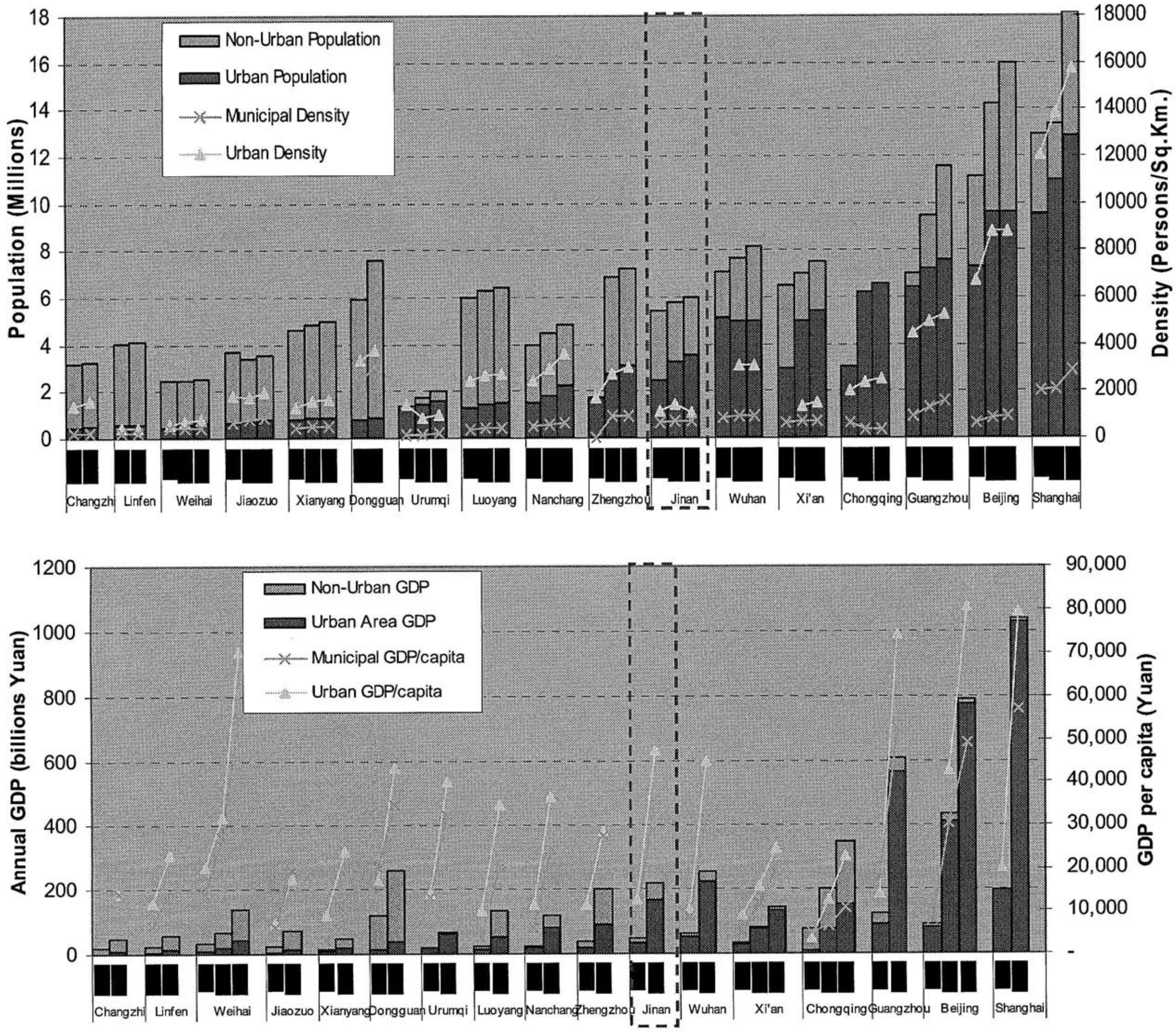
Figure 4-2 Jinan Master Plan 2005-2020



Source: Adapted from (Jinan Urban Planning Bureau, 2005)

Compared to other Chinese cities, Jinan is a typical medium-sized city with a much smaller urban population and a much lower GDP than Beijing, Guangzhou, and Shanghai, while it is similar to a bunch of medium cities such as Wuhan, Xi'an, Nanchang, Zhengzhou, etc. The urban density in Jinan is also much lower than that of all tier 1 cities and even some tier 2 cities (see Figure 4-3).

Figure 4-3 Population and Economic Trends in Chinese Cities



Source: Darido, *et al.* (2009), p. 4

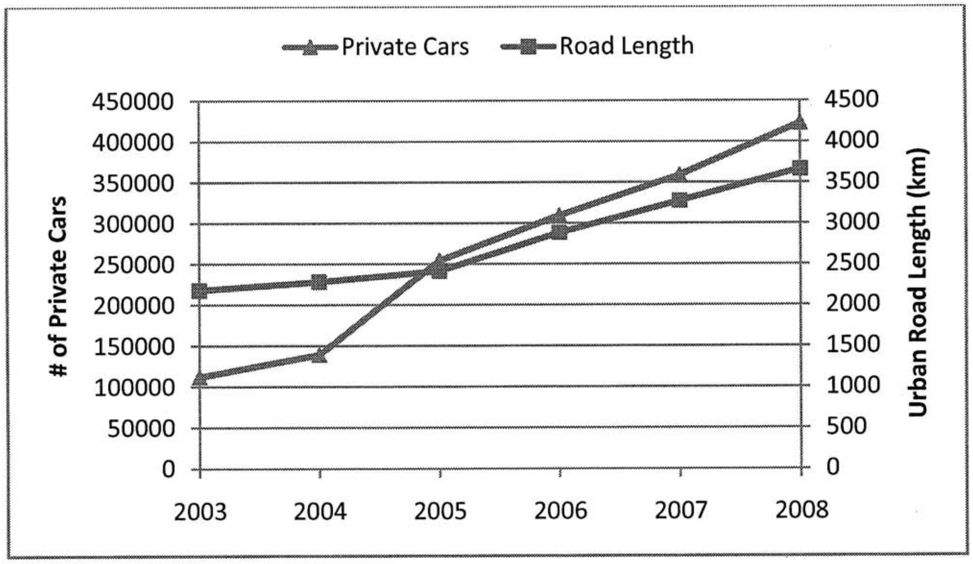
Although automobile ownership in Jinan is, again, lower than that in the largest Chinese cities (e.g., Beijing, Chongqing, etc.) and travel behavior changes have been less drastic (see Figure 4-4 and Figure 1-2), Jinan itself already suffers from serious congestion due to rocketing travel demand. Between 2005 and 2008, the average annual increase in the vehicle fleet in Jinan was about 16% (SDUTC, 2010). The local government's steady efforts in expanding the urban road infrastructure (mainly highways) in the past have failed to catch up with the even more rapidly expanding automobile population (see Figure 4-5 and Figure 4-6). Today, the average speed of vehicles operating on arterials in Jinan central areas is as low as 24.5 km/hr during peak-hours (SDUTC, 2010).

Figure 4-4 Car Ownership (Cars per 100 Households) across 36 Cities in China in 2006

Source: Li, et al. (2010), p. 8

Figure 4-5 Peak-Hour Congestion in Jinan

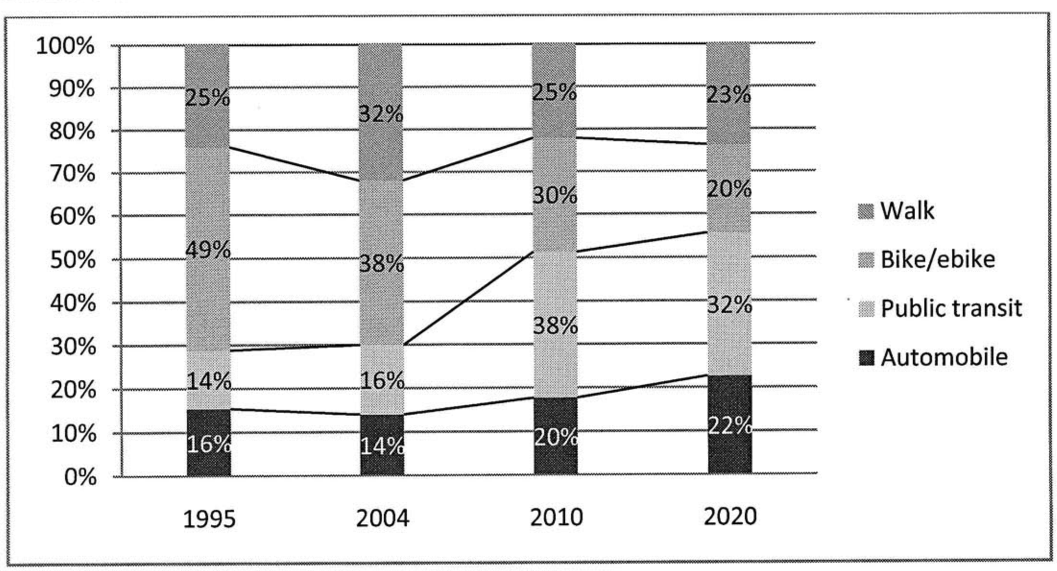
Figure 4-6 Private Car Population and Urban Road Length Trends in Jinan (2003-2008)



Source: (Jinan Statistics Bureau, 2009); urban road length in 2007 adjusted

To cope with this surge of urban travel demand and to help Jinan grow sustainably, the local government has recognized the important role of urban public transport. Aiming at establishing a "safe, efficient, ecological and diverse" urban transportation network, the city government has set a goal that in 2020: more than 95% of Jinan residents will spend less than 45 minutes per trip; more than 60% will travel less than 30 minutes per trip; and the transit mode share for trips will increase to 45% (SDUTC, 2010). Transit share is expected to rise considerably to slow down the increase of automobile uses (see Figure 4-7).

Figure 4-7 Jinan Measured and Forecasted Mode Shares 1995-2020

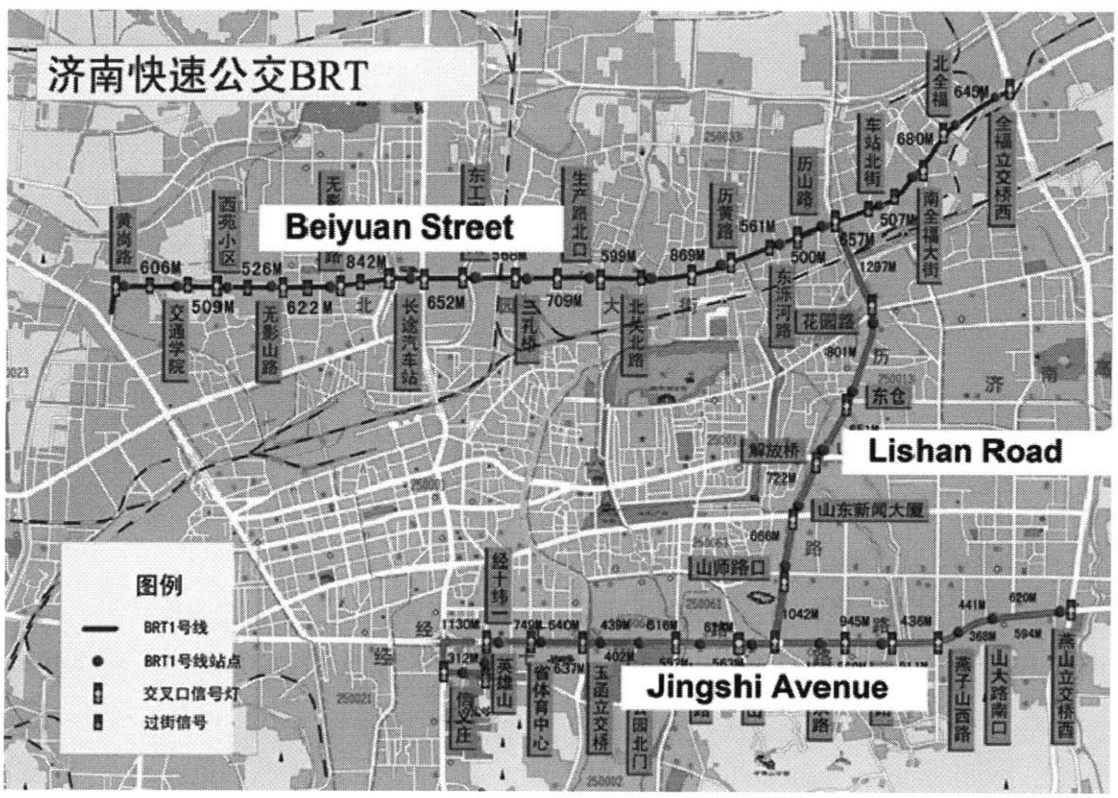


Source: Adapted from Montgomery, B. (2008), p.3

4.2 BRT Corridor Development in Jinan

One important strategy Jinan has embraced to achieve its transportation goals is to build a comprehensive bus rapid transit (BRT) system. In 2005, the city began planning the system and the Chinese central government then named it a "BRT Demonstration City". As of summer 2009, BRT lines on three corridors –the Jingshi Avenue, the Beiyuan Street, and the Lishan Road- were already in operation (see Figure 4-8 and Figure 4-9). It is planned that by the end of 2015, Jinan will have a complete BRT network with a length over 120 kilometers (SDUTC, 2010), as shown in Figure 4-10. The BRT corridor development generates clear policy relevance for this thesis, as we aim to examine whether households living next to BRT corridors consume less transportation energy and to better understand the types of neighborhood forms that should be encouraged when integrating urban development with BRT system expansion in future Jinan.

Figure 4-8 Jinan BRT Corridor Map (as of August, 2009)



Source: Adapted from local BRT maps provided by Ms. Wu Min at the Jinan Bus Company in 2009

Figure 4-9 Jinan BRT Corridor Photos

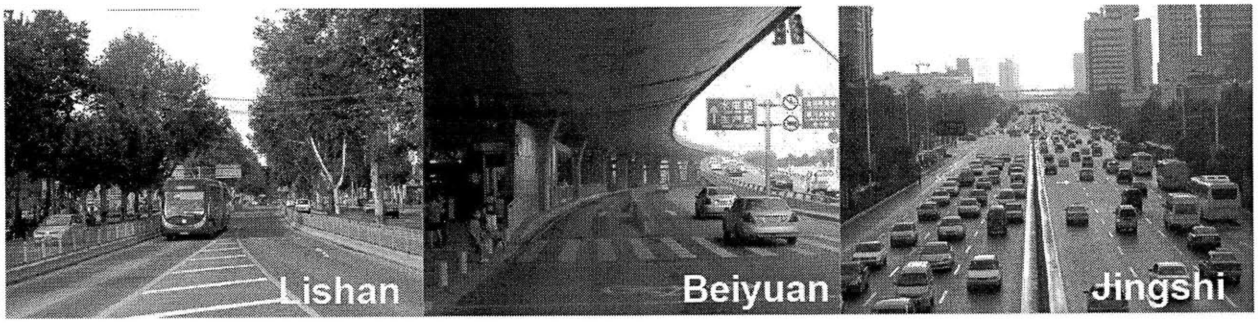
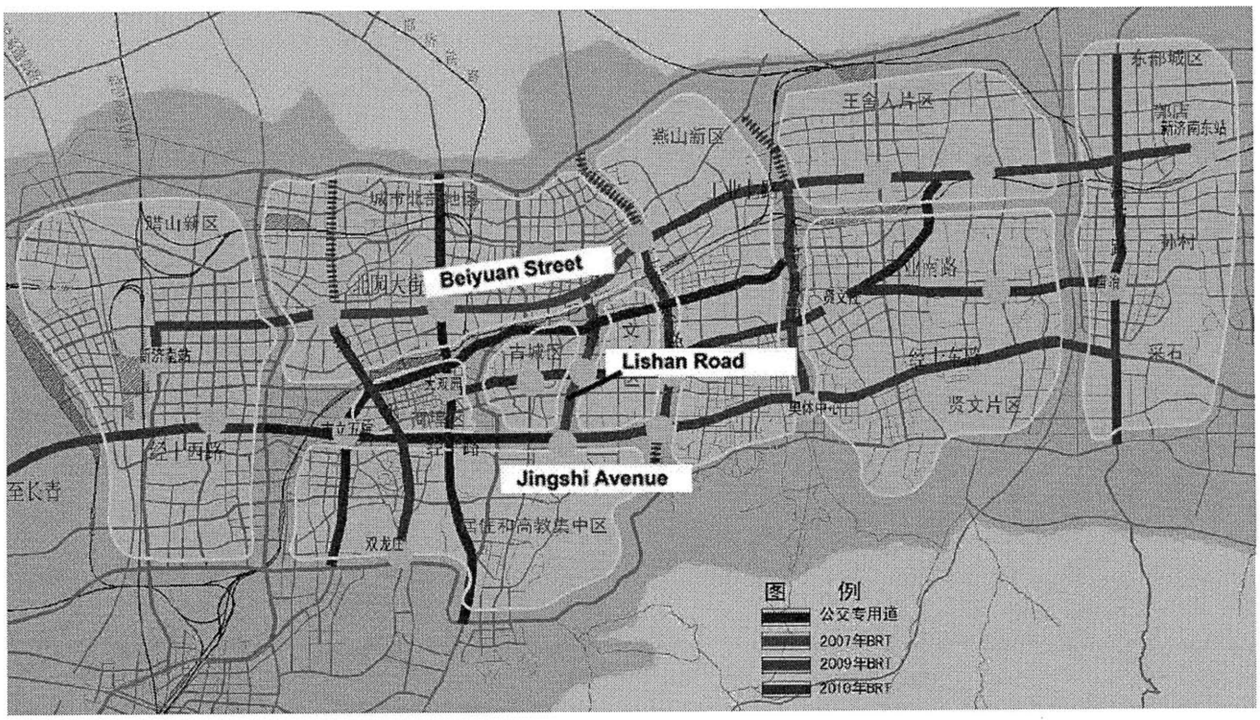


Figure 4-10 BRT Network Plan 2015



Source: Adapted from SDUTC (2010) p. 14

4.3 Neighborhood Typologies in Jinan

At the neighborhood development scale, the city of Jinan -with a long history of evolution- presents a variety of urban forms. Four main neighborhood typologies were identified through discussion with local public officials, urban planners and designers: "traditional", "grid", "enclave", and "superblock." Respectively, they represent characteristics of the local city development during different historic periods in a rough time sequence. A summary of the form features associated with each typology is shown in Table 4-1.

Table 4-1 Summary of Form Features across 4 Main Neighborhood Typologies

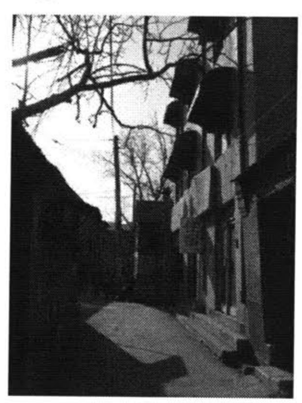
Typology	Building/Street/Function	Access/Parking
Traditional	1-3 story courtyards; fractal /dendritic fabric off a main shopping street, on-site employment	no cars
Grid (1920s)	Block structure with different building forms contained within each block, retail on connecting streets	Easy access; cars on-street; some parking lots
Enclave (1980-1990s)	Linear mid-rise walk-ups; housing integrated with communal facilities (kindergartens, clinic, restaurants, convenience shops, sports facilities, etc.)	Moderately gated (walls, fences and sometimes security guards at entries); Scarce on-courts parking lots
Superblocks (-2000s)	Towers in park with homogeneous residential use	Completely gated; sufficient parking lots (underground, surface, etc.)

Source: Derived in collaboration with partners in the Clean Energy City Project (see section 1.2) and local officials and planners.

4.3.1 The "Traditional"

The majority of "traditional" neighborhoods can be found in the inner city of Jinan. Some old villages of this type were also once developed at the edge of the inner city but now are surrounded by modern city development. This type of neighborhood is characterized by 1-3 story courtyards and narrow alleys. A main shopping street provides households with immediate access to local employment and service opportunities. Cars have little access into the neighborhood due to the narrow road space and complicated alley system. Almost no car parking spaces are provided (see Figure 4-11).

Figure 4-11 The "Traditional" Neighborhood Typology

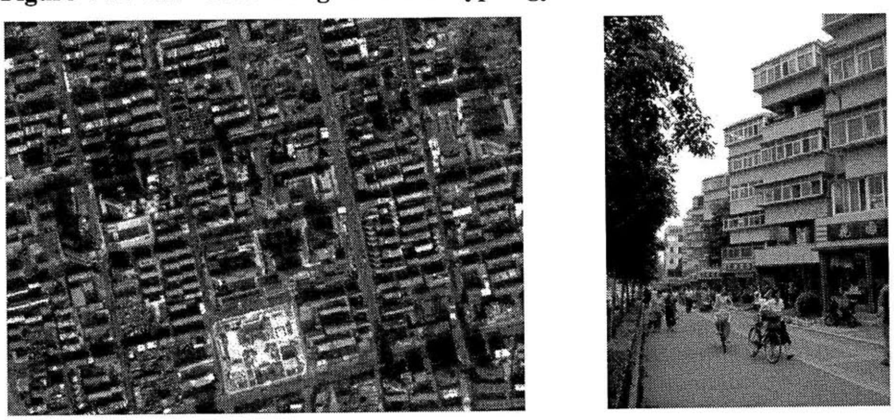


Source: (left) (Google Inc., 2009)

4.3.2 The "Grid"

The "grid" neighborhood typology was introduced in Jinan in the early 1920s. This typology shaped the old commercial district, which is located to the south of the Jinan railway station. The whole district is about 2 square kilometers with a length of 2.5 km and a width of 1km. The dimension of a typical block is about 160 meters by 160 meters (see Figure 4-12). Originally, the blocks were composed of traditional courtyards, but they have since evolved into more diverse building forms. As an old commercial district, jobs and housing supply are highly balanced in this area today. Another main feature of the grid neighborhood is its openness: public streets running between small blocks make the whole district very accessible. Retail development and large trees along connecting streets create a walking-friendly street space. Some on-surface parking lots exist in this district.

Figure 4-12 The "Grid" Neighborhood Typology



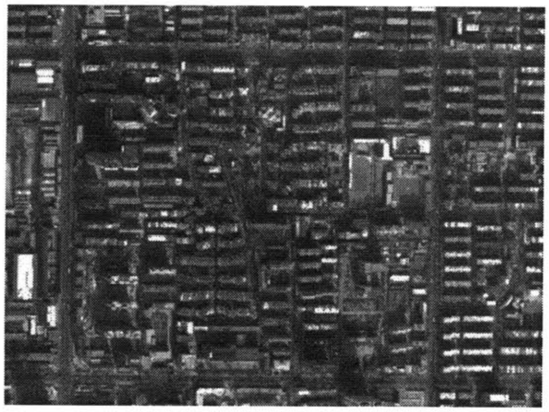
Source: (left) (Google Inc., 2009)

4.3.3 The "Enclave"

The "enclave" neighborhood form in Jinan (see Figure 4-13) originated in a national experiment of urban residential developments in the mid-1980s with the goal of achieving "high standards with relatively low cost, high quality with relatively low space standards, complete functions in small areas, and a pleasant environment despite limited land coverage" (Lü, *et al.*, 2001, p. 230). It is characterized by a north-south layout of buildings and an integration of housing units with communal facilities (e.g., kindergartens, clinics, restaurants, convenience shops, sports facilities, etc.). Jobs and housing are not necessarily matched in neighborhoods of this type today because 1) they were often built by municipal governments rather than a single work unit; and 2) housing units have been allowed for transaction on the real estate market

(Bray, 2006). Internal local roads within the neighborhood provide a safe outdoor space for people. Sometimes, roads have bends and turns, similar to "traffic calming" measures used in the west. Dead-end roads are often found within building clusters, to exclude through traffic. In some cases there is even a separation between pedestrian flows and vehicle flows in the road network. In terms of parking facilities, while the "enclave" provides plenty of bike storage space, very limited car parking spaces exist (Lü, *et al.*, 2001).

Figure 4-13 The "Enclave" Neighborhood Typology



Source: (left) (Google Inc., 2009)

4.3.4 The "Superblock"

As China entered the 1990s, a more formal housing market emerged and, at the same time, the "superblock" neighborhoods started to dominate the country's urban growth pattern (Cervero & Day, 2008; Monson, 2008). Jinan is no exception. Neighborhood of this type are usually entirely composed of housing units (i.e., with little mixed use) and completely enclosed by walls or fences, with only a few entrances. Such a physical setting combined with security and monitoring measures at access points, especially in the more affluent "superblock" neighborhoods, often creates significant isolation between the neighborhood and its surrounding urban space (Bray, 2006; Wu, 2005). In addition, the "superblock" is characterized by high-rise buildings, considerable landscaping, an auto-oriented internal road network, and ample parking for private motor vehicles (see Figure 4-14).

Figure 4-14 The "Superblock" Neighborhood Typology

Source: (left) (Google Inc., 2009)

4.4 Summary

The city of Jinan, China provides the context for the empirical research in this thesis. The city represents a typical mid-size city in China with a moderate-level of urban population and density, yet witnessing a trend of rapid urbanization, highway construction and motorization. Accompanying the rising travel demand, Jinan has been suffering from urban congestion, a situation shared by many other Chinese cities.

As one response, the local government in Jinan started to build a bus-rapid-transit system. As of summer 2009, there were 3 BRT corridors operating, with more corridors planned to eventually constitute a comprehensive BRT network. Recently, the city government has announced intentions to integrate ongoing BRT system construction with land development -i.e., TOD. This gives this research immediate policy relevance.

At the neighborhood development scale, the long history of Jinan's evolution endows the city today with a variety of neighborhood forms, including "traditional", "grid", "enclave", and "superblock". The first three typologies were shaped in older times, with relatively small blocks, mixed land uses, refined local pedestrian networks, and limited parking space. Today, neighborhoods of those types are experiencing deterioration, and some have even been destroyed to be replaced by the "superblock" typology, which is much more auto-oriented and characterized by homogenous residential use, low permeability and ample parking provision. Is this trend sustainable from an energy perspective? The empirical research in this thesis aims to shed light on answers to this question, again, signifying important policy relevance.

5 RESEARCH DESIGN

This chapter introduces the research design and methodologies employed for the empirical analysis of the relationship between neighborhood features and household transportation energy consumption in Jinan, China. An adequate research design poses an important challenge in this context. Recall from Chapter 2 that few relevant research precedents exist in China, and research examples from the West illuminate a number of challenges remaining among the variety of existing analytical approaches. Therefore, the development of an appropriate research design for Jinan needs to be both creative (building upon tools and lessons learned from the west) and realistic (based on the inevitable constraints in the local context).

Section 5.1 describes decisions involved in the neighborhood sample selection process. Section 5.2 introduces neighborhood measures obtained from visual surveys of the neighborhoods and from geo-coded information on neighborhood form. Section 5.3 describes the household-related measures from the household survey carried out by Shandong University. Section 5.4 describes how transport energy consumption and GHG emission measures are derived from the household travel activity data reported in the survey. Section 5.5 shows the full database structure at the end of data preparation. Section 5.6 discusses analytical approaches, both how they are chosen and how they are conducted. Finally, section 5.7 provides a summary.

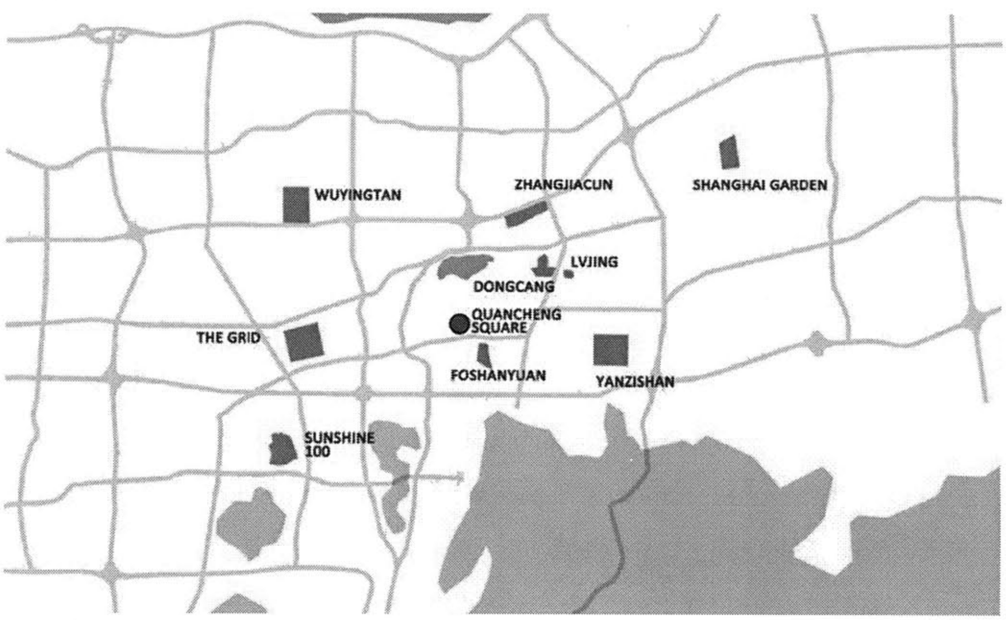
5.1 Neighborhood Sample Selection

Although it would perhaps have been ideal to carry out a detailed urban form and design analysis of all neighborhoods in Jinan for the purpose of completely identifying the variety of urban forms and their representative typologies, such an approach proved infeasible due to the lack of neighborhood form information available, particularly in geo-coded electronic form. To address this data problem, nine neighborhoods in Jinan were first identified in a collaborative process involving faculty from Shandong University, Tsinghua University and MIT, as well as officials from the Jinan Urban Planning Bureau. The purpose was to select a number of neighborhoods representative of the main four neighborhood typologies described in section 4.3, and with a variety of locational characteristics regarding their proximity to BRT corridors and the distance to the city center. The nine neighborhoods chosen include: Dong-Cang (Enclave), Wuying-Tan (Enclave), Fo-Shanyuan (Enclave), Yanzi-Shan (Enclave), Lv-Jing (Superblock), Sunshine-100 (Superblock), Shanghai-Garden (Superblock), Old Commercial Distract (Grid), and Zhang-Village (Traditional). As can be seen in Table 5-1, beyond the typology differences, the selected neighborhoods also offer relevant locational variations (in terms of BRT and center city proximities). Figure 5-1 illustrates the location of the 9 neighborhoods in Jinan.

Table 5-1 Neighborhoods' Variation by Typology and Location with Population Estimates

Typology	Neighborhood Case	On BRT Corridor	Distance to City Center	Population Estimate
Traditional	1. Zhang-Village	Yes	3.0km	11,100
Grid	2. Old Commercial District	No	3.6km	11,700
Enclave	3. Wuying-Tan	Yes	4.6 km	16,100
	4. Yanzi-Sshan	No	3.5 km	21,000
	5. Dong-Cang	Yes	2.3 km	5,600
	6. Foshan-Yuan	No	0.8 km	5,300
Superblock	7. Shanghai-Garden	No	7.3 km	6,400
	8. Sunshine-100	No	4.8 km	19,000
	9. Lv-Jing	Yes	2.8 km	2,500

Figure 5-1 Neighborhood Case Locations



Source: Provided by School of Architecture, Tsinghua University

5.2 Measures of Neighborhood Form

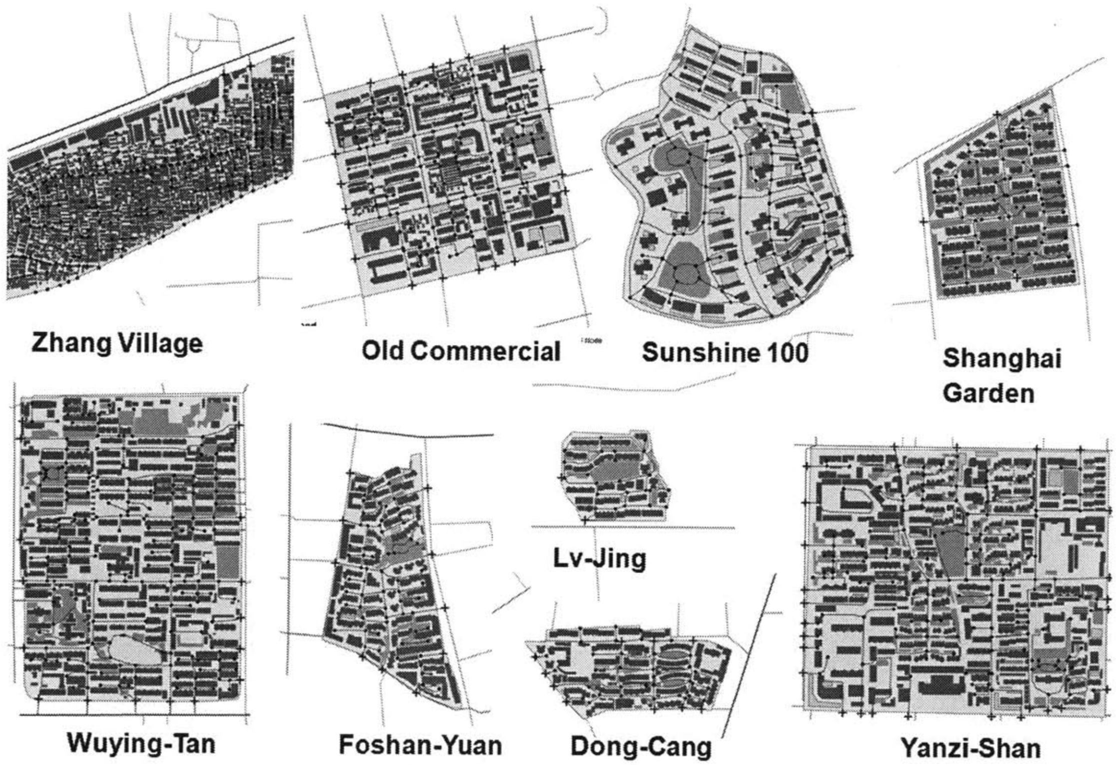
A geographic information system (GIS) database of the nine neighborhoods was developed by a technical team from Beijing Normal University. The team first procured a high-resolution aerial photo of the Jinan urban area, used the aerial imagery to identify relevant 2-dimensional information (e.g., building profile, road, open space, trees, etc.) of the nine neighborhoods, and further geo-coded the information in a GIS platform. Second, in summer 2009 the team carried out a visual survey of all nine neighborhoods to validate existing data and to collect additional physical data (e.g., building height, parking spaces, building functions, land uses, gates, bus stops, catchment area[4] land use, etc.) that could not be extracted from the aerial photo. Information obtained from the visual survey was then, again, geo-coded into GIS as well as an AutoCAD database, as shown in Figure 5-2 and Figure 5-3.

Based on these "raw" neighborhood form data, a series of form measures for each of the nine neighborhoods were calculated using the GIS software[5]. Table 5-2 presents those neighborhood form variables, their definitions, and further notes.

[4] In general, catchment area refers to an area within walking distance from the neighborhood in the context of this research.

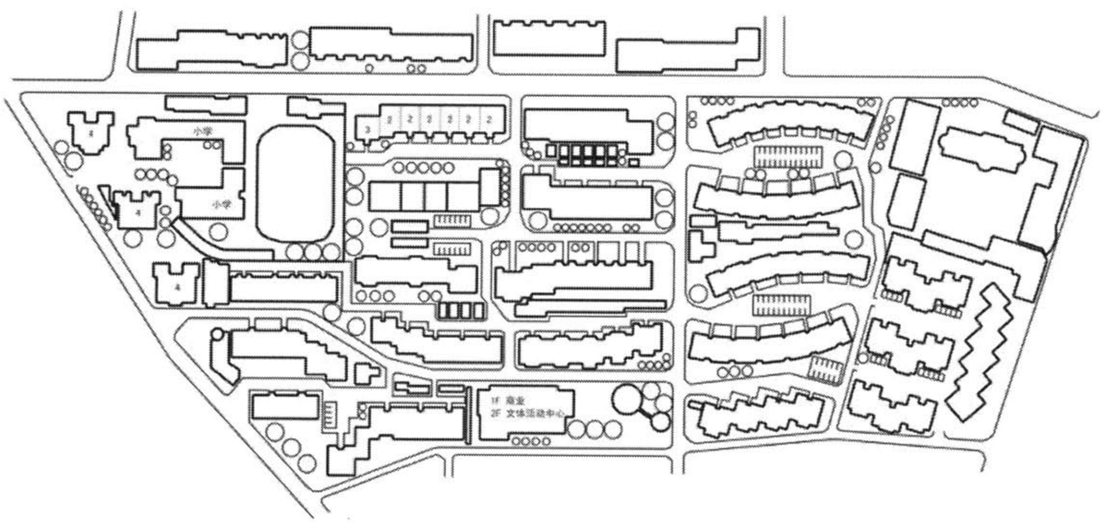
[5] I thank Ms. Chen, Yang, a PhD student at MIT, for her assistance with the GIS analysis.

Figure 5-2 GIS Maps of the Selected Nine Neighborhoods in Jinan



Source: Produced using the GIS dataset created by the School of Geography and Remote Sensing, Beijing Normal University

Figure 5-3 Layout of Dong-Cang Neighborhood (the "Enclave" Type)



Source: Produced using the AutoCad dataset created by the School of Geography and Remote Sensing, Beijing Normal University

Table 5-2 Neighborhood Measures in the Study

Measure	Definition	Note
Density Measures		
Population Density	Number of persons per square kilometer	
Floor Area Ratio (F.A.R)	The ratio of total floor area of buildings in the neighborhood to the size of the neighborhood land	
Building Coverage	Percentage of building footprint area to the neighborhood land area	
Average Building Height	Average number of building floors in the neighborhood	
Diversity Measures		
Land Use Mix	$MIX = 1 - (\left\|\frac{r}{T} - \frac{1}{5}\right\| + \left\|\frac{c}{T} - \frac{1}{5}\right\| + \left\|\frac{i}{T} - \frac{1}{5}\right\| + \left\|\frac{a}{T} - \frac{1}{5}\right\| + \left\|\frac{o}{T} - \frac{1}{5}\right\|) \cdot \frac{5}{8}$ where r= square meters of residential floor space (or land area) c= square meters of commercial/business/office floor space (or land area) i= square meters of industrial floor space (or land area) a= square meters of administrative/institutional floor space (or land area) o= square meters of open-space/recreational floor space (or land area) T= r + c + i + a + o	A value of 0 for this index means that building floor space (or land area) in the neighborhood has a single use and a value of 1 indicates perfect mixing among the five uses. Adapted from Rajamani, *et al.* (2003)
Building Function Mix	Same as above	
Built-up Land Use Mix	Same as above, except that land of open space is excluded in the indicator calculation	
Building Height Mix	Standard deviation of building height in the neighborhood	
Design		
Land Area	Hectares of neighborhood land	
Green Coverage	Green area as a percentage of neighborhood land area	Green area includes the area of lawns and tree canopy
Walkability Indicator 1	Percentage of residential building with street-level shops	
Parking Availability	Square meter parking space per household	Only designated parking lots are counted
Walkability Indicator 2	Percentage of Roads with Trees	
Walkability Indicator 3	Percentage of Roads with Walking Facilities	Walking facilities include roads with sidewalk, and pedestrian paths
Intersection Density	Number of intersections per kilometer-long roads	Intersections include 3-way and 4-way intersections
Gated/ Isolation Indicator	Average distance between neighborhood entry intervals	
Street Connectivity Indicator	Ratio of the number of cul-de-sacs to the total number of intersections	
Road Density	Road space as a percentage of neighborhood land area	
Regional Location Measures		
Distance to the City Center	Distance from the neighborhood centroid to Jinan spring city plaza	
BRT Corridor Proximity	A dummy variable taking a value of 1 if the neighborhood is within 200 meters' walk to the BRT corridor; and 0 otherwise	
500m Catchment land use mix	The land use mix within neighborhood catchment area	Catchment as a number of 500m radius buffer areas around neighborhood gates outside the neighborhood boundary
Transit availability indicator	Number of bus stops within 1km of the neighborhood boundary	

5.3 Household Survey Data

Parallel to the visual survey activities, in summer 2009 a team from Shandong University carried out a household questionnaire survey, using the nine identified neighborhoods as the sampling frame[6]. Households were selected, without replacement, using stratified random sampling based on building volumes within the neighborhoods. Eligible respondents were adults, aged 20 to 65, who resided in private dwellings such as houses or apartments. Respondents were interviewed at home by surveyors in all neighborhoods except for the Lv-Jing neighborhood. In Lv-Jing, face-to-face interviews had to be conducted at the gates due to tight security control; therefore passing households were randomly selected and surveyed[7]. A total of 2,629 eligible participants from the 9 neighborhoods filled out the survey questionnaires; about 2,500 of them provided generally complete information. The questionnaire was designed to collect data on both household travel and in-house energy expenditures; here we describe information relevant to the travel analysis only.

5.3.1 Measures of Travel Activity

At the beginning of the survey, participants were asked to provide a detailed travel diary of each family member during the past full week (including weekends). Specific travel-related information requested included:

- Trip purpose: work, school, shopping, hospital, visit, entertainment, other;
- Number of trips made for each purpose per week: a one-way trip counts as one trip; a round trip counts as two trips;
- Average trip distance for each purpose (in km);
- Mode of transport associated with trip distance: options include car, company car, bus, company shuttle, taxi, motorcycle, e-bike, bicycle, walking; and
- Trip duration associated with trip distance (in minutes).

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[6] The Survey was carried out by students and faculty from Shandong University under the guidance of Asst. Prof. Zhang Ruhua. The following description of the survey approach was provided to me by Ms. Zuo Weiwei from Shandong. I owe a deep debt of gratitude to Asst. Prof. Zhang and his colleagues for allowing access to and use of the survey for the research carried out in this thesis

[7] This part of sample selected may still be biased towards households with more non-motorized-travel (NMT) dominated travel patterns.

5.3.2 Measures of Socio-Demographics and Vehicle Ownership

The survey also collected information on household socioeconomics, demographics, and vehicle ownership; specifically:

- Family size: the number of persons in the household;
- Number of employees: the number of employed persons in the household;
- Family structure, e.g.: single, couple, couple with kid, parents with married children, grandparents and kid; and three generations;
- Gender (for each family member);
- Age (for each family member): age range options include <20, 20-30, 30-40, 40-50, 50-60, >60;
- Occupation (of each family member): options include teacher, student, worker, government official, company employee, small business, peasant, unemployed, retired, and other;
- Monthly income (of each family member): income range options include <600, 600~1000, 1000~2000, 2000~5000, 5000~10000, >10000 in RMB[8];
- Housing tenure type: rented, owned outright, and owned with a mortgage;
- Vehicle ownership: number of cars, number of motorcycles, number of E-bikes, number of bikes.

5.3.3 Measures of Household Attitudes

At the end of the survey, respondents were asked to rate a number of statements based on the level of agreement, on a scale of 1 to 5 (1 = strongly disagree, 3 = neutral, 5 = strongly agree). Relevant statements in our study include:

- "Car is a sign of prestige."
- "Taking public transit is convenient."
- "I enjoy bicycling."
- "Time spent in traveling is a waste of time."

[8] 1 US$= 6.8 RMB, approximately, as of May 18, 2010

5.4 Household Transport Energy Use and Emission Data

5.4.1 Measure of Household Transport Energy Use Measure

Using the reported weekly travel diary data, I calculated the estimated weekly transportation energy consumption of each household in our sample. As discussed in Chapter 2, the weekly scope is important to capture relevant activities over a longer time period than a day or two. The household focus is important because a household, in aggregate, ultimately occupies a residential unit, so the energy consumption of all relevant members should be accounted for; furthermore, some travel decisions (especially for non-work trips) are made by more than one member of the family and vehicles are often shared by household members.

Specifically, we summed up the household weekly travel distance by each mode, adjusted for trip-based occupancy. Then, the distances by mode were converted into energy consumption by using the mode's energy intensity. The energy intensity comes from vehicle fuel economy and the fuel energy content factor. In equation form:

$$\mathrm{E^T}_\mathrm{i} = \textstyle\sum_\mathrm{m} \mathrm{E_i^m},\ \mathrm{m} \in \{\mathrm{car, taxi,\ bus,\ motorcycle,\ ebike}\} \quad (1)$$

$$\mathrm{E_i^m} = \textstyle\sum_\mathrm{j}\sum_\mathrm{k}\left(\mathrm{FR^m_{i,j,k}} * \frac{\mathrm{TD^m_{i,j,k}}}{\mathrm{OC^m_{i,j,k}}}\right) * \mathrm{EI^m} \quad (2)$$

$$\mathrm{EI^m} = \mathrm{FU^m} * \mathrm{EC^m} \quad (3)$$

where

$\mathrm{E^T}_\mathrm{i}$= Total household weekly transport energy consumption, by household *i*, in mega joules per household per week (MJ/ HH/ Week)

$\mathrm{E_i^m}$= Weekly household transport energy consumption, by household *i* using mode *m*, in mega joules per household per week (MJ/ HH/ Week)

$\mathrm{FR^m_{i,j,k}}$= Trip frequency (Trips/ Week), by mode *m*, for purpose *k*, by person *j* in household *i*

$\mathrm{TD^m_{i,j,k}}$= Average travel distance per trip (Km/Trip), by mode *m*, for purpose *k*, made by person *j* in household *i*

$\mathrm{OC^m_{i,j,k}}$= Trip occupancy, by mode *m* for purpose *k*, by person *j* in household *i*

$\mathrm{EI^m}$= Energy intensity factor for mode *m* (MJ/ km)

$\mathrm{FU^m}$= Fuel economy factor (L/km; kwh/km) associated with mode *m*

$\mathrm{EC^m}$= Energy content factor (MJ/L) of the fuel type consumed by mode *m*

Occupancy rates of automobile, taxi, motorcycle and e-bike can be associated with each trip, and thus were estimated using reported person trip data from the survey. Specifically, person trips with exactly the same reported purpose, length and time among two or more household members were treated as one trip shared by all. For transit, the system-wide occupancy rate was estimated at 18 persons per bus based on reported system operation performance data in 2007[9].

Table 5-3 presents the average fuel consumption and energy consumption data used in the analysis, with the estimation process described in the footnotes.

Table 5-3 Fuel Economy, Fuel Energy Content and Energy Intensity Assumptions

Mode (m)	Fuel Economy (FU^m)	×	Fuel Energy Content (EC^m)	Energy Intensity Factor (EI^m)
Car	0.092L/km[a]		32.2 MJ/L[f]	2.962 MJ/km
Taxi	0.083L/km[b]		32.2 MJ/L[f]	2.673 MJ/km
Bus	0.3L/km[c]		35.6 MJ/L[f]	10.680 MJ/km
Motorcycle	0.019L/km[d]		32.2 MJ/L[f]	0.612 MJ/km
E-bike	0.021kwh/km[e]		--	0.076 MJ/km

Notes:

a. derived from (National Bureau of Statistics, 2008). I used on average fuel economy of existing automobile engine types in China weighted by their nationwide market composition. Specifically, fuel economies of existing automobile engine types (with the market share) are: 6.5L/100km (4.96%), 8.3L/100km (53.69%), 10.2L/100km (32.09%), 11.9L/100km (8.65%), 13.9L/100km (0.62%).

b. I used on average fuel economy of seven taxi vehicle types in Jinan, including: JETTA (6.7L/100km), SANTANA (7L/100km), SANTANA2000 (8L/100km), FUKANG (8.3L/100km), PASSAT(9L/100km), BUICK(11L/100km). This information was provided by Mr. Liu Kai from Tsinghua Univeristy based on his interview with officials from the Jinan Transportation Bureau.

c. (Zheng & Chen, 2008)

d. derived from (National Bureau of Statistics, 2008). Again, I used on average fuel economy of motorcycles in China and weighted by vehicle fleet composition. The market shares of motorcycles with fuel consumption rates of 0.8L/100km (special light duty type; 15%), 1.3L/100km (light duty type; 30%), 2.2L/100km (engine-90 type; 40%), 3.3L/100km (engine-125 type; 15%).

e. (Cherry, *et al.*, 2009a)

f. (MIT Energy Club, 2009) assuming all cars, motorcycles and taxis use gasoline, and all buses use diesel.

The energy consumption estimation described above only considers the direct fuel or electricity-associated energy use; up-stream energy is currently not included (e.g., energy required to refine and distribute gasoline or generate and transmit electricity), nor is the full life-cycle energy embodied in the vehicles. Also, I do not include the energy consumption (e.g., calories) associated with walking or bicycling, nor the associated energy embodied in relevant

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[9] Indicators for the Jinan transit operation performance in 2007 were used for the occupancy estimation, including: operating distance as 160000000 km per year; daily passenger volume as 1930000 passenger-trips per day; average trip length as 4.04 km per passenger-trip (SDUTC, 2008). The occupancy rate is calculated by: (930000 × 365 × 4.04 /160000000) = 18 passengers per bus.

equipment, such as footwear and bicycles (likely negligible in any case, compared to the embodied energy in other forms of transport). Finally, the speed and traffic condition effects on the energy efficiency of vehicle operations are not reflected in the current estimation.

5.4.2 Measure of Household Transport GHG Emissions

Although the household transport energy use is our main focus of this thesis, it will be very interesting to know corresponding GHG emissions and compare the patterns of the two. To estimate household transport GHG emissions, I followed equations (1), (2) and (3) for calculating transport energy use, except I replaced mode specific energy intensity factors ($\mathrm{EI^m}$) in those equations with mode specific GHG emission factors ($\mathrm{EF^m}$) measured in $kgCO_2/km$, and

$$\mathrm{EF^m} = \mathrm{FU^m} * \mathrm{CC^m} \tag{4}$$

where:
$\mathrm{FU^m}$= Fuel economy factor (L/km; kwh/km) associated with mode m
$\mathrm{CC^m}$= GHG content factor ($kgCO_2/L$; $kgCO_2/kwh$) of the fuel consumed in mode m

Table 5-4 presents the average fuel consumption and GHG emission data used in the analysis.

Table 5-4 Fuel Economy, Fuel Carbon Content and GHG Emission Factor Assumptions

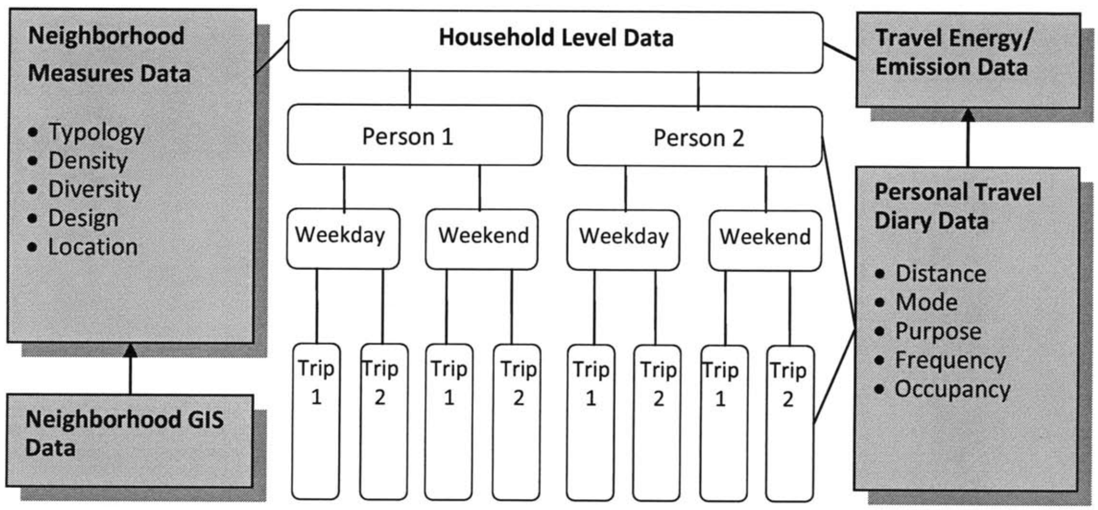
Mode (m)	Fuel Economy (FU^m)	×	GHG Content Factor (CC^m)	GHG Emission Factor (EF^m)
Car	0.092L/km		2.165 $kgCO_2/L$[a]	0.199 $kgCO_2/km$
Taxi	0.083L/km		2.165 $kgCO_2/L$[a]	0.180 $kgCO_2/km$
Bus	0.3L/km		2.470 $kgCO_2/L$[a]	0.741 $kgCO_2/km$
Motorcycle	0.019L/km		2.165 $kgCO_2/L$[a]	0.041 $kgCO_2/km$
E-bike	--		--	0.026 $kgCO_2/km$[b]

Notes:
a. (MIT Energy Club, 2009) assuming all cars, motorcycles and taxis use gasoline, and all buses use diesel.
b. (Cherry, *et al.*, 2009a)

5.5 Database Structure

Figure 5-4 shows the structure of the fully constructed database, based on the data described in the previous sections, and including the links between the neighborhood data, the household data and the estimated energy consumption data.

Figure 5-4 Framework for Database Construction



Source: Inspired by Frank, *et al.* (2000), p.184

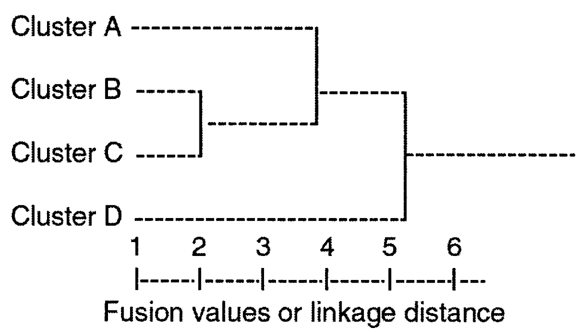
5.6 Analytical Procedures and Models

5.6.1 Descriptive Analysis

Descriptive analysis based on empirical data serves three main purposes: 1) better understanding the neighborhood forms in Jinan, China; 2) depicting the picture of household travel pattern and associated energy use and emissions, and to see whether and how those patterns differ across neighborhood typologies; and 3) identifying potential confounding factors that are also related to household transport energy use.

For task 1), I performed cluster analysis on the 9 neighborhoods using measured urban form indicators (see Table 5-2) to test whether the *a priori* categorization of the Jinan neighborhoods into four hypothesized neighborhood typologies was appropriate or not. Specifically, I ran a hierarchical cluster analysis[10] in the Statistical Package for the Social Sciences (SPSS) software, which calculates "distances" between data points of our form indicators, and produces a hierarchical tree diagram (dendrogram) to visualize how the neighborhood cases are distinct to each other at the integrated level (see Figure 5-5). Further, I compared those form indicators (i.e., individual elements constituting a typology) across the four neighborhood typologies to explore the major source of their distinction (if it exists). Household attributes were also compared to see how neighborhood typologies differed from a social perspective.

Figure 5-5 A Hierarchical Tree Diagram



Source: Burns & Burns (2008); p.555

For task 2), I compared means of travel pattern indicators (e.g., distance, frequency, mode share, time, etc.) and associated transport energy use and emissions in our sample. For household transport energy use, I also explored their distributions and used single-factor ANOVA analysis to test the significance of the difference in on average energy use across the four neighborhood types after controlling for the heterogeneity of energy use within each type.

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[10] Hierarchical cluster analysis a major statistical tool for identifying relatively homogeneous clusters of cases based on measured characteristics. It starts with each case as a separate cluster, and combines the clusters (in our case, the nine neighborhoods) sequentially, reducing the number of clusters at each step until only one cluster is left. For details, see (Burns & Burns, 2008; Romesburg, 2004).

For task 3), I plotted a number of interrelationships between household transport energy use/GHG emissions and socioeconomic demographics or neighborhood characteristics. Results provided insights for the next-step multivariate statistical model specification.

5.6.2 Multivariate Analysis: Base Regression Models

The basic multivariate regression analysis regresses household weekly travel energy consumption on variables including neighborhood form measures and the disaggregate household-level data. Based on the theoretical discussions and framework developed in Chapter 3, we can translate the main short-term relationships among energy consumption, neighborhood variables and other relevant factors into a series of equations, as shown below:

$$\mathbf{E^T} = \mathbf{f(T)} = \mathbf{f(\Delta B; y, V)} \tag{5}$$

$$\Delta \mathrm{B} = \mathrm{B} - \mathrm{C} = \mathrm{f}(\mathbf{N}, \mathbf{D}; \mathbf{S}, \mathbf{A}) \tag{6}$$

$$\mathrm{y} = \mathrm{f}(\mathbf{S}) \tag{7}$$

where

E^T =household weekly total travel energy consumption
T= household weekly travel activity pattern
ΔB = the net utility associated with a certain weekly travel pattern
y = household travel budget
B = the utility sum derived at destinations associated with a certain weekly travel pattern
C = the disutility sum (time, $, discomfort) associated with a certain weekly travel pattern
S = a vector of socio-demographic variables
V = a vector of vehicle ownership variables
N = a vector of neighborhood form and location characteristics, and
D = a vector of fixed destination form and location characteristics, and
A = a vector of household attitudes towards trip modes

In equation (5), travel energy use derives from the household travel pattern, and the travel pattern is determined by a household maximizing net utility (ΔB) among a set of travel pattern choices under the constraint of the household travel budget (y) and vehicle availability (V). Equation (6) indicates that the net utility is the benefit derived from activities at destinations (B) less the disutility (general cost) of the travel effort (C); both (B) and (C) can be influenced by the neighborhood characteristics (N), destination characteristics (D), household socioeconomics and demographics (S), plus household attitudes and preferences (A). Finally, equation (7) assumes that the household travel budget is mostly affected by household socioeconomics and demographics (S), such as income, family size and structure, etc..

To obtain a reduced form model, we assume that differences in net utility (ΔB) and variances in travel budget (y) can both be completely explained by differences in the neighborhood characteristics (N), fixed destination characteristics (D), household socioeconomics and demographics (S), and their attitudes and preferences (A). Therefore, equation (6) and (7) can be substituted into equation (5) to yield,

$$\mathrm{E}^{\mathrm{T}} = \mathrm{f}(\mathbf{N}, \mathbf{D}; \mathbf{S}, \mathbf{V}, \mathbf{A}) \tag{8}$$

Equation (8) offers a convenient model form for conducting regression analysis; the common specification would follow the linear ordinary least square (OLS) model with the form:

$$\mathrm{E^T}_{\mathrm{i}} = \beta_0 + \beta_1{}'\boldsymbol{N} + \beta_2{}'\boldsymbol{S} + \beta_3{}'\boldsymbol{V} + \beta_4{}'\boldsymbol{A} + \beta_5\boldsymbol{D} + \varepsilon_{\mathrm{i}} \tag{9}$$

However, there are three potential problems associated with this specification. First, equation (9) assumes a linear relationship between any explanatory variable and the energy consumption. This may not be true for many variables. For example, as income increases it may have a diminishing effect on travel energy use, due to, for example, households' travel time budget or spatial constraint. Therefore, log-transformation of some variables in the OLS model may be more appropriate.

A second problem with the OLS model may come from the distribution of household transportation energy consumption. In developed countries, we may expect a somewhat normal distribution because most households drive cars every week. In China, however, the majority of people still do not have access to automobiles. Some may even only walk and bike. Their energy consumption, as we have defined it here, would be zero. In the case of energy consumption, these cases are left censored at zero. There may be several reasons for this "censoring" at zero, which have important implications for the regression technique employed. For example, households who only walk and bike will record 0 values for transportation energy consumption. But, those zeros may be qualitatively different than a random zero (that is, the chance that the household made no motorized energy consumption travel on that particular week). In other words, those households may purposefully choose zero energy use and, in fact, would prefer to choose "negative" energy use. Given such an impossibility, the subsequent estimating of a OLS regression line to all the observations, including the zeroes may underestimate the actual relationship between the independent variables and energy use. The statistics literature refers to this as a censoring problem of the dependent variable.

In this context, a TOBIT model, first developed by Tobin (1958), seems to be an appealing solution. To address the censoring problem, the TOBIT model assumes that for each observation, there is a latent variable ${E^T}_i^*$, which linearly depends on a vector of independent variables $\mathbf{X_i}$with a normally distributed error term ε_i (Sigelman & Zeng, 1999):

$$ {E^T}_i^* = \beta' * \mathbf{X_i} + \varepsilon_i \qquad (10) $$

Under TOBIT, the observed variable E_i equals the latent variable whenever ${E^T}_i^*$ is greater than zero, and zero otherwise:

$$ {E^T}_i = \begin{cases} {E^T}_i^* & \text{if } {E^T}_i^* > 0 \\ 0 & \text{if } {E^T}_i^* \leq 0 \end{cases} \qquad (11) $$

A third problem is the now well-known "self-selection" problem, as we identified in Chapter 2. As we recall from Section 2.2.3, Section 3.1.4 and some literature (Mokhtarian & Cao, 2008; Zegras, 2010), common challenges to a single-stage, cross-sectional multivariate regression model attempting to assess the relationship between neighborhood form and travel behavior include:

1) The possibility of sample selection bias. This can exist when we only collect observations which can only be a subset of the full sample. For example, as we are interested in the energy consumption outcome, if we only observe energy-consumed households without having those who only walk and bike, our estimates from the regression analysis will be biased.
2) The possibility of endogeneity: This is a classic "self-selection" problem in the built environment-travel behavior literature, where variables, such as attitudes, were omitted in the multivariate regression analysis. In our case, this means people may

choose to live in the "superblocks" or buy cars, simply because (or at least simultaneously) they are addicted to an energy-intensive travel pattern (e.g., car prestige). Were not such effects excluded, we could have been biased in concluding a *causal* relationship between neighborhood features and travel energy use from modeling results.

To address the challenge 1), I randomly interviewed households in neighborhoods allowing for observations on non-energy-consumed samples, and included them in estimating my models.

For the challenge 2), in terms of the mostly concerned "attitude" effect, I attempt to address it in my models via statistical control. In other words, the attitudinal information collected in the household survey is included in the reduced form model as control variables. This is exactly the way socioeconomics and demographics are statistically controlled in the multivariate regression analysis. If the "self-selection" effect exists, attitude variables will be revealed significant and explain a good level of variance in dependent variable values in the sample. Presumably self-selection could also be dealt with through a neighborhood choice model if we had enough information to specify more advanced models (e.g., structural equations model) so as to further address the "simultaneouty" concern.

However, omitted variables other than attitudes may still exist and cause endogeneity. In the survey, we did not collect any information on household's major destinations. The reduced form regression models therefore can only take the form,

$$\mathrm{E}^{\mathrm{T}} = \beta_0 + \beta_1{}'\mathbf{S} + \beta_2{}'\mathbf{V} + \beta_3{}'\mathbf{N} + \beta_4{}'\mathbf{A} + \mu \qquad (12)$$

But according to my updated conceptual framework, fixed-destination characteristics (together with neighborhood characteristics) can influence travel costs and realization benefits. Although our household transport energy use measure is not trip-specific, such destination information is likely to be relevant. For example, if people work in downtown where parking costs are high, they might be less auto-dependent and use less energy. In this vein, if we would omit **D** when we run our regression in equation (12). The effect of this factor would therefore be absorbed by the error term and we would actually estimate,

$$E^T = \beta_0 + \beta_1'\mathbf{S} + \beta_2'\mathbf{V} + \beta_3'\mathbf{N} + \beta_4'\mathbf{A} + \varepsilon$$
$$(\text{where } \varepsilon = \beta_5\mathbf{D} + \mu) \quad (13)$$

Since correlation exists between **V** (vehicle ownership) and **D** (e.g., destination parking cost), and **D** also separately correlates with E^T, **V** is now correlated with the error term, μ. Both OLS and TOBIT models assume the error term is exogenous to all independent variables. In this case, this assumption no longer holds and the estimates will be biased and inefficient.

5.6.3 Multivariate Analysis: Advanced Two-Step Instrumental Models

To correct this problem, I adopt the instrumental variable modeling approach, following a two-step modeling procedure.

<u>Step 1: Logistic Regression Model for Household Vehicle Ownership</u>

In the first stage, we regress household vehicle ownership (**V**) on instrumental variables and save predicted values of V:

$$V = f(\boldsymbol{I}^*; \boldsymbol{S}, \boldsymbol{N}, \boldsymbol{A}) \quad (14)$$

where $\boldsymbol{I}^*$ is one or a vector of instrument variables. To be qualified as instrument variables, these variables must be 1) correlated with the vehicle ownership; and 2) uncorrelated with vehicle use or energy consumption (Mokhtarian & Cao, 2008). Otherwise, the variables would be weak instruments and the 2-step modeling technique would not help.

Since the vehicle ownership variables (**V**) are discrete variables (being 1 for households owning vehicles, and 0 otherwise), the binary logistic regression model (LOGIT) is the appropriate model type of the form:

$$\log\left(\frac{\Pr(V=1)}{\Pr(V=0)}\right) = \beta_0 + \beta_1'\boldsymbol{I}^* + \beta_2'\mathbf{S} + \beta_3'\mathbf{N} + \beta_4'\mathbf{A} + \delta \quad (15)$$

For the probability of ownership for a certain vehicle type,

$$\Pr\big(V = 1 | \boldsymbol{I}^*, \boldsymbol{S}, \boldsymbol{N}, \boldsymbol{A}\big) = \frac{\exp(\beta_0+\beta_1'\boldsymbol{I}^*+\beta_2'S+\beta_3'N+\beta_4'A)}{1+\exp(\beta_0+\beta_1'\boldsymbol{I}^*+\beta_2'S+\beta_3'N+\beta_4'A)} \quad (16)$$

The predicted vehicle ownership from the logistical regression will, by construction, be uncorrelated with other determinants of vehicle use and thus energy consumptions.

Step 2: Linear Regression Model for Household Weekly Travel Energy Use

In the second stage, the regression of interest is estimated as usual, except that in this stage vehicle ownership ($\mathbf{V}$) is replaced with the predicted ownership values ($\widehat{\mathbf{V}}$). Therefore, we regress E^T taking the form:

$$E^T = f(\widehat{\mathbf{V}}, \mathbf{N}; \mathbf{S}, \mathbf{A}) \tag{17}$$

where $\widehat{\mathbf{V}}$ is a vector of predicted vehicle ownership values from the first stage regression in equation (15) using calculation equation (16).

5.6.4 Multivariate Analysis: Sub Instrumental Models on Household Travel Distance by Mode

Finally, to further explore the detailed relationships between neighborhood characteristics and travel energy use, we may want to know how neighborhood characteristics directly affect travel by different modes. We may also want to know whether different modes are substitutes or complements. For this purpose, we can estimate travel distance for each mode (car, transit, motorcycle, E-bike, bike and walk) using the same approach as in Models 1 and 2. The only difference is that the dependent variables are changed to household weekly travel distance (by mode).

5.7 Summary

The research design described in this chapter aims to address both operational constraints in China and some of the methodological challenges identified in Chapter 2. While in the following chapters I will illustrate the application to the Jinan case, it can be generalized and transferred for research in other cities in China.

Since reliable and publicly-shared databases on urban form is currently rare in China, one realistic strategy we applied in Jinan is to select a limited number of neighborhoods -representing realistic ranges in possible urban forms- in the city for careful study. Researchers can build a raw database for those neighborhoods via GIS digitalization from aerial photos and by visual surveys. To obtain household data, those neighborhoods can then serve as the sampling frame for a stratified survey. Ideally, such a survey would include attitudinal information for statistical control in the modeling, so as to partly address the "self-selection" problem. Based on the travel data from the survey, energy consumption data can be derived from collected, using straightforward calculations and energy conversion factors.

After data cleaning, descriptive analysis, multivariate regression analysis, including using instrumental models provide a means to quantify the relationships between neighborhood types and energy use, as will be demonstrated in the following chapters.

6 DESCRIPTIVE ANALYSIS RESULTS

Following the research design and methodologies described in Chapter 5, this Chapter presents results and findings from the descriptive analysis, grouped into seven sections, including: neighborhood form (section 6.1), socioeconomic and demographics (section 6.2), vehicle ownership (section 6.3), attitudes (section 6.4), travel activity patterns (section 6.5), travel energy consumption patterns (section 6.6) and inter-relationships among some of these factors (section 6.7). Most of the discussion focuses on transportation energy use, specifically; in a few occasions, I also discuss GHG emissions, however, since the two are highly correlated, I focus primarily on the former to avoid redundancy. Overall findings are summarized in section 6.8.

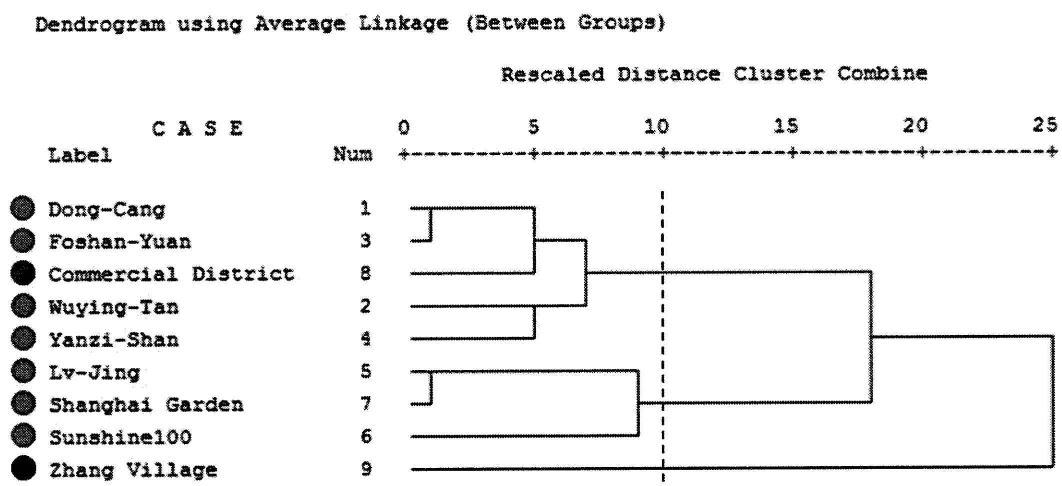
6.1 Neighborhood Forms

6.1.1 Cluster Analysis

A series of disaggregated neighborhood form indicators, as described in Table 5-2, were calculated for each of the 9 neighborhoods, as discussed in section 5.2. A cluster analysis, based on these indicators, generally confirms our hypothesis that the 9 neighborhoods selected can be grouped into the four neighborhood typologies. As shown in Figure 6-1, Zhang-Village (the *a priori* "traditional" typology) stands out as a unique case. In addition, the three neighborhoods of Lv-Jing, Shanghai-Garden, and Sunshine-100 are grouped together, suggesting a similarity of the three in terms of their "superblock" typological characteristics.

Nonetheless, the clustering exercise fails to differentiate between the old commercial district, which we hypothesized as a "grid" typology, and the four "enclave" neighborhoods (i.e., Dong-Cang, Foshan-Yuan, Wuying-Tan, and Yanzi-Shan), as also shown in Figure 6-1. From an urban design point of view, these two typologies definitely look different. Since most of the indicators calculated for the cluster analysis draw from those widely used in the western literature, they may not fully capture the neighborhood forms in China. For example, both the "grid" and the "enclave" neighborhoods are revealed to have a relatively large number of transit stops within 1km boundary. However, the stop distribution is quite different: the old commercial district has an evenly distributed bus stop network due to its grid-pattern public roads allowing buses to pass through, whereas "enclave" neighborhoods tend to concentrate all transit stops around their entrances and no bus stop can be located inside. If we had considered a better proxy indicator of "transit accessibility" reflecting the distribution of bus stops (which affects the average access distance to bus stops), the commercial district may have been identified as an independent category, as opposed to clustering with the "enclaves."

Figure 6-1 Hierarchical Cluster Analysis Result



While the cluster analysis provides some statistics-based support for the differentiation of the four neighborhood typologies, the analysis masks the underlying differences. To explore the more subtle differences, we now turn to a comparison of specific, disaggregate neighborhood indicators. Our discussion follows the three dimensions (density, diversity, design) now somewhat widely used to characterize relevant dimensions of neighborhood form, as detailed below.

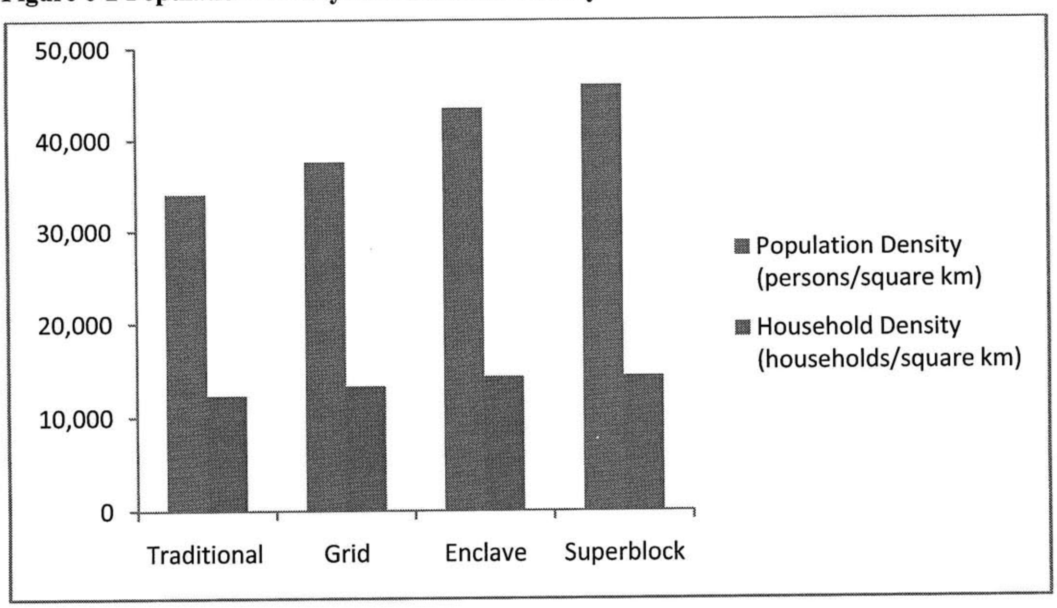
6.1.2 Density Elements

Population density, household density, floor area ratio (F.A.R.) and building coverage constitute some of the more common density measures used in the western literature. Table 6-1 presents results of these indicators calculated for the main neighborhood typologies in Jinan using the GIS data. In terms of population density, the "superblock" neighborhoods have the highest average density of 46,000 persons per square kilometer, followed by the "enclave" with a density of 43,500 persons per square kilometer. The "traditional" has the lowest. However, after accounting for potential household size effects, we can see that the density of the "superblock" becomes relatively more modest (see Figure 6-2). This shows that the "superblock" tends to house larger families than the other neighborhood typologies. The comparison of floor area ratios (F.A.R) is generally consistent with our expectations, showing the higher values associated with the taller buildings in the "superblocks"; we can also see this in the building height metric, as the superblock's average is much higher than the "enclave" and "grid" neighborhoods, where 5-6 story buildings predominate. The "traditional" neighborhood has the lowest height on average, because most buildings inside are courtyard houses with 2-3 stories. These indicators, and the green space coverage, support the idea of "superblock" representing a version of the "tower in the park" urban design mindset.

Table 6-1 Density Measures in the Four Neighborhood Typologies

	Traditional	Grid	Enclave	Superblock
Population Density (persons/square km)	34,000	37,500	43,500	46,000
Household Density (households/square km)	12,300	13,300	14,300	14,300
F.A.R.	1.2	1.7	1.8	2.0
Building Coverage	54%	31%	34%	22%
Average Building Heights (floors)	2.2	5.5	5.3	10.1

Figure 6-2 Population Density vs. Household Density



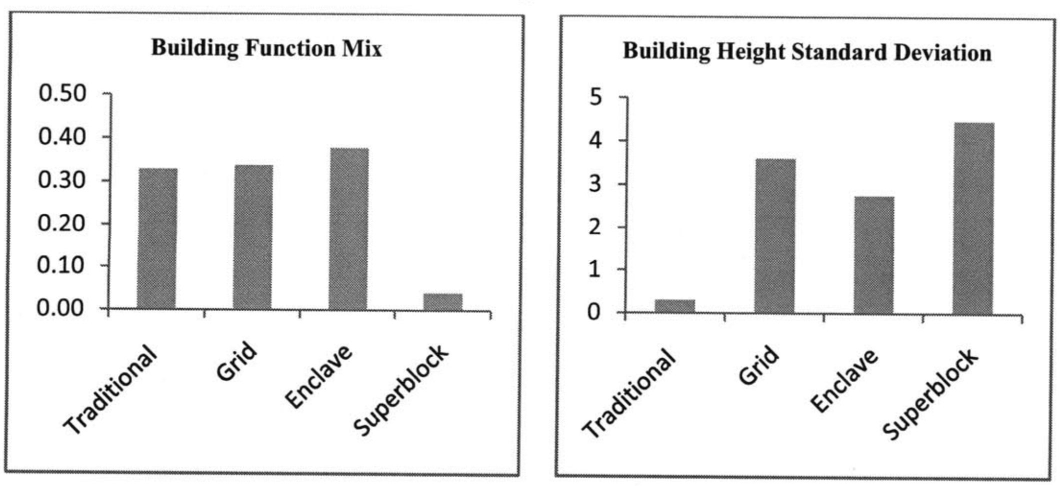
6.1.3 Diversity Elements

In terms of diversity measures, we calculated land use mix, building function mix, and the standard deviation of building height, as shown in Table 6-2. The "Superblock", as expected, has almost homogenous residential use measured, by both land use mix and building function mix. The land and building use diversity levels of the "grid", "enclave" and "traditional," are higher than the "superblock", and quite similar to each other. However, measured by building form diversity[11] (i.e., building height standard deviation), "superblock" becomes the most diverse (see Figure 6-3). This suggests that the "superblock," as a market oriented typology, introduces different types of building products (e.g., low-rise, high-rise, etc.). The "grid" neighborhood has the second most diverse building form, reflecting a complex physical nature deriving, perhaps, from the long history of urban evolution in the district.

Table 6-2 Diversity Measures in the Four Neighborhood Typologies

	Traditional	Grid	Enclave	Superblock
Land Use Mix	0.21	0.30	0.36	0.09
Land Use Mix (for built-up land only)	0.23	0.32	0.37	0.07
Building Function Mix	0.33	0.34	0.38	0.04
Building Height Standard Deviation	0.3	3.6	2.75	4.47

Figure 6-3 Building Function Mix vs. Building Form Mix



[11] This is in fact more of a dimension from the urban design perspective, given that a variety of building forms could presumably create a more interesting street view, and further encourage walking.

6.1.4 Design Elements

Table 6-3 presents a number of design-related indicators of the four neighborhood typologies. The most prominent distinction between the "superblock" and other neighborhood typologies is the level of car-parking supply (see Figure 6-4). While the "traditional" has no parking space and the "grid" and "enclave" provide only a little due to space constraints, the "superblock" provides parking lots for every 3 households, on average. In some recent "superblock" housing projects (e.g., the extension project of the Sunshine-100), the "parking-housing unit" ratio has been set higher than 1.

In addition, the "superblock" has a much higher degree of enclosure/physical isolation than the other neighborhood typologies, as evidenced by the fewer number of gates and the longer distances between entrances. In other words, all else equal the "superblock" makes it more inconvenient for walking because the limited number of entrances to the neighborhood require long detours just to get out. On the other hand, one advantage of the "superblock" over the others is provision of green space, evidenced by a higher green coverage and more trees planted along roads, perhaps because developers value the image of the neighborhoods. However, good-looking green space does not necessarily lead to a walking-friendly environment. The "superblock" tends to prioritize car use in its infrastructure and facilities; therefore, pedestrian facilities and street activities receive less attention, as evidenced by related indicators (e.g., percentage of roads with walking facilities, the percentage of residential buildings with street-level shops, etc.).

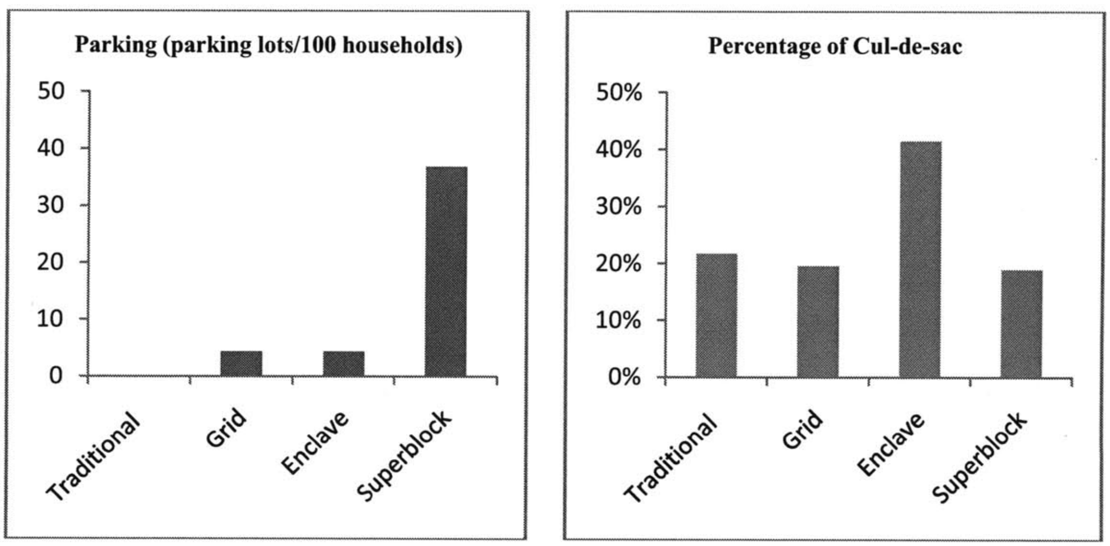
Regarding the road network, the measured results of the cul-de-sacs percentage is intriguing, as the percentage is lowest in the "superblock" and highest in the "enclave" (see Figure 6-4). In the western context, a higher share of cul-de-sacs tends to indicate more auto-dependent road systems. However in the Jinan context, this is not true. In fact, the high share of cul-de-sacs is often due to the dead-end road network within building clusters; such road structures may help reduce car road connectivity and prevent through-traffic in local areas.

Interesting observations can also be found by comparing the "average roadway width" across the 4 neighborhood typologies. The "grid" neighborhood has relatively wide roadways because it allows urban arterials to cut through. On the contrary, the "traditional" is characterized by very narrow lanes which almost completely prevent car use within the neighborhood.

Table 6-3 Design Measures across the Four Neighborhood Typologies

	Traditional	Grid	Enclave	Superblock
Parking (parking lots/100 households)	0	4	4	37
Entry Interval Distance (m)	218	107	148	730
Green Coverage	0%	12%	17%	31%
Percentage of Roads with Trees	0%	42%	42%	85%
Percentage of Residential Building with Street-level Shops	21%	18%	24%	4%
Percentage of Roads with Walking Facilities	98%	87%	51%	64%
Road Density (km/square km)	37.4	29.6	25.6	36.0
Intersection Density (# intersections / km)	18	12	9	10
Percentage of Cul-de-sac	22%	20%	42%	19%
Average Roadway Width (m)	5	13	8	8
Average Building Footprint Area (sq m)	114	316	573	635

Figure 6-4 Parking versus Percentage of Cul-de-sac



6.2 Pattern of Socioeconomics and Demographics

Table 6-4 and Figure 6-5 illustrate the 4 neighborhood typologies in regards to the socioeconomic and demographic characteristics of their resident households, as measured by household size, number of workers, household monthly income, and household structure. The results show that the average family size is around 3 persons, with the "superblock" slightly larger at 3.2 persons per household. The "superblock" also presents the highest number of workers per family and the highest share of young couples with kids, although the differences across neighborhood typologies in terms of employment and family structure are modest. A main difference is found in the income levels. As expected, the "superblock" is the most affluent and the "traditional" is the poorest, with average household income in the former 3 times as much as in the latter. This contrast can also be seen through income distribution patterns across the four neighborhood types, although household incomes within each neighborhood type tend to vary a lot (see Figure 6-6).

Table 6-4 Socioeconomic and Demographic Measures across the Four Neighborhood Typologies

	Traditional	Grid	Enclave	Superblock
Household size (persons)	2.8	2.8	3.0	3.2
Household employment (workers)	1.5	1.6	1.7	1.9
Household income ($/month)	759	1,326	1,341	2,157

Notes: Income reported in RMB was converted to US$ at 1 US$ = 7 RMB Yuan

Figure 6-5 Household Structures across the Four Neighborhood Typologies

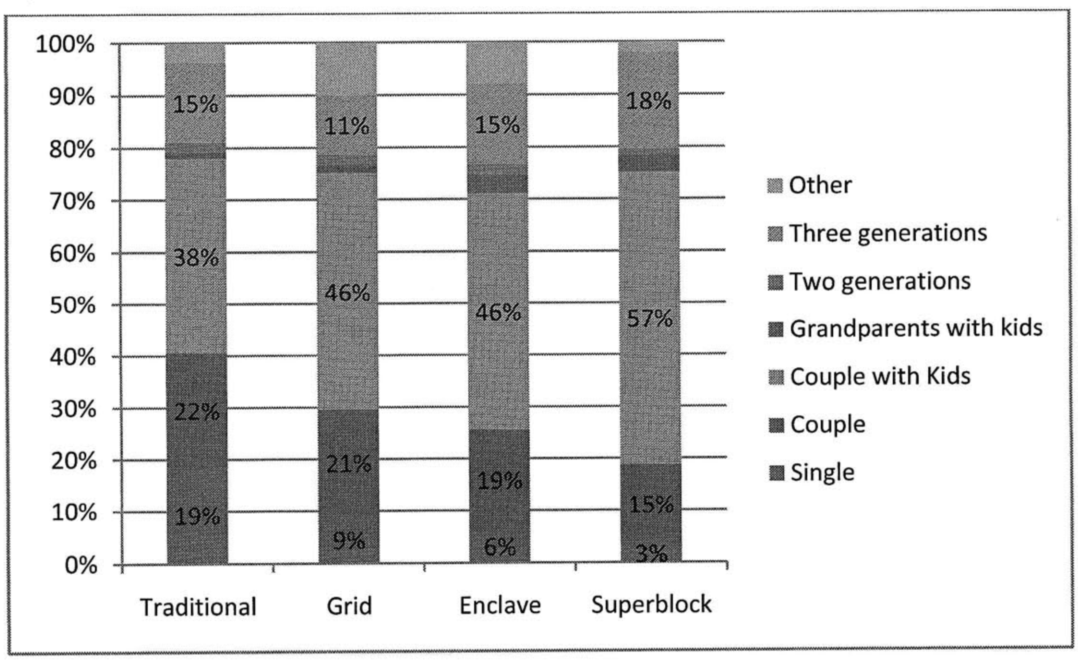
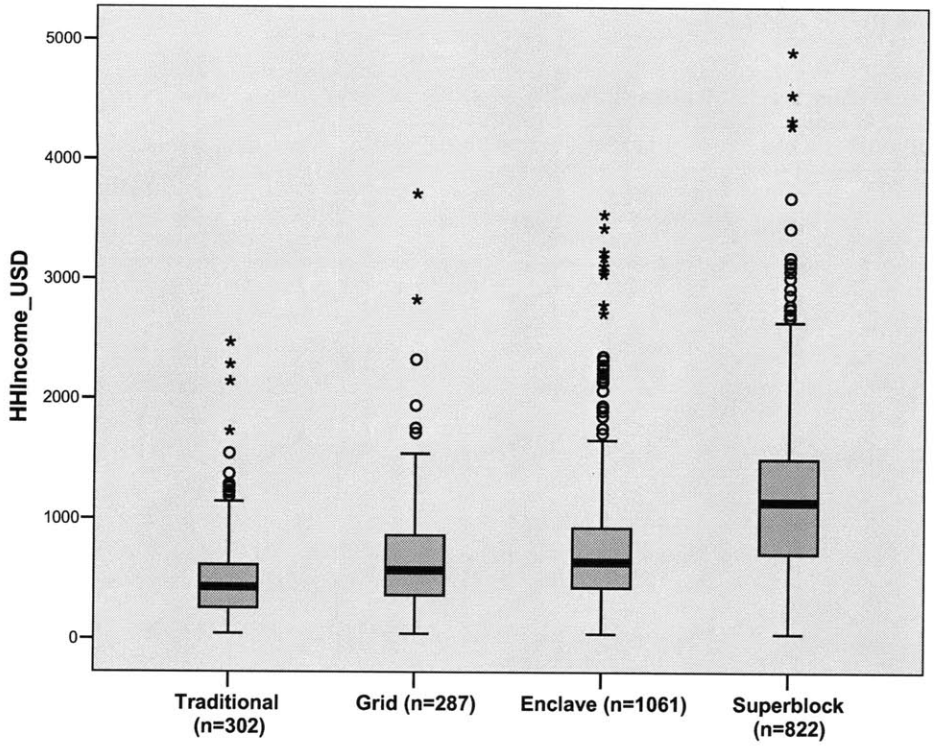


Figure 6-6 Household Monthly Income (US$) across the Four Neighborhood Typologies



6.3 Pattern of Vehicle Ownership

Table 6-5 tabulates average ownership of different vehicle types by three income groups. The income effects on vehicle ownership vary according to vehicle type, regardless of neighborhood typology. For example, private car ownership increases as household income grows, as expected. For motorcycles and E-bikes, the ownership seems relatively constant across the three income groups in each neighborhood type (except for the "traditional"); this seems to suggest no income effect at all. Conversely, bicycle ownership declines as income rises in all neighborhood types (again, except for the "traditional").

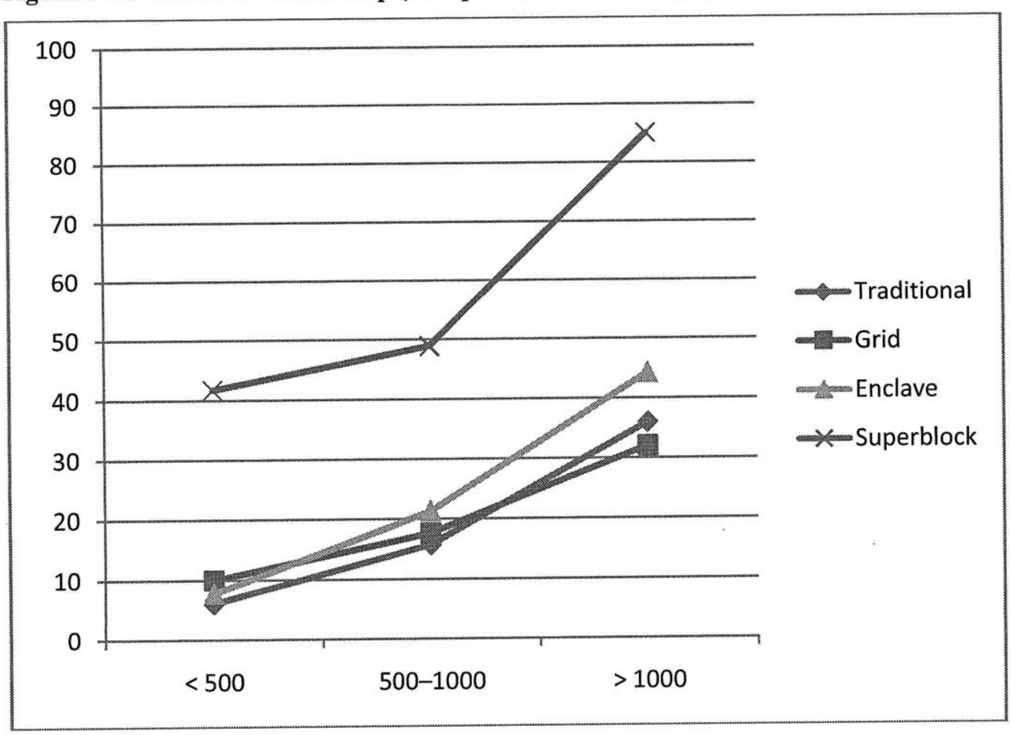
Neighborhood types seem to somehow affect vehicle ownership. For example, the "traditional" is associated with a unique income-vehicle pattern, probably because the particular form prevents households from easily owning cars even with higher income. The "superblock" also displays a notable relationship with household vehicle ownership. As illustrated in Figure 6-7, at the same income level, households in the "superblock" are much more likely to own cars than those in the other neighborhood types. It is striking to see that even for households in the "superblocks" with a monthly income of less than 500 dollars, more than 40% of them own cars (there are 76 observations in our sample).

Table 6-5 Vehicle Ownership (vehicles per 100 households) by Monthly Income

	Traditional	Grid	Enclave	Superblock
< US$500				
Private Car	6	10	8	42
Motorcycle	22	8	7	3
E-bike	46	28	31	48
Bike	82	79	86	78
US$500–1000				
Private Car	16	18	21	49
Motorcycle	28	14	16	7
E-bike	76	41	46	44
Bike	82	109	88	65
> US$1000				
Private Car	36	32	44	85
Motorcycle	40	11	10	5
E-bike	92	45	43	39
Bike	136	98	84	71

Notes: Presentation style inspired by Pan, *et al.* (2009) p.286

Figure 6-7 Private Car Ownership (cars per 100 households) by Household Monthly Income (US$)



6.4 Pattern of Household Attitudes

Table 6-6 tabulates household attitudes across the four neighborhood typologies, revealing several interesting findings. In general, household attitudes in the "superblock" are quite different from others, while attitudes among "traditional", "grid" and "enclave" neighborhoods are similar.

First, "superblock" households have a lower rate of agreement with the statement that driving is a "privilege," although in the other neighborhood types the shares agreeing with that statement are also not that high (less than 30%). This may seem somewhat surprising since we might imagine that, in the "superblock," richer people, owning more cars, must feel privileged. Here, in fact, an opposite meaning may be implied: those owning cars do not consider it a privilege, while those who do not own vehicles do consider it a privilege- a condition for the "elite." Additionally, and not in contradiction to the previous interpretation, as auto ownership increases in prevalence across China, the elite "status" associated with driving declines. Second, households in the "superblock" have a less favorable view of public transit, although not much less so than "traditional" neighborhood households; notably, the majority of households in all neighborhoods have a positive view of transit convenience. Third, households in the "superblock" exhibit, through their response, a qualitatively higher value of travel time- over half of "superblock" households think travel is a waste of time whereas in other neighborhood typologies the share is only a third. Somewhat interestingly, opinions on bicycling show the least total variation across the neighborhoods; again, a majority of households across all neighborhoods still have favorable views on biking.

These observations suggest some relationship between neighborhood type (particularly, the "superblock") and household attitudes, providing some evidence in support of "self-selection." In other words, if we take the attitudes as valid and reliable indicators for households' latent desired lifestyles, households living in "superblocks," vis-à-vis the other typologies, view driving as a more everyday (less privileged) behavior and transit as less convenient; perhaps they have chosen the "superblock" in part because of those travel preferences.

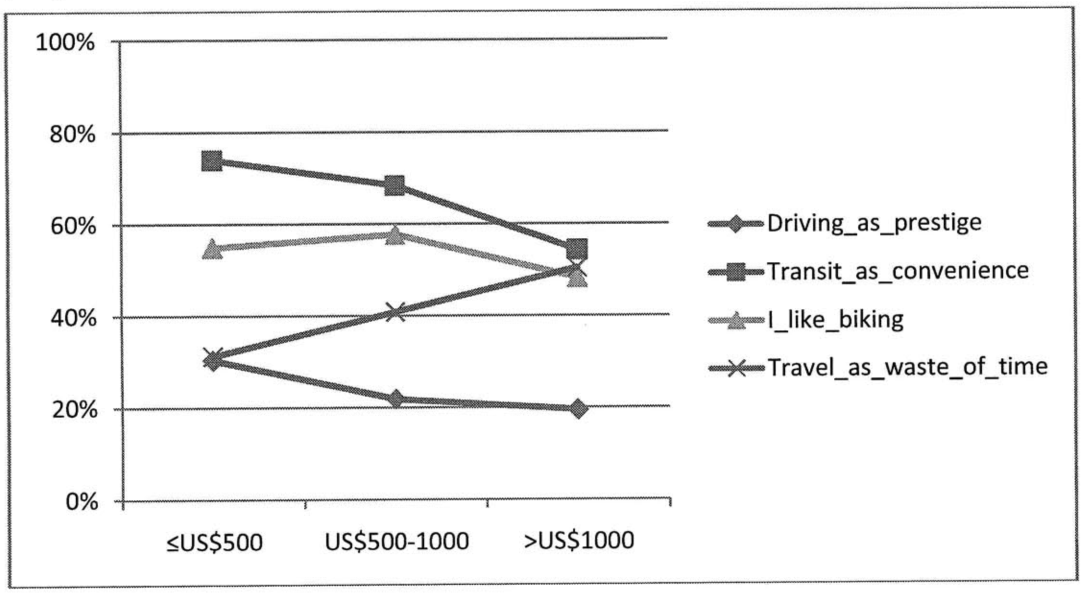
However, there is one caveat: maybe households' attitudes are not driven by neighborhood types, but rather their income levels. As shown in Figure 6-8, richer people do value more on travel time and favor less in transit and biking. Poorer people tend to regard the car ownership more of a privilege.

Table 6-6 Comparison of Percentage of Households Agreeing with Attitude-Related Statements

	Neighborhood Type			
	Traditional (n=303)	Grid (n=293)	Enclave (n=1086)	Superblock (n=832)
Driving as Privilege	28%	29%	27%	17%
Transit as Convenience	63%	69%	74%	55%
I like Biking	60%	59%	53%	51%
Travel as a Waste of Time	34%	33%	35%	53%

Notes: With the level of agreement on a scale of 1 to 5 (1 = strongly disagree, 3 = neutral, 5 = strongly agree), households rating both 4 and 5 are categorized as households "agreeing" with the statement.

Figure 6-8 Attitudes (Percentage of Households Agreeing with Statements) versus Household Monthly Income (US$)



6.5 Pattern of Household Travel Activity

We now explore household weekly activity by examining travel frequency, travel distance, mode share, and travel time.

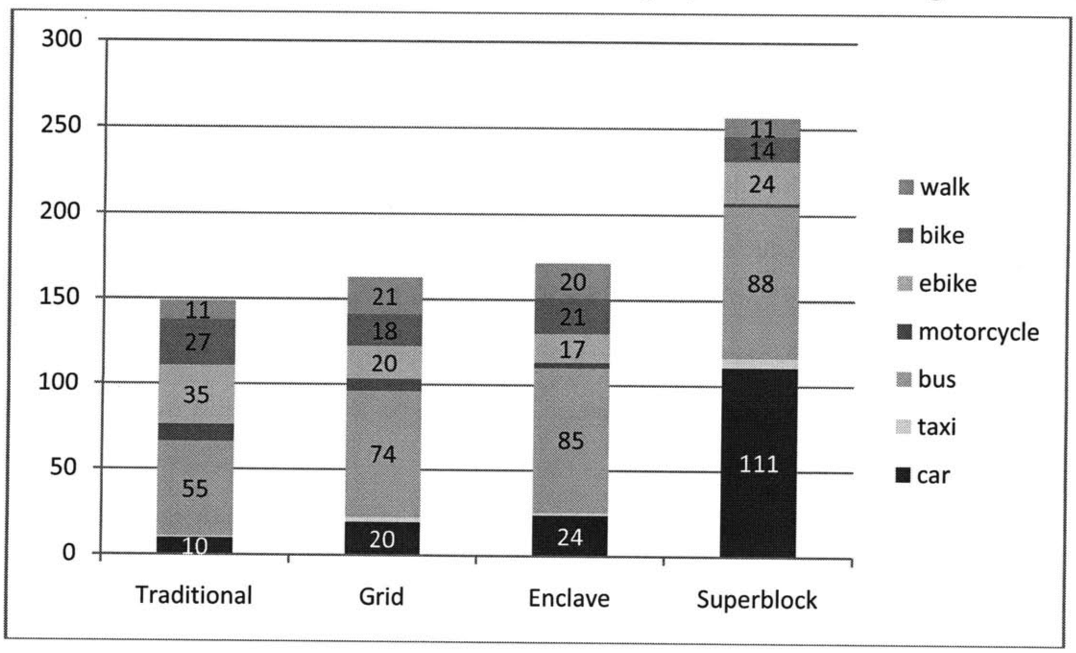
As shown in Table 6-7, household frequency does not vary much across neighborhood types. On average, a household in Jinan made 30-40 trips per week, or 4-6 trips per household per day, or 1.5-2 trips per person per day. The numbers look quite a bit lower than international figures in 2-4 trips per person per day on average (Schäfer, 2000) One the one hand, the difference may be explained by a less travel demand from locals in Jinan than that from rich people in the developed world; on the other hand, it may suggest a under-reporting, which is likely given the nature of the diary (people are unlikely to remember all trips over a week but only the more important ones, and they may not have counted very short trips).

Table 6-7 Average Household Weekly Trip Frequency (trips) across the Four Neighborhood Typologies

	Traditional	Grid	Enclave	Superblock
Trips per Household	29	38	39	34
Trips per Person	10	14	13	11

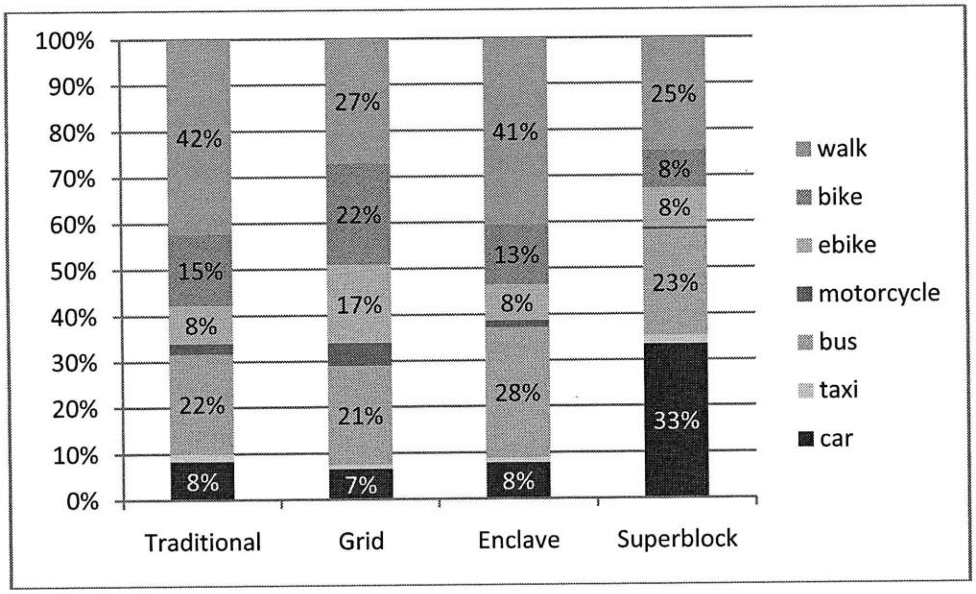
While the trip frequencies are similar across neighborhoods, weekly travel distances show large differences. Households in the "superblock" travel 250 km per week on average, whereas households in the other three types travel much shorter distances (150-170 km). As seen in Figure 6-9, the difference comes mostly from car travel distances, not distances by other modes. In addition, the composition of travel distance by mode is somewhat unique for the "traditional" typology, where households use less transit and very little car compared to others; instead, they travel more with E-bikes and less distance overall.

Figure 6-9 Average Household Weekly Travel Distance (Km) across the Four Neighborhood Typologies



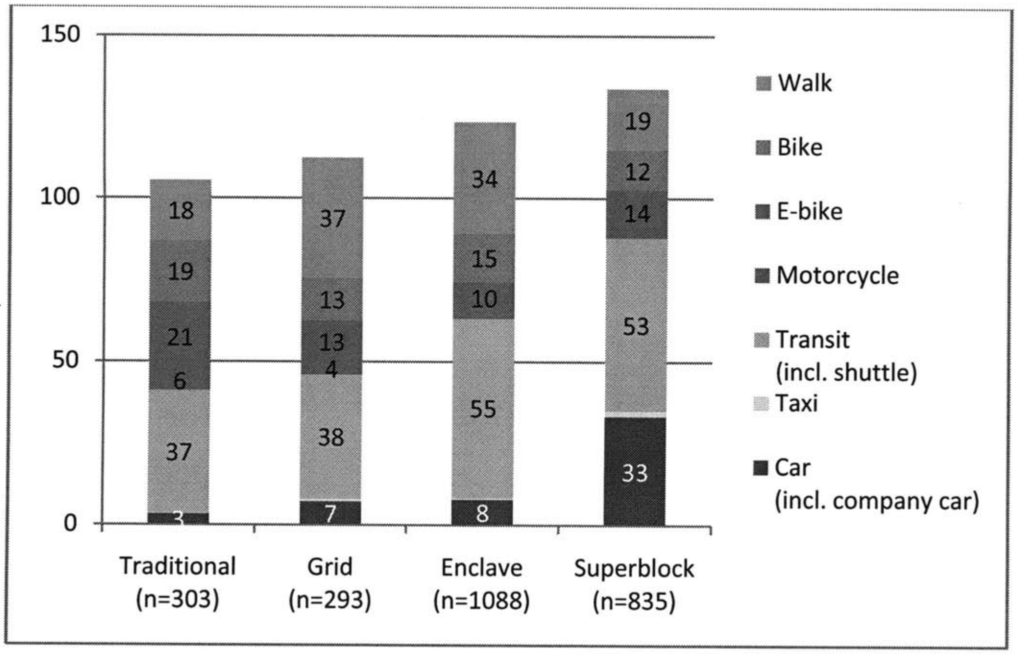
In comparing the mode share, we also find a large difference in car use between the "superblock" and the others. In the "superblock", among all weekly trips, about 33% of trips are made by car, whereas the shares in other neighborhood types are lower than 8% (see Figure 6-10). Regarding walk trips, the shares in the "traditional" and "enclave" exceed 40%, much higher than walk shares in the "grid" as well as the "superblock" (25-27%). However, the lower walk shares in the "grid" and the "superblock" have different explanations. In the "grid", the lower share of walk trips is supplemented with trips by bike and E-bike, whereas in the "superblock", the gap is filled almost entirely by a much higher share of car trips.

Figure 6-10 Average Household Weekly Travel Mode Share across the Four Neighborhood Typologies



Finally, let's examine, across the four neighborhood types, the average household travel time, a measure calculated from reported travel distances using the speed of each mode. For this calculation, I assume the speeds of car, transit, motorcycle, E-bike, bike and walk are: 30km/hr, 18 km/hr, 16 km/hr, 15 km/hr, 12 km/hr and 5 km/hr, respectively. Figure 6-11 shows that, although the composition of time by modes, is somewhat different, households in Jinan tend to spend a reasonably constant amount of time per week in travel, regardless of the neighborhood types. This echoes findings, from international comparisons, that households have relatively constant average travel time budget, approximately 1.1 hours per day (Schäfer, 2000). The average value we find for Jinan is lower than the international data; possibly due to under-reporting of trips, incorrect assumption of vehicle speeds, and/or actual lower travel times in Jinan. Households in the "superblock" spend slightly more time traveling, perhaps because they are richer and travel more by car, thus opting to invest that additional money and speed into longer total distances and time spent traveling.

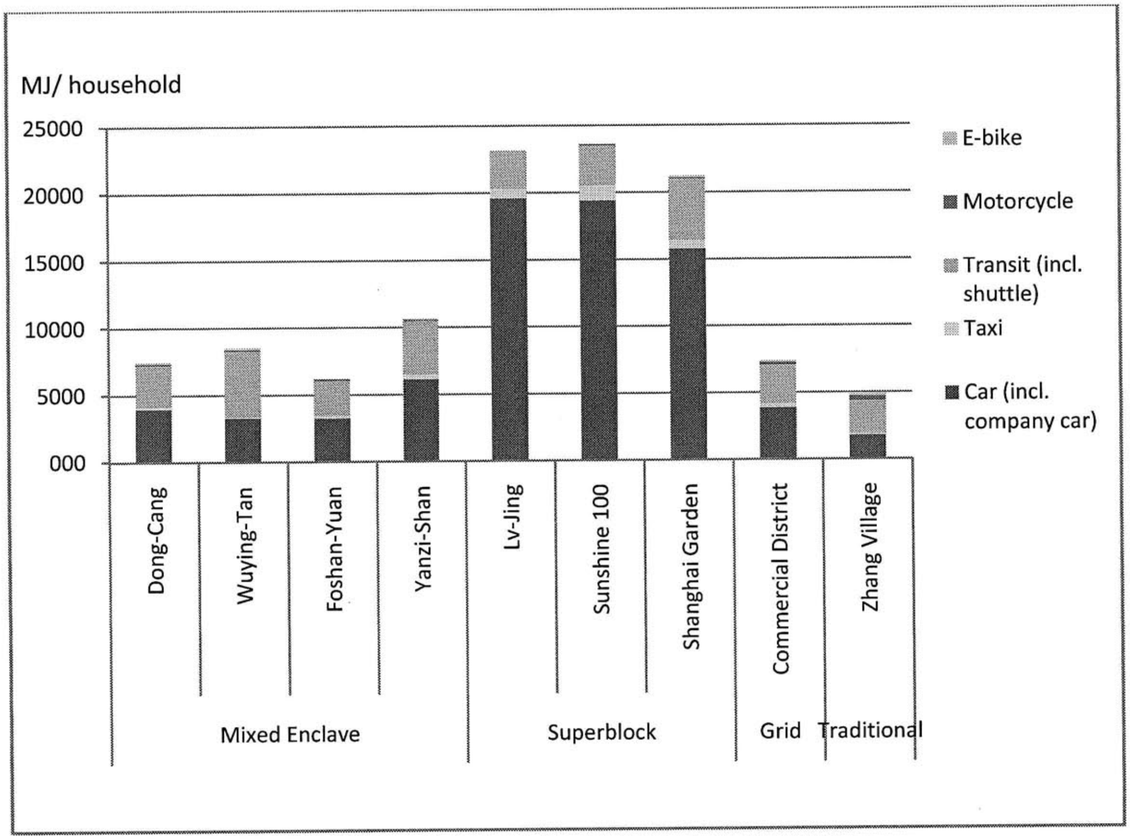
Figure 6-11 Average Household Daily Travel Time (Min) across the Four Neighborhood Typologies



6.6 Pattern of Household Transport Energy Use and GHG Emissions

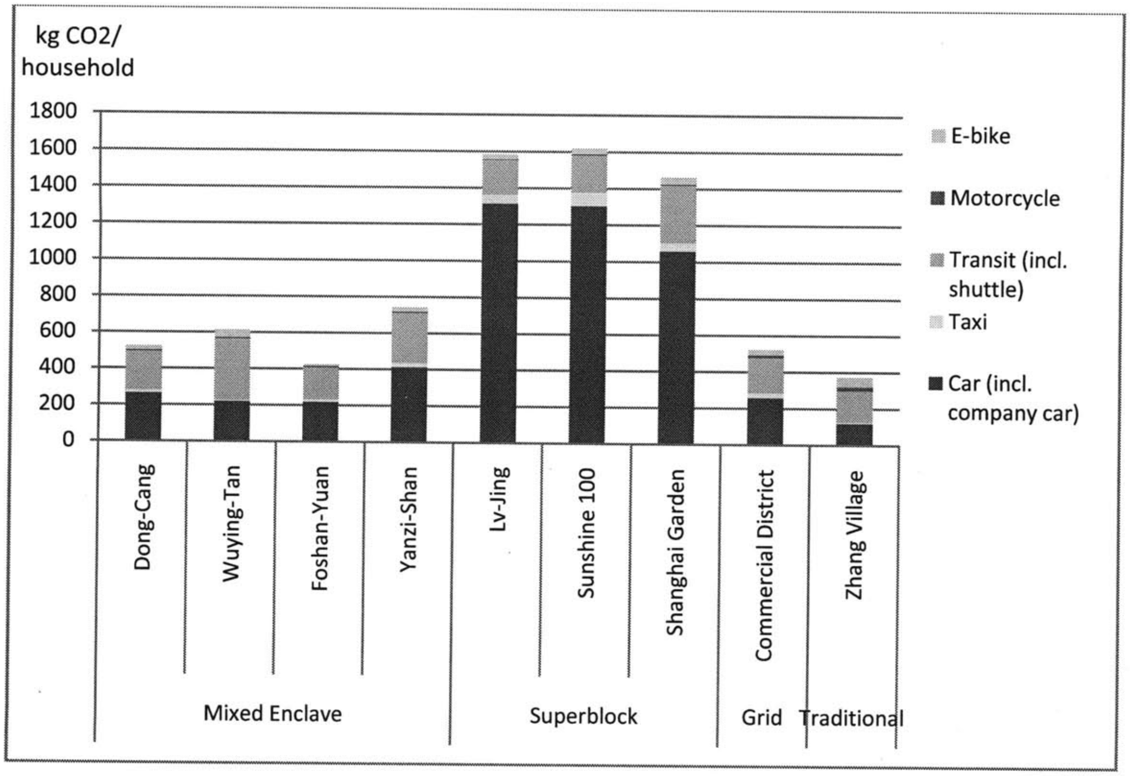
After observing the differences of household travel activity patterns between the "superblock" and others, we should not be surprised to observe that the "superblock" is associated with the highest level of household transportation energy consumption among the four typologies, as illustrated in Figure 6-12. The gap between the "superblock" and others results from much higher energy use by car, a similar pattern we seen for travel distance and mode share.

Figure 6-12 Average Household Annual Transport Energy Use



Patterns of transportation energy use and GHG emission are also compared. As shown in Figure 6-13, the GHG emission pattern looks quite similar to the pattern of energy, confirming the argument that these two components are highly correlated with each other in the transportation sector (Darido, *et al.*, 2010). Households in the "superblocks" on average emit 1500-1600 kg carbon dioxides per year, about 1000 kg more than the amount emitted by households in other neighborhood types. That said, we may find one noticeable, although not big, difference regarding the role of E-bike use. Figures suggest that the share of E-bike use contributing to total household emissions is larger than that contributing to total energy consumption. This implies that electricity in Jinan is more carbon intensive than the fuels.

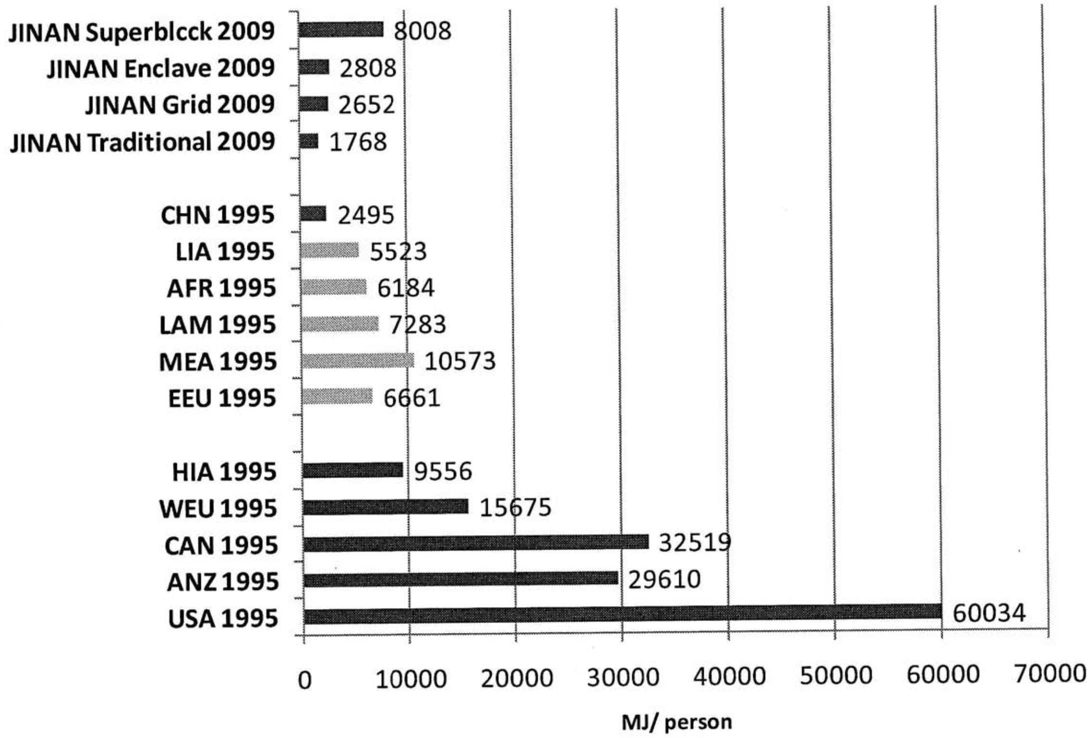
Figure 6-13 Average Household Annual Transport GHG Emissions



To put the estimated travel energy consumption numbers for Jinan into a broader context, we compare the calculated personal annual travel energy use in Jinan with similar figures for international cities. As shown in Figure 6-14, it is clear that the current level of passenger travel energy use in Jinan is still much lower than the level in cities of developed countries (even the level of year 1995).[12] That said, the average person in the "superblock" consumes travel energy at a level close to that of affluent cities in Asia, and higher than most cities in the developing world. It is also interesting to see that the per capita passenger energy consumption in Jinan non-"superblock" neighborhoods today is not much different from the average level of Chinese cities more than a decade ago.

[12] Note, however, that under-reporting of trips the Jinan survey may downward bias this estimate versus the "real" thing.

Figure 6-14 International Comparison on Personal Annual Transport Energy Use



Notes: Data for international cities extracted from (Kenworthy, 2008), p. 215-220.

USA- US cities, ANZ- Australia/New Zealand cities, CAN- Canadian cities, WEU- Western European cities, HIA- High income Asian cities, EEU- Eastern European cities, MEA- Middle Eastern cities, LAM- Latin American cities, ARF- African cities, LIA- Low income Asian cities, CHN- Chinese cities

To compare the average energy consumption across the four neighborhood types, considering the household heterogeneity within each neighborhood type, I conduct a single-factor ANOVA test. First, however, we must examine the critical assumption about the normality of the distribution of the observed values for the ANOVA test. Figure 6-15 (left) shows that weekly household energy consumption data in the sample have a positively skewed distribution, with about 500 zero values (as expected, given that many Chinese people today only walk and bike. This suggests the assumption of ANOVA is violated. To solve this problem, I adopt an adjusted logarithmic transformation for energy values by taking the natural log of each observation's energy use plus 1 (i.e., E^T+1), and then exclude the 500 zero values in the test. Now the assumption about the normality is nicely met, as shown in Figure 6-15 (right). Results of the test are presented in Table 6-8. For energy-consuming households, the consumption level of the "superblock" is significantly higher than others at the 0.05 level, whereas the "traditional" has the lowest travel energy consumption. There is no significant mean difference in energy consumption between the "enclave" and the "grid".

Figure 6-15 Distribution of Weekly Household Transport Energy Use Before/After Adjusted Log-Transformation

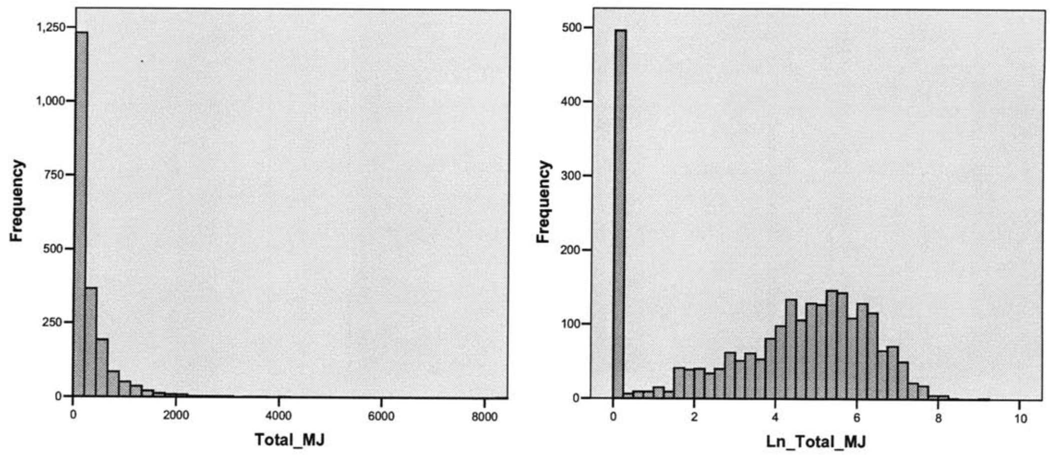


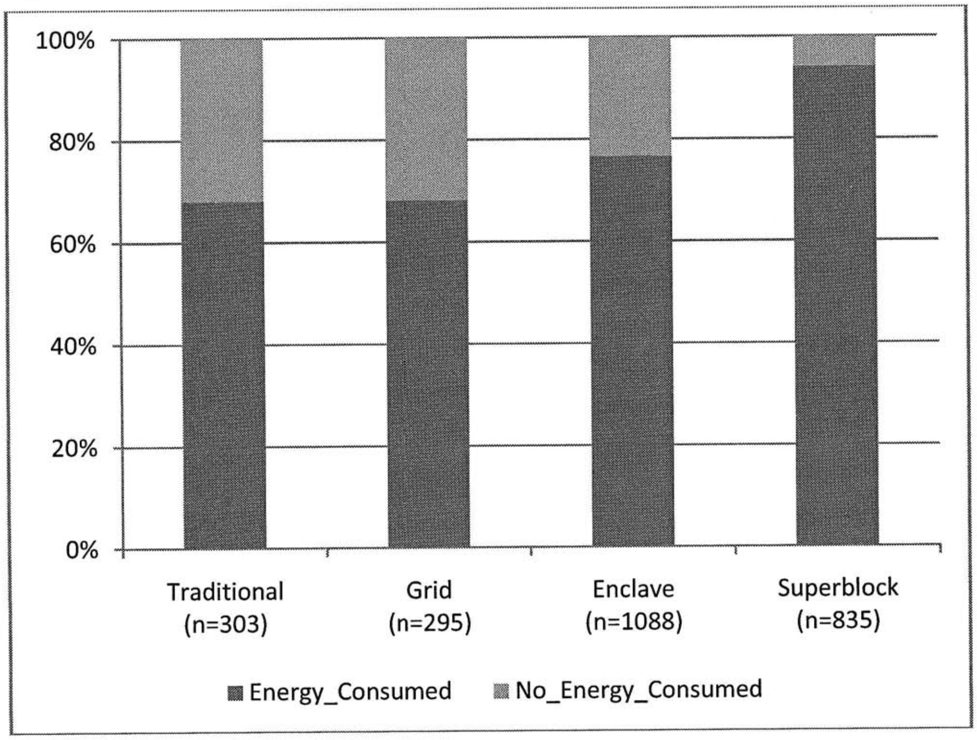
Table 6-8 Single-Factor ANOVA Test Result

(I) Neighborhood Type	(J) Neighborhood Type	Mean Difference (I-J)	Std. Error
Traditional	Grid	-0.39*	0.14
	Enclave	-0.42*	0.11
	Superblock	-1.47*	0.11
Grid	Traditional	0.39*	0.14
	Enclave	-0.03	0.11
	Superblock	-1.08*	0.11
Enclave	Traditional	0.42*	0.11
	Grid	0.03	0.11
	Superblock	-1.05*	0.07
Superblock	Traditional	1.47*	0.11
	Grid	1.08*	0.11
	Enclave	1.05*	0.07

Note: * The mean difference is significant at the .05 level.

Finally, I investigate those 500 excluded zero-values, which we might say represent "super-efficient" transportation energy households from a transport, are investigated. As shown in Figure 6-16, the share of no-energy-consumed households in the "superblock" is much lower than that in the other studied neighborhood typologies. This, again, confirms that the "superblock" is much less energy efficient from the household travel point of view.

Figure 6-16 Shares of No-Energy-Consumed Households across the Four Neighborhood Types



6.7 Some Interactions

6.7.1 Energy Use vs. Household Income

Since households in the "superblock" are richer on average, one may argue that the higher income determines the patterns of higher energy consumption observed there. Figure 6-17 shows that income is indeed an important factor in affecting household travel energy use, but the neighborhood typology seems to remain relevant. Specifically, households in the "superblock" consume a much higher level of travel energy at each income level (low, medium, high). Similar patterns can be found for the household transport GHG emissions, as shown in Figure 6-18. That said, from these two figures, one could still argue that, for example, the average income of rich people in the "superblock" is higher than the average income of rich people in other types. Therefore, I further plot a comparison showing the average household weekly travel energy use associated with each observed income level in the "superblock" versus non-"superblock" (see Figure 6-19). The "superblock" effect apparently remains. The best-fit non-linear curves suggest a diminishing-return styled income effect on household travel energy consumption.

Figure 6-17 Comparison of Household Weekly Transport Energy Use vs. Income (a)

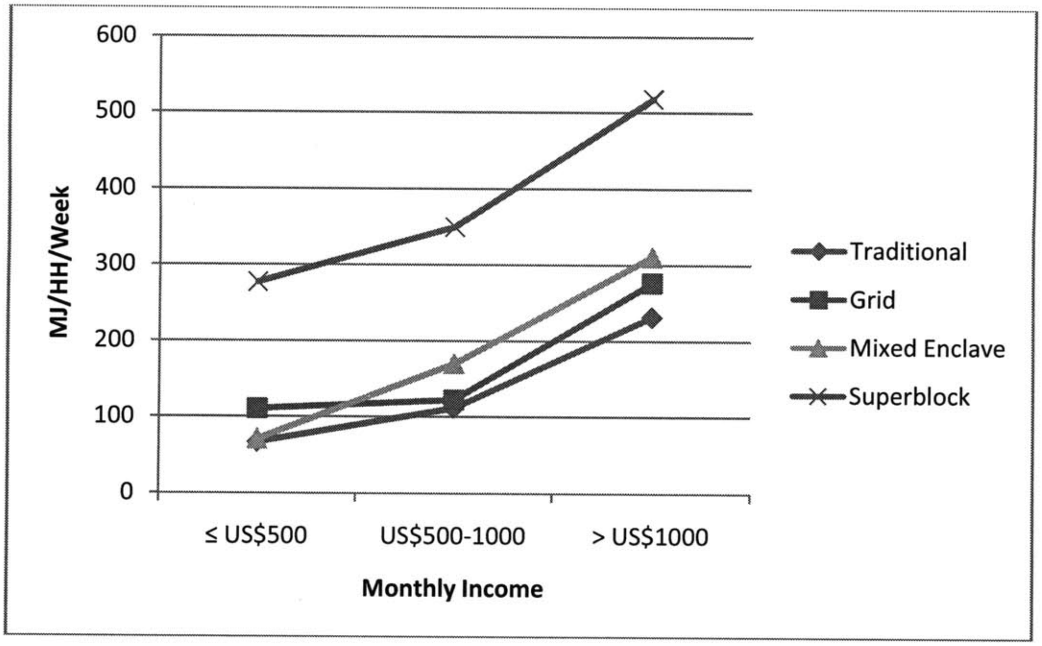


Figure 6-18 Comparison of Household Weekly Transport GHG Emissions vs. Income

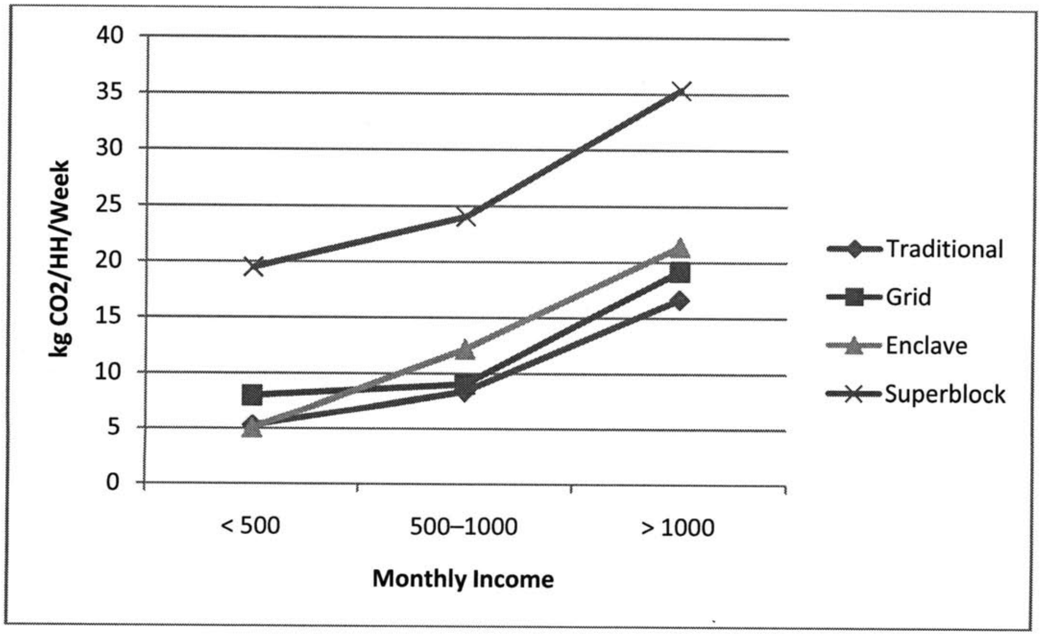
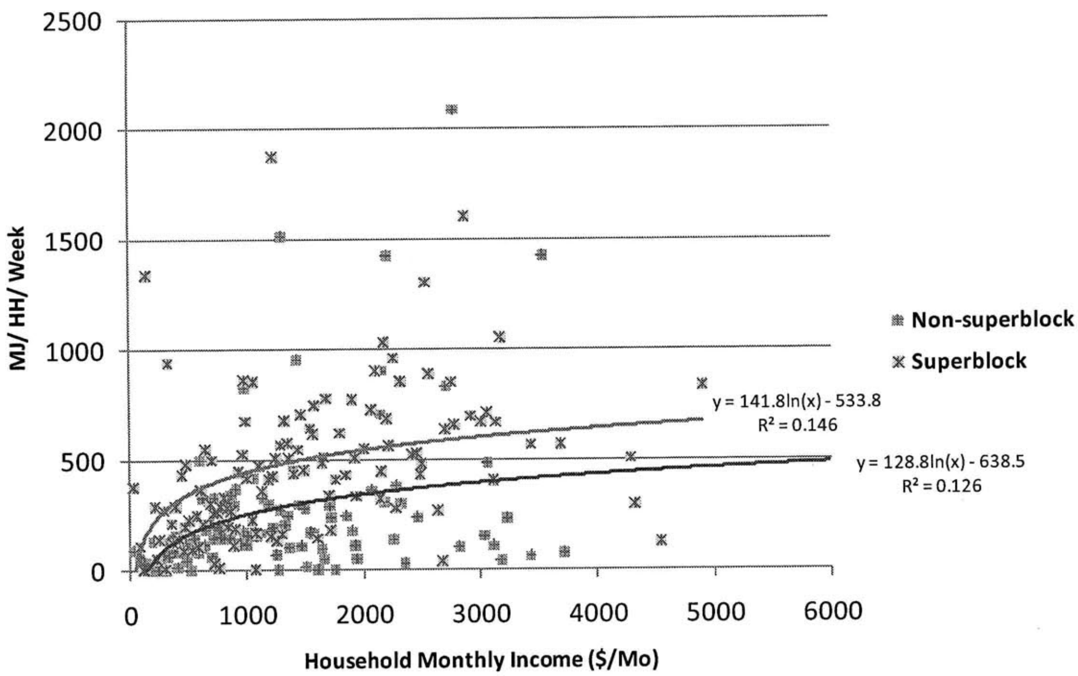


Figure 6-19 Comparison of Household Weekly Transport Energy Use vs. Income (b)



6.7.2 Energy Use vs. Household Size and Car Ownership

Figure 6-20and Figure 6-21 confirm an expected relationship between the household transportation energy use and household size and car ownership. Specifically, the number of persons in a household is proportional to energy use, although for more-than-3-perosn households the effect of adding household members is small (see Figure 6-20). Households with private cars consume much more energy than otherwise (Figure 6-21). Interestingly, households having a company car on average consume more energy than those owning a private car do.

Figure 6-20 Household Weekly Transport Energy Use vs. Household Size

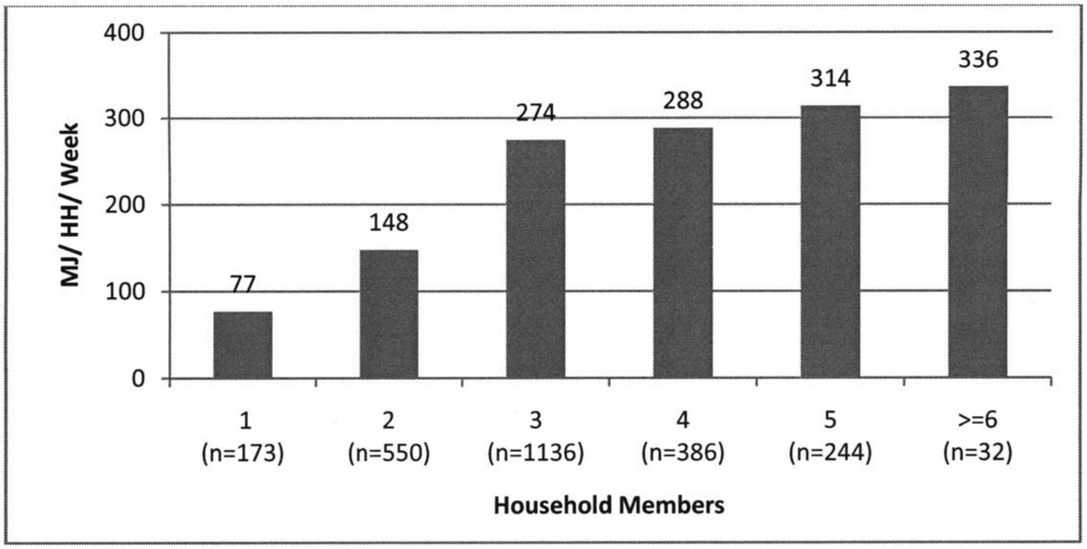
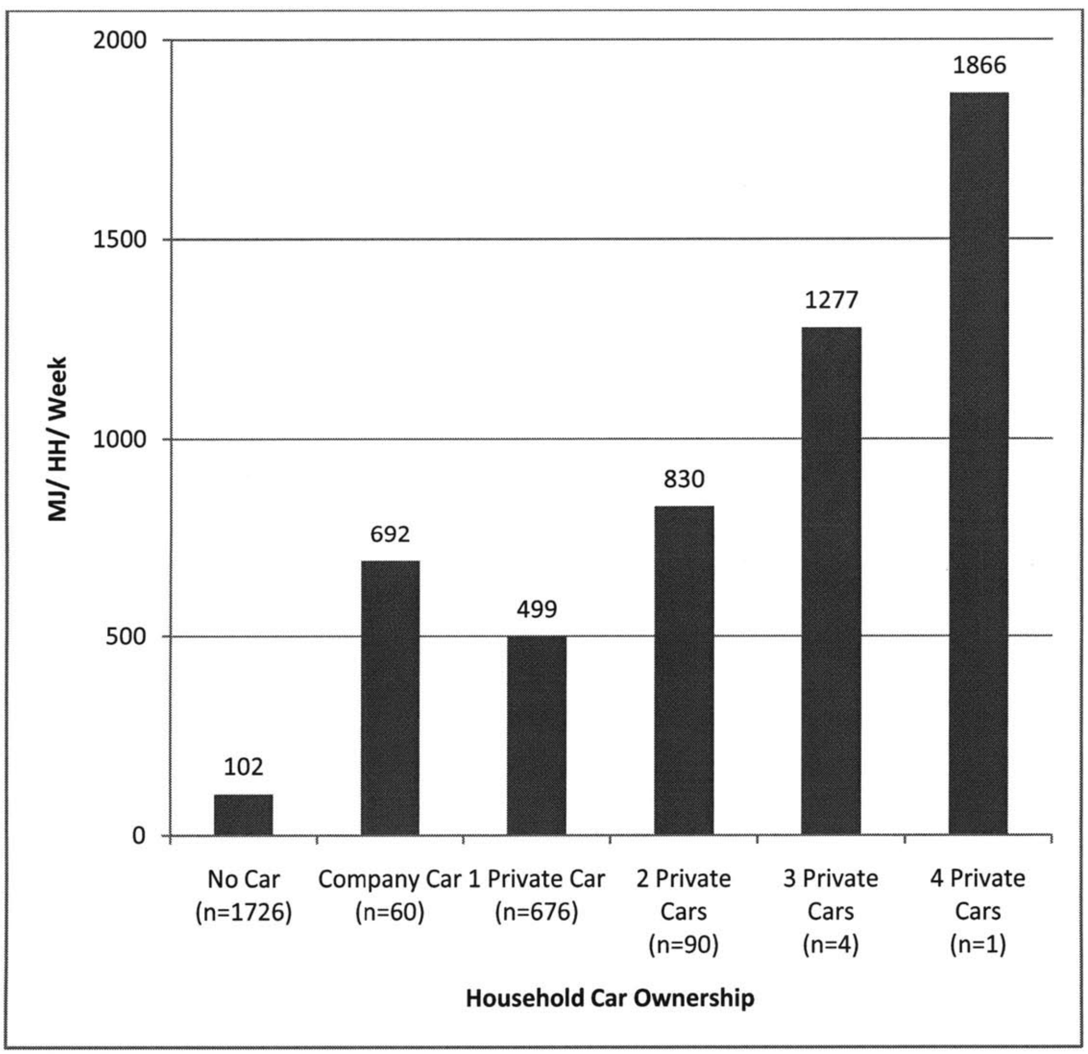


Figure 6-21 Household Weekly Transport Energy Use vs. Car Ownership



6.7.3 Energy Use vs. Neighborhood Location

Being further away from the city center appears to increase travel energy consumption exponentially, as shown in Figure 6-22. Figure 6-23 shows that households living close to BRT corridors in Jinan consume less energy on average, with the efficiency gain mainly from less car use. However, according to our socioeconomic data, households living on BRT corridors are also poorer: the average household monthly income for on-BRT-corridor households is US$741, whereas the average for off-BRT-corridor households is as high as US$941. Given that household income has an effect on household transportation energy use as well, the pure effect of BRT-corridor location feature seems unclear.

Figure 6-22 Household Weekly Transport Energy Use vs. Distance to the City Center

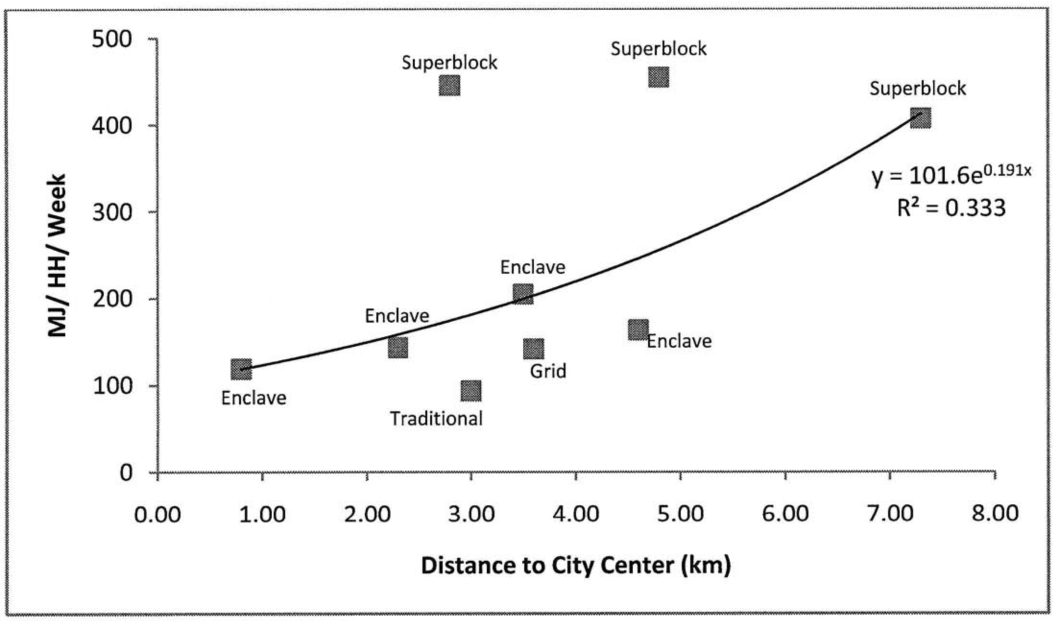
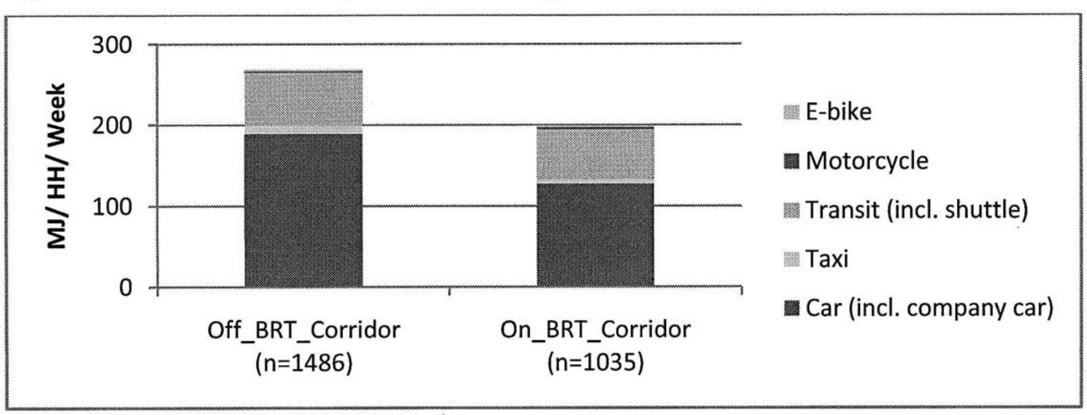


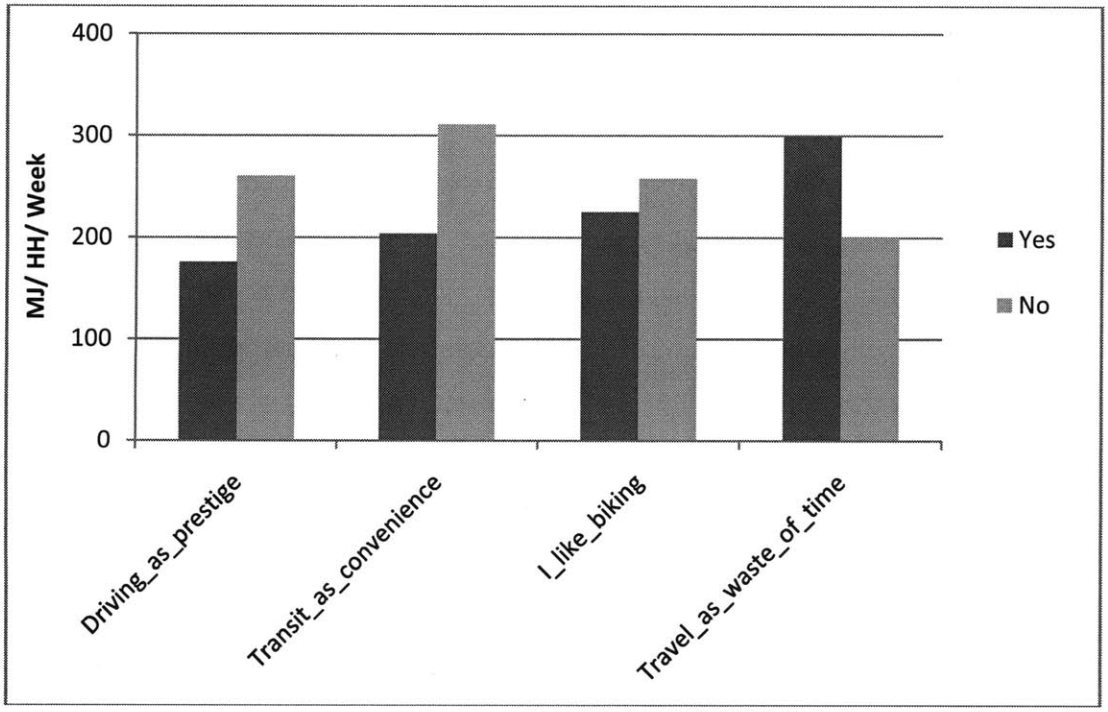
Figure 6-23 Household Weekly Transport Energy Use vs. Proximity to BRT Corridors



6.7.4 Energy Use vs. Household Attitudes

Finally, do household attitudes matter in transportation energy consumption? A comparison in Figure 6-24 suggests the answer to be yes. For example, households who perceive driving as a sign of prestige consume significantly less energy than otherwise. A similar reduction can be found in households who see transit as a convenient travel means. Conversely, much greater energy consumption is associated with households who apparently have high value of time (indicated by agreeing on the statement that "travel is a waste of time"). Household preferences for biking have a less pronounced observed effect on energy use.

Figure 6-24 Household Weekly Travel Energy Use versus Attitudes



6.8 Summary

Descriptive analysis is an early but crucial step towards our better understanding of the relationship between the neighborhood and household transport energy use patterns. The cluster analysis of neighborhood characteristics to a large extent supports our classification of the 9 selected neighborhoods by 4 typologies in the context of Jinan. The failure of cluster analysis in distinguishing between the "enclave" type and the "grid" as well as detailed investigation of western conventional neighborhood indicators (e.g., cul-de-sac ratio) further raises some doubts about those indicators to be capable of describing urban form in China.

A comparison of household transport energy use across neighborhood types seems to suggest a strong connection between the two. Households in Jinan's "superblocks" on average consume 2-3 times more energy than those in other neighborhood types do, while the differences among non-"superblock" neighborhood types are modest. Although Chinese still consume a relatively low level of transport energy compared to developed countries, consumption levels in the "superblock" already comes close to that of affluent cities in Asia. In terms of neighborhood location characteristics, distance to city center appears to increase travel energy consumption exponentially; households with a proximity to BRT corridors use less energy, yet this may be because of the fact that those households are in general poorer.

These empirical findings from comparative analysis does not account for confounding effects, some of which are revealed by our exploration of inter-relationships. For example, higher income increases travel energy use, yet in a diminishing returns manner. Bigger families consume more. Owning private cars increase considerably travel energy use; having a company car consumes even more. Household attitudes seem relevant, too. According to our data, interestingly and perhaps somewhat surprisingly, households which view car driving as a sign of prestige tend to own fewer cars and use less energy for travel. One explanation for this result is that on the one hand, non-car-owning households clearly perceive this good as prestigious, or out of their current reach; on the other hand, people using cars intensively tend to treat them only as common tools.

Nonetheless, while the descriptive statistics begin to paint a basic picture of relevant influencing factors in household transportation energy use, to isolate the effects of neighborhood characteristics as well as to address the "self-selection" problem, we need to conduct multivariate regression analysis and use advanced instrumental variable models, which will be the focus of next chapter.

7 MULTIVARIATE ANALYSIS RESULTS

In this chapter, we examine weekly household travel energy consumption and GHG emissions, in an attempt to identify the relative role of neighborhood typology and location features. In our analysis we specify a number of multivariate regression models, as presented generally in Chapter 5. The dependent variable for most of those models is the household weekly travel energy use, although in a few cases the dependent variable is vehicle ownership or household weekly travel distance by different modes. For independent or explanatory variables, we have: variables representing neighborhood characteristics (the vector **N** in equation (12); see Table 7-1), variables representing socioeconomics and demographics (the vector **S**; see Table 7-2), variables of vehicle ownership (the vector **V**; see Table 7-3), and finally, variables representing household attitudes (the vector **A**; see Table 7-4).

Table 7-1 Neighborhood Variables

Variable Name	Description	Mean	Valid Sample (n=)
Traditional	a dummy variable equal to one if the household lives in a traditional neighborhood	0.12	2521
Grid	a dummy variable equal to one if the household lives in a grid neighborhood	0.12	2521
Enclave	a dummy variable equal to one if the household lives in an enclave neighborhood	0.43	2521
Distance_to_Center	The distance from the neighborhood to the city center of Jinan (the Spring City Plaza)	3.37	2521
On_BRT_Corridor	a dummy variable equal to one if the household is located on a BRT corridor	0.41	2521
Neighborhood_Size	the land area of the neighborhood containing the household sample	27.13	2521

Note: the mean of a dummy variable indicates the share of "yes" cases in the full sample.

Table 7-2 Socioeconomic and Demographic Variables

Variable Name	Description	Mean	Valid Sample (n=)
Ln_Income	log transformed household monthly income	6.51	2473
Income100	Household monthly income (in 100US$)	8.58	2473
Adult_1	a dummy variable equal to one if the household has only one adult	0.08	2519
Adult_3_or_more	a dummy variable equal to one if the household has 3 or more adults	0.37	2519
Child_1_or_more	a dummy variable equal to one if the household has 1 or more children	0.53	2519
Elderly_1_or_more	a dummy variable equal to one if the household has 1 or more elderly people	0.23	2519
Worker_0	a dummy variable equal to one if household members are all unemployed or retired	0.11	2519
Worker_2_or_more	a dummy variable equal to one if the household has 2 or more workers	0.68	2519

Table 7-3 Vehicle Ownership Variables

Variable Name	Description	Mean	Valid Sample (n=)
Car_1_or_more	a dummy variable equal to one if the household owns 1 or more private cars	0.31	2497
Company_Car	a dummy variable equal to one if the household has 1 or more company cars	0.02	2521
Motorcycle_1_or_more	a dummy variable equal to one if the household owns 1 or more motorcycles	0.10	2515
Ebike_1_or_more	a dummy variable equal to one if the household owns 1 or more E-bikes	0.36	2511
Bike_1	a dummy variable equal to one if the household owns 1 bike	0.38	2517
Bike_2_or_more	a dummy variable equal to one if the household owns 2 or more bikes	0.15	2517

Table 7-4 Household Attitude Variables

Variable Name	Description	Mean	Valid Sample (n=)
Car_as_Prestige	a dummy variable equal to one if the household "strongly agree" or "agree" that "Car is a sign of prestige".	0.24	2519
Transit_as_Convenience	a dummy variable equal to one if the household "strongly agree" or "agree" that "Taking public transit is convenient".	0.66	2520
I_Like_Biking:	a dummy variable equal to one if the household "strongly agree" or "agree" that "I enjoy bicycling".	0.54	2515
Travel_is_Waste_of_Time	a dummy variable equal to one if the household "strongly agree" or "agree" that "Time spent in traveling is a waste of time".	0.41	2520

The chapter is organized by four sections. Section 7.1 presents results of base regression models predicting transport energy use. Section 7.2 discusses how previous models might be wrong, and how a 2-step instrumental incorporating vehicle models is performed. In section 7.3 I then followed the same 2-step routine in predicating vehicle use by mode to explore some sub-effects of neighborhood on vehicle use. Section 7.4 provides a summary.

7.1 Base Regression Models on Household Transport Energy Use

The base regression models of travel energy use include four classes of explanatory variables: 1) socioeconomic and demographic variables that are expected to influence travel pattern and associated energy use, such as household size, income, number of works, family structure and age, etc.; 2) vehicle ownership of private car, company car, motorcycle, e-bike and bike; 3) proxy measures of household attitudes towards travel modes to partially address the "self-selection" problem; 4) neighborhood characteristics associated with the household, including location characteristics- such as distance to city center and proximity to the BRT corridors- and the neighborhood form typology. It is worth noting that we also include the neighborhood size as a variable in the model (and all following models). This is more of a purpose for statistical control: our neighborhood samples vary in size even within the same form typology (e.g., the "superblock" Lv-Jing versus Sunshine-100). Since size is often determined by physical barriers (e.g., walls, fence, arterials, etc.), we expect households living in those big neighborhoods will have poor connection to surrounding public transit (except for the "grid" which allows transit passing through the neighborhood), and that the location effect of proximity to BRT corridors will have a relatively weak impact on energy consumption and vehicle ownership.

7.1.1 OLS Models

As we saw in our updated conceptual framework (see Figure 3-1), household transportation energy consumption can be estimated from their travel behavior patterns, which are *directly* affected by household socioeconomic and demographics, vehicle ownership, attitudes, neighborhood characteristics, and features of fixed destinations (e.g., workplace). In the absence of information on fixed destinations, we can model the relationship using OLS as long as the assumption holds that the error term is not correlated with any explanatory variables in the model. In the specific specification, we use the adjusted log-transformed value of energy consumption to reflect some hypothesized non-linear relationship (e.g., energy vs. income, energy vs. distance to center), an insight from the results of the descriptive statistics (see discussions in section 6.7). The OLS model takes the form,

$$\log(E^T + 1) = \beta_0 + \beta_1{}'\mathbf{S} + \beta_2{}'\mathbf{V} + \beta_3{}'\mathbf{N} + \beta_4{}'\mathbf{A} + \mu \qquad (18)$$

Table 7-5 shows the results of fitting our base models on the Jinan neighborhood form and household data. In column "control model", we only include the socioeconomic and demographics (S) and vehicle ownership (V) as control variables in the model. Most variables are significant with expected signs. For example, the significant and positive coefficient of the log-transformed income variable suggests a positive, with diminishing return, effect of income on household travel energy use. In other words, the richer a household is, the more travel energy it consumes, but less so. This is intuitive given that people have time, budget and physical constraints, somewhat evidenced in Figure 6-11. Families with children consume more travel energy use whereas aging families consume less. The reason for this contrast may be that children raise overall household travel demand as they require more activities (e.g., recreational, educational, hospital, etc.), whereas elderly people may be more physically constrained and/or have less out of home commitments and thus prefer to stay at home or travel in short distances.

Vehicle ownership variables (**V**) have significant impacts on energy use as well. Households with cars use more energy, and particularly, households with a company car tend to consume more energy than those with a private car. The latter has not, apparently, been revealed in the literature. It suggests that company cars induce more auto use, as households do not pay for fuels. Or perhaps people are assigned company cars because of their intensive business travel requirement.

Most of the neighborhood variables (**N**), added to the regression in column "plus neighborhood" (Table 7-5) are significant at the 5 percent level. The neighborhood variables include location factors, size and form typologies. Distance to the city center has an expected positive impact on travel energy use since neighborhoods further away from the center, all else equal, are further geographically from all other potential destinations in the city (assuming a center-city density gradient) and may imply worse transit and nearby public services. Households close to BRT corridors tend to consume more travel energy. This may seem counter-intuitive, yet it can be explained by potential trade-off among different aspects of travel patterns, as discussed in section 3.2. We will examine those sub-effects later in this chapter. Regarding the neighborhood typology, all non-"superblock" neighborhood typologies have significant effects in reducing household travel energy use. It seems that the diverse land use, parking restriction and walkable street design (e.g., refined internal road network) encourage households to travel with higher energy efficiency. The only neighborhood characteristic that has a non-significant effect is the neighborhood size. Also notice that the coefficients and their significance remain almost the same as those in the first "control model".

Finally, the household attitudes (**A**) are added to the model in column "plus attitudes". Out of five attitude variables, only the attitude of car prestige/status ("Car_as_Prestige") is revealed to be significant. It is interesting to see its coefficient is negative, suggesting that all else equal, households that view the car as a sign of prestige do consume less travel energy; and vice versa. One possible explanation, as phrased earlier in section 6.7, is that people who have the car and drive a lot in Jinan today regard it as a common travel means. On the other hand, such a finding perhaps also implies that among people without much driving experiences, the status symbol perception still exist and may serve as a strong motive for their future transition to car owners.

By comparing the adjusted R square statistics, we can see that the "plus neighborhood" model improves the explanation power perceptibly (although not much) whereas there is hardly any improvement from the "plus neighborhood" to the "plus attitude" model.

Table 7-5 Comparison of OLS Models Predicting Log Transformed Household Weekly Total Travel Energy Use (ln_total_mj)

	Control Model		Plus Neighborhood		Plus Attitudes	
	Coefficient	t-test	Coefficient	t-test	Coefficient	t-test
Household Characteristics						
Ln_Income	**0.521****	7.94	**0.322****	4.79	**0.313****	4.63
Adult_1	**-0.435****	-2.60	**-0.452****	-2.75	**-0.447****	-2.71
Adult_2	ref.		ref.		ref.	
Adult_3_or_more	**0.158***	1.68	**0.234****	2.53	**0.257****	2.77
Child_1_or_more	**0.285****	3.96	**0.235****	3.32	**0.239****	3.37
Elderly_1_or_more	**-0.220****	-2.04	**-0.227****	-2.13	**-0.233****	-2.19
Worker_0	**-1.265****	-8.03	**-1.272****	-8.25	**-1.246****	-8.03
Worker_1	**-0.262****	-2.40	**-0.224****	-2.09	**-0.209***	-1.95
Worker_2_or_more	ref.		ref.		ref.	
Car_1_or_more	**1.790****	18.90	**1.563****	16.16	**1.552****	15.90
Company_car	**2.046****	8.05	**2.030****	8.17	**2.010****	8.08
Motorcycle_1_or_more	**0.418****	3.27	**0.620****	4.89	**0.624****	4.91
Ebike_1_or_more	**-0.168****	-2.02	**-0.168****	-2.05	**-0.172****	-2.09
Bike_1	-0.084	-0.98	-0.09	-1.08	-0.087	-1.02
Bike_2_or_more	**-0.374****	-3.22	**-0.365****	-3.19	**-0.384****	-3.31
Neighborhood Characteristics						
Distance_to_Center			**0.081****	2.47	**0.072****	2.19
On_BRT_Corridor			**0.224****	2.24	**0.223****	2.23
Neighborhood_Size			0.005	1.43	0.005	1.63
Traditional			**-1.317****	-6.62	**-1.304****	-6.55
Grid			**-0.814****	-5.03	**-0.793****	-4.87
Enclave			**-0.653****	-4.46	**-0.654****	-4.43
Superblock			ref.		ref,	
Household Attitudes						
Car_as_Prestige					**-0.252****	-2.79
Transit_as_Convenience					0.082	0.98
I_Like_Biking					-0.024	-0.31
Travel_is_Waste_of_Time					0.105	1.33
Transport_as_Key_to_Housing_Choice					-0.005	-0.05
(Constant)	0.003	0.01	**1.362****	2.76	**1.405****	2.77
No. Observations	2432		2432		2431	
F	101.626		79.048		62.561	
R^2	0.353		0.384		0.385	

Note: *p<.10, **p<.05

7.1.2 *TOBIT Models*

One shortcoming of the OLS model results from the distribution of the dependent variable (ln_total_mj) values. In section 6.6, we saw that in our sample log-transformed energy values had a normal distribution but with about 500 zero values (see Figure 6-15). In section 5.6, we phrased it as a dependent variable censoring problem and introduced the TOBIT model to address it.

Table 7-6 presents the results of fitting the TOBIT model in our Jinan household data in comparison with the results from the OLS model estimation. All variables that are statically significant at the .001 level in the OLS model remain significant in the TOBIT model, except for the E-bike ownership ("Ebike_1_or_more"). Signs of coefficients in the TOBIT model are also identical to those in the OLS model.

The major difference comes from the values of coefficients in two models. Table 7-6 shows that for all variables, their coefficients in the TOBIT model are greater than those in the OLS model. We should be cautious on directly comparing them since the coefficients in TOBIT indicate marginal effect on latent variable, not the observed variable which is of our interest here. However, the logic still goes that, as negative latent dependent values are allowed in estimation, the fitting line for TOBIT should become steeper and suggest more significant effects. It seems to be safe to say that the censoring problem of the dependent variable does exist in the OLS model and zero energy values are indeed associated with some latent negative values. As the statistics literature suggests, if we drew the conclusion only from the OLS model, effects of explanatory variables in our model would have been underestimated (Sigelman & Zeng, 1999). Along this line, the TOBIT model seems to perform better than the OLS model from both the theoretical and practical perspectives.

Table 7-7 compares results of conducting TOBIT models predicting household weekly transportation energy consumption and GHG emissions in our Jinan data, respectively. All effects of variables are identical, except that for E-bike ownership, it has a significant positive impact on GHG emissions, whereas it does not affect energy use. This probably reflects that E-bike is powered by electricity which is mostly generated by coal power plants in the Jinan region (Cherry, *et al.*, 2009b). Coefficients in Table 7-7 indicates that having an E-bike in Jinan is somewhat closely as "dirty" as owning a motorcycle from a GHG emission perspective, whereas the former is relatively more energy efficient.

Unfortunately, neither of the two models have fully addressed the endogeneity problem if, for example, some latent factor influences both vehicle ownership and vehicle usage (thus energy consumptions) at the same time. I the next section we will use the 2-stage modeling technique in an attempt to address this concern.

Table 7-6 Final OLS vs TOBIT on Predicting Log Transformed Household Weekly Total Transport Energy Use (ln_total_mj)

	Final OLS		Final TOBIT	
	Coefficient	t-test	Coefficient	t-test
Household Characteristics				
Ln_Income	**0.314****	4.68	**0.385****	4.65
Adult_1	**-0.455****	-2.77	**-0.677****	-3.24
Adult_2	ref.		ref.	
Adult_3_or_more	**0.256****	2.76	**0.293****	2.58
Child_1_or_more	**0.241****	3.40	**0.273****	3.15
Elderly_1_or_more	**-0.237****	-2.24	**-0.294****	-2.24
Worker_0	**-1.254****	-8.13	**-1.754****	-8.92
Worker_1	**-0.216****	-2.02	**-0.225***	-1.72
Worker_2_or_more	ref.		ref.	
Car_1_or_more	**1.551****	16.04	**1.644****	14.05
Company_car	**2.009****	8.09	**2.169****	7.28
Motorcycle_1_or_more	**0.621****	4.90	**0.782****	5.09
Ebike_1_or_more	**-0.173****	-2.10	-0.043	-0.43
Bike_1	-0.087	-1.04	-0.119	-1.16
Bike_2_or_more	**-0.378****	-3.30	**-0.471****	-3.34
Neighborhood Characteristics				
Distance_to_Center	**0.077****	2.36	**0.085****	2.16
On_BRT_Corridor	**0.214****	2.15	**0.252****	2.05
Neighborhood_Size	0.005	1.46	0.006	1.63
Traditional	**-1.303****	-6.56	**-1.570****	-6.47
Grid	**-0.806****	-4.99	**-0.957****	-4.83
Enclave	**-0.646****	-4.42	**-0.736****	-4.15
Superblock	ref.		ref.	
Household Attitudes				
Car_as_Prestige	**-0.243****	-2.70	**-0.314****	-2.83
(Constant)	**1.472****	2.98	0.763	1.25
No. Observations	2431		2431	
F	75.75			
LR chi2 (20)			1091.57	
Log likelihood			-4840.34	
Adjusted R^2	0.381			
Pseudo R^2			0.383	

Note: *p<.10, **p<.05

Table 7-7 Comparison of Single-Stage TOBIT Models on Predicting Log Transformed Household Weekly Total Transport Energy Use (ln_total_mj) vs. GHG Emissions (ln_total_co2)

	ENERGY		EMISSION	
	Coefficient	t-test	Coefficient	t-test
Household Characteristics				
Ln_Income	**0.385****	4.65	**0.596****	4.18
Adult_1	**-0.677****	-3.24	**-1.263****	-3.54
Adult_2	ref.			
Adult_3_or_more	**0.293****	2.58	**0.389****	1.99
Child_1_or_more	**0.273****	3.15	**0.388****	2.61
Elderly_1_or_more	**-0.294****	-2.24	**-0.490****	-2.18
Worker_0	**-1.754****	-8.92	**-3.149****	-9.37
Worker_1	**-0.225***	-1.72	-0.33	-1.47
Worker_2_or_more	ref.			
Car_1_or_more	**1.644****	14.05	**1.901****	9.43
Company_car	**2.169****	7.28	**2.819****	5.49
Motorcycle_1_or_more	**0.782****	5.09	**1.291****	4.88
Ebike_1_or_more	-0.043	-0.43	**0.941****	5.47
Bike_1	-0.119	-1.16	-0.255	-1.45
Bike_2_or_more	**-0.471****	-3.34	**-0.836****	-3.45
Neighborhood Characteristics				
Distance_to_Center	**0.085****	2.16	**0.119***	1.75
On_BRT_Corridor	**0.252****	2.05	**0.364***	1.73
Neighborhood_Size	0.006	1.63	0.011	1.58
Traditional	**-1.570****	-6.47	**-2.464****	-5.90
Grid	**-0.957****	-4.83	**-1.547****	-4.54
Enclave	**-0.736****	-4.15	**-1.123****	-3.68
Superblock	ref.			
Household Attitudes				
Car_as_Prestige	**-0.314****	-2.83	**-0.490****	-2.57
(Constant)	0.763	1.25	**2.666****	2.55
No. Observations	2431		2431	
LR chi2 (20)	1091.57		882.22	
Log likelihood	-4840.34		-4840.34	
Pseudo R^2	0.383		0.319	

Note: *p<.10, **p<.05

7.2 **Advanced Two-Step Instrumental Models on Household Transport Energy Use**

In section 5.6.2, we illustrated the possibility that some omitted variables (e.g., parking cost at household workplaces) in our dataset may be correlated with both transportation energy consumption and vehicle ownership and, if that is the case, the endogeniety problem results. In response, we introduce a two-stage instrument modeling approach. This section will present the application of this method in the Jinan case.

7.2.1 *Step One: Incorporating Household Vehicle Choice*

In the first step, we focus on modeling the endogenous explanatory variables of household vehicle ownership. We hypothesize that a certain type of household vehicle ownership can be influenced by neighborhood characteristics, household socioeconomics and demographics, household attitudes, and other types of vehicle ownership. We specify binary logistical regression models for each vehicle type (i.e., automobile, motorcycle, E-bike, and bike), with the form:

$$\log\left(\frac{\Pr(V=1)}{\Pr(V=0)}\right) = \beta_0 + \beta_1{}'\mathbf{S} + \beta_2{}'\mathbf{V}^* + \beta_3{}'\mathbf{N} + \beta_4{}'\mathbf{A} + \beta_5{}'\boldsymbol{I}^* + \delta \quad (19)$$

where V* is a vector of other vehicle ownerships, and I* is a vector of instrumental variables. Recall from section 5.6.2, choosing "good" instruments requires some consideration. Specifically, they should correlate with vehicle ownership but be uncorrelated with vehicle use or energy consumption. Through some reasoning and experimentation, six instrument variables are selected, as shown in Table 7-8.

Table 7-8 Instrumental Variables

Variable Name	Description	Reasoning
Home_owned	a dummy variable equal to one if the household owns the house outright, and 0 otherwise	Housing tenure and vehicle ownership are both long-term choice and should correlate; housing tenure should not affect travel behavior pattern which is a short-term choice.
Home_mortgaged	a dummy variable equal to one if the household owns the house with a mortgage, and 0 otherwise	Same as above.
Small_business	a dummy variable equal to one if the household runs small business and 0 otherwise	Households running small business need automobile or light truck for loading activities. But the business may not require intensive travel.
Transit_as_Convenience I_Like_Biking Travel_is_Waste_of_Time	proxy dummy variables of travel-related attitudes	These are all ownership-related attitudes, but none correlate with energy use as evidenced in the single-stage models.

In regressing vehicle ownership choice of a certain type, an incremental model specification approach is taken, similar to what we have done in single-stage models. The basic model is a "control model" including only household socioeconomic and demographic variables(S) and other vehicle ownership variables (V*). Then neighborhood variables (N) are included. Lastly, I add the household attitude variables (A) to get a "full" model ("plus attitude").

I first use instruments to model the household car ownership. Results are reported in Table 7-9. Several observations can be made.

- The significance and signs of explanatory variables remain consistent across the three models. Inserted instrumental variables are all significant at 0.05 level, except the variable for attitudes favoring biking ("I_Like_Biking"). This suggests some promise in terms of using the vehicle ownership models to instrument in the second-stage model of energy use.

- The "plus attitude" model shows the best goodness of fit among all three models, evidenced by an application of the likelihood ratio test. [13] Therefore, I use this "full model to calculate the predicted values of car ownership for each household. In the second stage model, these predicted values replace observed car ownership values to correct for the endogeneity problem in the single-stage models.

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[13] We first compare the "Plus Neighborhood" model to the "Control" model with the following statistic, which has a chi-square distribution with 20-14=6 degree of freedom: -2(L(Control Model) - L(Plus Neighborhood Model)) = -2(-1112.133 +1059.197) = 115.872. 115.872> the critical value of 12.592 (at a 5% level of significance). Thus, we reject the null hypothesis of non-neighborhood effect.

Second, we compare the "Plus Attitudes" model to "Plus Neighborhood" model using the following statistics, which has a chi-square distribution with 20-16=4 degree of freedom: -2(L(Plus Neighborhood Model) - L(Plus Attitudes Model)) = -2(-1059.197+1038.013) = 42.368. 42.368> the critical value of 9.488 (at a 5% level of significance). Thus we reject the null hypothesis of non-attitude effect.

Table 7-9 Binary Logistical Regression Models Predicting Car Ownership

	Control Model		Plus Neighborhood		Plus Attitudes	
	Coefficient	Z-test	Coefficient	Z-test	Coefficient	Z-test
Household Characteristics						
Income_100USD	**0.139****	12.44	**0.105****	9.11	**0.099****	8.45
Adult_1	0.216	0.73	0.034	0.11	-0.027	-0.09
Adult_2	ref.		ref.		ref.	
Adult_3_or_more	-0.196	-1.49	-0.095	-0.69	-0.052	-0.38
Child_1_or_more	**0.491****	5.04	**0.423****	4.18	**0.431****	4.20
Elderly_1_or_more	**-0.495****	-3.22	**-0.429****	-2.68	**-0.383****	-2.36
Worker_0	**-1.378****	-4.70	**-1.248****	-4.18	**-1.148****	-3.82
Worker_1	**-0.478****	-3.03	**-0.448****	-2.74	**-0.399****	-2.40
Worker_2_or_more	ref.		ref.		ref.	
Company_car	-0.094	-0.28	-0.128	-0.38	-0.223	-0.66
Motorcycle_owned	**-0.698****	-3.55	**-0.577****	-2.81	**-0.577****	-2.80
Ebike_owned	**-0.669****	-5.92	**-0.675****	-5.74	**-0.714****	-5.98
Bike_owned	**-0.785****	-7.18	**-0.724****	-6.35	**-0.711****	-6.07
Small_business (IV)	**0.366****	3.01	**0.379****	2.97	**0.361****	2.79
Home_owned (IV)	**1.601****	8.60	**1.391****	6.84	**1.425****	6.97
Home_mortgaged (IV)	**1.726****	7.86	**1.059****	4.21	**1.057****	4.16
Neighborhood Characteristics						
Distance_to_Center			**-0.163****	-3.82	**-0.151****	-3.46
On_BRT_Corridor			**-0.249***	-1.66	-0.231	-1.52
Neighborhood_Size			**0.013****	2.93	**0.011****	2.52
Traditional			**-1.212****	-4.04	**-1.106****	-3.64
Grid			**-1.660****	-7.22	**-1.522****	-6.52
Enclave			**-1.684****	-8.90	**-1.535****	-7.98
Superblock			**ref.**		**ref.**	
Household Attitudes						
Car_as_Prestige					**-0.416****	-2.98
Transit_as_Convenience (IV)					**-0.510****	-4.39
I_Like_Biking (IV)					-0.040	-0.36
Travel_is_Waste_of_Time (IV)					**0.363****	3.24
(Constant)	**-2.759****	-12.71	**-0.940****	-2.82	**-0.751****	-2.16
No. Observations	2,404		2,404		2,398	
LR χ^2	750.38		856.25		892.57	
Prob > χ^2	0.000		0.000		0.000	
Log likelihood	-1112.133		-1059.197		-1038.013	
Pseudo R^2	0.252		0.288		0.301	

Note: *p<.10, **p<.05, (IV) Instrument Variables

The models also provide important evidence for understanding the factors influencing household car ownership in the context of Jinan, China. Since we are modeling households' probability of owning one or more cars, a positive coefficient sign indicates that the explanatory variable has a positive effect on household car ownership; and vice versa.

The most important finding in the larger research context is that neighborhood form characteristics play an important role in affecting household car ownership choice after controlling for confounding factors (including attitudes). The signs on the coefficients for all three non-"superblock" neighborhood typology dummies are negative, suggesting that households living in the "superblock" neighborhoods have a higher probability of car ownership. This is probably due to the difference between the automobile-oriented design features of "superblock" neighborhoods versus the more walking-oriented design of the other neighborhood typologies. Note, that as travel attitudes figure significantly in the model (as discussed further below), we can assert at least partial control for the fact that auto-oriented households might prefer to live in the "superblocks". The neighborhood form is significant even after controlling for attitudes.[14] The neighborhood size shows a positive sign, indicating that households living in bigger neighborhoods are more likely to own cars. An explanation might be that neighborhoods in Jinan often do not have transit service within themselves (except the "grid" one), the size of a neighborhood thus is correlated to on average transit walking access distance among residents; bigger neighborhoods will make transit less accessible, and people, as a result, shift towards driving and owning cars.

Neighborhood location characteristics matter too. The model results indicate that car ownership tends to be higher for households living close to the city center than otherwise. This is contrary to most findings in the west, yet consistent with recent findings in Beijing and Chengdu, China (Li, *et al.*, 2010). Authors in that article argue that urban centers in most Chinese cities provide good urban amenities, and households with cars are often rich and still prefer to live there; in the US, however, middle-class and affluent families tend to prefer suburban communities along with the post World War-II city center decline. This argument, although true to some extent, may not be convincing given that household income is already controlled for in their models. In my case, I speculate that the distance to city center effect may be because 1) we have little variation in the distance to city center among the neighborhoods studied; or 2) the variable of distance to city center itself is not a good proxy for measuring regional accessibility given that Jinan has already evolved into more of a multi-center city structure.

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[14] Of course, this does not account for more complex likely behavioral effects, such as attitudes changing based on neighborhood, neighborhood choice conditional on vehicle ownership preferences, joint decision-making, among others.

The effect of proximity to bus-rapid-transit (BRT) corridors on household car ownership reveals interesting potential dynamics. In the "plus neighborhood" model, the results suggest the effect is significant and negative. However, this effect becomes insignificant after controlling for household attitudes, as evidenced in the "plus attitude" model. This change in significance, combined with the revealed negative and significant effects of the transit convenience attitude, suggests a self-selection effect going on: households may live on the BRT corridor because they like transit, and it is such a travel mode preference that lowers their likelihoods of owning cars.

Household characteristics also show some interesting effects. The effect of household income is positive as expected: richer households have a higher probability of owning cars. Having children appears to be an incentive for households to buy cars, while having elderly people has the opposite effect. The pattern is similar to what we see in the energy consumption models. This is also intuitive since walking, biking or taking transit with children is often inconvenient and unsafe; for elderly people, driving may become much difficult than taking other modes and/or they may simply have different lifestyle habits and expectations. The number of workers has a positive impact on car ownership. Households running small business are more likely to own a car, probably reflecting their demand for business flexibility and logistics. Households who own a house outright have a higher chance of owning a car than households owning a house with a mortgage; renting households have the lowest car ownership likelihood. Renters or mortgage payers have less disposable income relative to the households owning their house outright. Family size does not have a significant effect on car ownership. Other type of vehicle ownership decreases the probability of owning cars, indicating a substitution effect among different vehicle type choices.[15]

Finally, attitudes have critical impacts on car ownership. Households that see car a sign of prestige are less likely to own cars. This can be interpreted in two ways: 1) households without cars envy those who have one (a sign of car prestige/status effect); and 2) as households own cars, the car becomes perceived as more of a perceived need than a sign of status. Perceiving

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[15] Ideally this substitution effect can be scrutinized via having a nested model structure. This is one of future research interests.

transit as a convenient mode decreases the household's likelihood of owning cars, suggesting that transit seems at least a partial perceived substitute to driving in Jinan. Finally and interestingly, households viewing travel as a waste of time are more likely to own cars, suggesting these households have a higher value of time and thus prefer the speed and convenience of car ownership.

Beyond modeling car ownership, I follow similar approach to constructing models for two-wheeled vehicles (2-WV); that is ownership of motorcycle, E-bike and bike. The results are shown in Table 7-10. For 2-WV ownership, neighborhood characteristics seem still relevant. For example, households living further away from the city center and in bigger neighborhood are more likely to own e-bikes, suggesting the value of power assist to traverse the extra distances The proximity of BRT corridors has a positive effect on household bike ownership, suggesting a possibly complementary relationship among these modes. Compared to the "superblock", the "traditional" neighborhood typology increases likelihood of households owning motorcycles, e-bikes and bikes all together, probably because car is physically inhibited by the narrow lanes and lack of parking. The "grid" neighborhood typology has similar impacts except its impact on household E-bike ownership is insignificant. The enclave neighborhood typology increases likelihood of household motorcycle ownership.

The household characteristics' role in 2-WV ownership is much different from those in the car ownership choice, and more obscure. Income has no significant impact on motorcycle ownership, while presenting even a negative effect on E-bike and bike ownership. Here we see something of a substitution effect: low-income households who cannot afford cars tend to have more E-bikes and bikes. Single families have a lower probability of 2-WV ownership, an effect not found in the car ownership model. The effect of older adults in the family is negative, the only household effect consistent across all vehicle ownership choice models. This may be because 1) older people have lower travel demand; and 2) older adults feel less comfortable handling any vehicle type.

That said, by comparing pseudo R squares, we can see that models for 2-WV ownership have very modest explanatory power. Furthermore, many of the proposed instrumental variables are insignificant in the models. In terms of 2-WV ownership, perhaps important influencing factors were not available from the survey. Or, perhaps the choice of 2-WV ownership involves more random or less well-understood decision making processes, given that a common

2-wheeled vehicle is much cheaper than a car. This is of interest for future research. Unfortunately, for our 2-stage instrument modeling approach, the results suggest that for 2-WV ownership I have very weak instruments. In fact, I tested using predicted 2-WV ownerships in the second-stage model, but the models performed poorly. As the statistics literature warns, poor instruments are no solution to the endogeneity problem (Ebbes, 2007).

Table 7-10 Binary Logistic Regression Models Predicting Other Types of Vehicle Ownership

	Motorcycle_Owned		E-bike_Owned		Bike_Owned	
	Coefficient	Z-test	Coefficient	Z-test	Coefficient	Z-test
Household Characteristics						
Income_100USD	0.016	1.15	-0.008	-0.86	**-0.026****	-3.00
Adult_1	**-0.551***	-1.74	**-0.503****	-2.31	**-0.619****	-3.22
Adult_2	ref.		ref.		ref.	
Adult_3_or_more	0.103	0.59	**0.322****	2.91	**0.712****	6.39
Child_1_or_more	0.110	0.88	**0.354****	4.25	**0.277****	3.29
Elderly_1_or_more	**-0.422****	-1.97	**-0.379****	-2.93	**-0.263****	-2.05
Worker_0	**-0.830****	-2.20	**-0.705****	-3.53	-0.207	-1.14
Worker_1	0.186	1.04	**-0.253****	-2.01	**-0.211***	-1.68
Worker_2_or_more	ref.		ref.		ref.	
Car_owned	**-0.574****	-2.83	**-0.752****	-6.31	**-0.706****	-6.14
Company_car	-0.376	-0.70	**-0.734****	-2.21	n.a	
Motorcycle_owned	n.a		**0.514****	3.57	-0.098	-0.66
Ebike_owned	**0.506****	3.50	n.a		**-0.375****	-3.88
Bike_owned	-0.093	-0.62	**-0.368****	-3.82	0.001	0.00
Small_business (IV)	**0.378****	2.50	0.116	1.10	-0.085	-0.80
Home_owned (IV)	-0.124	-0.64	**0.579****	4.02	**0.817****	5.94
Home_mortgaged (IV)	-0.212	-0.63	**0.663****	3.33	**0.951****	4.86
Neighborhood Characteristics						
Distance_to_Center	0.003	0.04	**0.080****	2.05	-0.010	-0.26
On_BRT_Corridor	-0.096	-0.47	-0.080	-0.65	**0.477****	4.01
Neighborhood_Size	-0.005	-0.75	**0.008****	2.14	0.001	0.23
Traditional	**1.663****	3.99	**0.993****	4.01	**0.460***	1.86
Grid	**0.784****	2.33	-0.209	-1.05	0.296	1.53
Enclave	**0.820****	2.43	-0.012	-0.07	-0.013	-0.08
Superblock	ref.		ref.		ref.	
Household Attitudes						
Car_as_Prestige	-0.025	-0.16	-0.026	-0.24	0.081	0.77
Transit_as_Convenience (IV)	0.119	0.78	**-0.294****	-2.98	0.131	1.35
I_Like_Biking (IV)	0.006	0.04	0.090	0.98	**0.700****	7.84
Travel_is_Waste_of_Time (IV)	0.173	1.21	0.083	0.89	-0.111	-1.21
(Constant)	**-2.997****	-6.35	**-1.173****	-4.14	**-0.659****	-2.39
No. Observations	2,398		2,398		2,398	
LR χ^2	141.38		237.97		320.32	
Prob > χ^2	0.000		0.000		0.000	
Log likelihood	-737.465		-1449.484		-1476.666	
Pseudo R^2	0.088		0.076		0.098	

Note: *p<.10, **p<.05

7.2.2 *Step Two: Household Weekly Transport Energy Use*

In the second stage model, I first predict car ownership probabilities for all observations in our sample and insert these predicted values into the initial regression equation for household weekly total travel energy use, replacing the observed car ownership values. For 2-WV ownership, I stick with the observed values, since the instrument variables in 2-WV ownership models were unqualified. For techniques of calculating the predicted probability of car ownership, see section 5.6.2.

In regressing travel energy consumption with the instrumented car ownership values, both OLS and TOBIT models are tested. Table 7-11 presents results from a series of models, including the OLS and TOBIT models following the two-step procedures as well as single-stage models derived in section 5.6. The purpose is to compare results from alternative approaches and see whether the neighborhood effects remain robust as we are trying to solve the endogeneity problem.

As can be seen in Table 7-11, the significance and signs of the coefficients for most explanatory variables are almost the same across all models. With respect to the neighborhood characteristics, the coefficients of the three neighborhood typology dummies are all negative and significant, which gives us much confidence in concluding that households in the "traditional", "grid" and "enclave" neighborhoods consume less energy in travel than those living in the "superblock" neighborhoods. Households living on BRT corridors remain strongly correlated with more travel energy consumption. We are also quite confident that the distance to city center has a positive effect on household energy use despite a less significant effect in the 2-stage TOBIT model. Neighborhood size turns out to be significant at 10% confidence level after correcting the censoring and endogeneity problems by using the 2-stage TOBIT model. This suggests our statistical control on the neighborhood size is useful and effective.

Most effects of household socioeconomic, demographics and vehicle ownership on transportation energy use are also consistent with those in the single-stage models. The only exception is that the negative effect of single-worker family on household transportation energy consumption was found significant in the single-stage models but not significant in two-stage models.

Finally, we compare the results of the models of household transportation energy consumption and GHG emissions. As shown in Table 7-12, most effects (except the E-bike ownership) on energy use described above can be applied in explaining the variance in GHG emissions.

Table 7-11 Comparisons of Models Predicting Log Transformed Household Weekly Total Travel Energy Use (ln_total_mj)

	2-Stage OLS		2-Stage TOBIT		1-Stage OLS		1-Stage TOBIT	
	Coefficient	t-test	Coefficient	t-test	Coefficient	t-test	Coefficient	t-test
Household Characteristics								
Ln_Income	**0.348****	4.16	**0.475****	4.55	**0.314****	4.68	**0.385****	4.65
Adult_1	**-0.517****	-2.98	**-0.772****	-3.50	**-0.455****	-2.77	**-0.677****	-3.24
Adult_2	ref.		ref.		ref.		ref.	
Adult_3_or_more	**0.254****	2.61	**0.294****	2.46	**0.256****	2.76	**0.293****	2.58
Child_1_or_more	**0.219****	2.77	**0.273****	2.81	**0.241****	3.40	**0.273****	3.15
Elderly_1_or_more	**-0.256****	-2.25	**-0.340****	-2.42	**-0.237****	-2.24	**-0.294****	-2.24
Worker_0	**-1.273****	-7.71	**-1.856****	-8.79	**-1.254****	-8.13	**-1.754****	-8.92
Worker_1	-0.186	-1.62	-0.208	-1.48	**-0.216****	-2.02	**-0.225***	-1.72
Worker_2_or_more	ref.		ref.		ref.		ref.	
Car_1_or_more	n.a		n.a		**1.551****	16.04	**1.644****	14.05
P_Car_Owned (Instrumented)	**1.639****	4.77	**1.451****	3.44	n.a		n.a	
Company_car	**1.952****	7.38	**2.090****	6.59	**2.009****	8.09	**2.169****	7.28
Motorcycle_1_or_more	**0.609****	4.52	**0.750****	4.58	**0.621****	4.90	**0.782****	5.09
Ebike_1_or_more	**-0.154***	-1.65	-0.05	-0.44	**-0.173****	-2.10	-0.043	-0.43
Bike_1	-0.039	-0.41	-0.101	-0.88	-0.087	-1.04	-0.119	-1.16
Bike_2_or_more	**-0.398****	-3.21	**-0.527****	-3.46	**-0.378****	-3.30	**-0.471****	-3.34
Neighborhood Characteristics								
Distance_to_Center	**0.083****	2.31	**0.084***	1.92	**0.077****	2.36	**0.085****	2.16
On_BRT_Corridor	**0.252****	2.40	**0.298****	2.31	**0.214****	2.15	**0.252****	2.05
Neighborhood_Size	0.005	1.53	**0.008***	1.93	0.005	1.46	0.006	1.63
Traditional	**-1.204****	-5.03	**-1.576****	-5.40	**-1.303****	-6.56	**-1.570****	-6.47
Grid	**-0.748****	-3.63	**-1.005****	-3.98	**-0.806****	-4.99	**-0.957****	-4.83
Enclave	**-0.589****	-2.99	**-0.787****	-3.28	**-0.646****	-4.42	**-0.736****	-4.15
Superblock	ref.		ref.		ref.		ref.	
Household Attitudes								
Car_as_Prestige	**-0.246****	-2.58	**-0.338****	-2.87	**-0.243****	-2.70	**-0.314****	-2.83
(Constant)	**1.125****	2.13	0.23	0.35	**1.472****	2.98	0.763	1.25
No. Observations	2421		2421		2431		2431	
F	59.00				75.75			
LR chi2 (20)			926.95				1091.57	
Log likelihood			-4902.44				-4840.34	
Adjusted R^2	0.324				0.381			
Pseudo R^2			0.326				0.383	

Note: *p<.10, **p<.05

Table 7-12 Comparison of Two-Stage Models on Predicting Log Transformed Household Weekly Total Travel Energy Use (ln_total_mj) vs. GHG Emissions (ln_total_co2)

	Energy				GHG			
	2-Stage OLS		2-Stage TOBIT		2-Stage OLS		2-Stage TOBIT	
	Coefficient	t-test	Coefficient	t-test	Coefficient	t-test	Coefficient	t-test
Household Characteristics								
Ln_Income	**0.348****	4.16	**0.475****	4.55	**0.605****	4.33	**0.797****	4.55
Adult_1	**-0.517****	-2.98	**-0.772****	-3.50	**-1.021****	-3.54	**-1.406****	-3.83
Adult_2	ref.		ref.		ref.		ref.	
Adult_3_or_more	**0.254****	2.61	**0.294****	2.46	**0.331****	2.04	**0.389***	1.94
Child_1_or_more	**0.219****	2.77	**0.273****	2.81	**0.339****	2.56	**0.418****	2.56
Elderly_1_or_more	**-0.256****	-2.25	**-0.340****	-2.42	**-0.465****	-2.45	**-0.593****	-2.52
Worker_0	**-1.273****	-7.71	**-1.856****	-8.79	**-2.433****	-8.84	**-3.321****	-9.43
Worker_1	-0.186	-1.62	-0.208	-1.48	-0.305	-1.59	-0.337	-1.43
Worker_2_or_more	ref.		ref.		ref.		ref.	
Car_1_or_more	n.a		n.a		n.a		n.a	
P_Car_Owned (Instrumented)	**1.639****	4.77	**1.451****	3.44	**1.415****	2.44	**1.114***	1.86
Company_car	**1.952****	7.38	**2.090****	6.59	**2.443****	5.55	**2.657****	4.99
Motorcycle_1_or_more	**0.609****	4.52	**0.750****	4.58	**0.988****	4.39	**1.195****	4.36
Ebike_1_or_more	**-0.154***	-1.65	-0.05	-0.44	**0.686****	4.40	**0.863****	4.52
Bike_1	-0.039	-0.41	-0.101	-0.88	-0.23	-1.52	-0.318*	-1.71
Bike_2_or_more	**-0.398****	-3.21	**-0.527****	-3.46	**-0.693****	-3.23	**-0.905****	-3.41
Neighborhood Characteristics								
Distance_to_Center	**0.083****	2.31	**0.084***	1.92	**0.103***	1.72	0.102	1.40
On_BRT_Corridor	**0.252****	2.40	**0.298****	2.31	**0.360****	2.06	**0.427****	1.97
Neighborhood_Size	0.005	1.53	**0.008***	1.93	**0.011***	1.81	**0.015****	2.08
Traditional	**-1.204****	-5.03	**-1.576****	-5.40	**-2.090****	-5.22	**-2.651****	-5.39
Grid	**-0.748****	-3.63	**-1.005****	-3.98	**-1.403****	-4.10	**-1.799****	-4.26
Enclave	**-0.589****	-2.99	**-0.787****	-3.28	**-1.082****	-3.29	**-1.388****	-3.44
Superblock	ref.		ref.		ref.		ref.	
Household Attitudes								
Car_as_Prestige	**-0.246****	-2.58	**-0.338****	-2.87	**-0.414****	-2.61	**-0.551****	-2.79
(Constant)	**1.125****	2.13	0.23	0.35	**3.143****	3.58	**1.798***	1.65
No. Observations	2421		2421		2431		2431	
F	59.00				50.23			
LR chi2 (20)			926.95				813.29	
Log likelihood			-4902.44				-5957.91	
Adjusted R^2	0.324				0.289			
Pseudo R^2			0.326				0.294	

7.2.3 *Combined Effects: Overall Relative Influence of Neighborhood Characteristics*

In this section, we adopt the two-step modeling approach comprised of two main equations: (1) the household's transportation energy consumption (controlling for car ownership); and (2) the household's car ownership. By estimating these 2 models, we can distinguish between *direct* effects of a neighborhood variable (or another) on household travel energy consumption and the *indirect* effects of the same variable on the energy consumption via the influence of this variable on household car ownership.

The relative influences can be estimated in the form of marginal effects, which enables an assessment of the relative magnitude of the impact of different variables of interest on transportation energy use. Specifically in our case, we measure the unit change in energy consumption (before adjusted log-transformation, in MJ/household/week) caused by a one-unit change in an independent variable (or a hypothesized scenario change) while holding other independent variables constant. To calculate the marginal effects, I adapt Zegras (2010)'s method of estimating the elasticity[16].

[16] A series of estimation procedures are followed. (1) For each observation, a "baseline" total transportation energy and car ownership probability is estimated, using the coefficient estimates from the 2nd stage OLS model (see Table 7-11) and expected automobile ownership probabilities. For the investigated dummy variable, I set the value to 0 for all samples. (2) a change of value from 0 to 1 in this investigated dummy variable (or a doubling value of the continuous variable if investigated) was applied to each observation for the car ownership model; (3) new vehicle ownership probabilities were estimated based on that change; (4) the marginal effect of a certain variable on the car ownership probability was then calculated by: (Pnew – Pbaseline); (5) new energy consumption estimates (Enew) were calculated for all samples, using the 2nd stage OLS coefficients, the new predicted vehicle ownership probabilities, and the original variable (or 0 for dummy variable)- this enabled an isolation of the vehicle ownership effect on energy use (presented in "Car ownership" column in Table 7-13), calculated by: (Enew - Ebaseline); (6) Enew was re-estimated by including the changed variable directly in the transportation energy use estimation model also. This Enew2 was used to calculate a new marginal effect, which appears in the "Combined Marginal Effect of Travel Energy Use" column in Table 7-13.

Table 7-13 Conservative Estimation of Marginal Effects of Selected Variables on Household Transportation Energy Use and Car Ownership based on the 2-Stage OLS Model Results

Variable	Marginal Effect of Car Owning Probability	Marginal Effect of Travel Energy Use (MJ/Household/Week) Due to Variables' Effect on:		Combined Marginal Effect of Travel Energy Use (MJ/Household/Week)
		Car Ownership	All Vehicle Use	
Traditional (ref Superblock)	-24%	-75	-55	-130
Grid (ref Superblock)	-30%	-86	-30	-116
Enclave (ref Superblock)	-31%	-86	-21	-107
2× Distance to City Center	-8%	-18	+42	+23
On BRT Corridor	-4%	-6	+29	+22
Double Current Neighborhood Size	+4%	+8	+16	+24
Double Income	+12%	+31	+15	+46
Have Company Car (ref no company car)	-	-	+562	+562
Own Motorcycle (ref no motorcycle)	-8%	-14	+76	+61
Own E-Bike (ref no E-bike)	-10%	-13	-23	-36
Own Bike (ref no bike)	-10%	-10	-29	-40

Results from the marginal effect estimation are shown in Table 7-13. Most factors (except for the company car variable) have both *direct* impact on transportation energy use via vehicle use and *indirect* impact through the car ownership- to- vehicle use chain. In terms of the magnitude of impacts, neighborhood characteristics are among the most important factors influencing household travel energy use. Non-"superblock" neighborhood typologies decrease both car ownership and vehicle use significantly, achieving a total marginal reduction of 100-130 megajoules for each household per week in travel energy use. Conversely, doubling the size of neighborhoods can increase both car ownership and vehicle use, resulting in a marginal increase of travel energy use by 24 megajoules per household per week[17]. In our sample, most

[17] In the model specification assumptions, we do not differentiate the effect of doubling the size of a "superblock" neighborhood versus a non-"superblock" one. In reality this is probably not true given that destination opportunities in the "superblock" are much more scarce than those in the rest types, and thus doubling the size of a "superblock" neighborhood would greatly worsen the walking accessibility. An interaction term between the

neighborhoods do not allow transit service running through for the sake of security (except the "grid" one); therefore, such a doubling size effect can imply a longer access distance to transit system which will in return encourage automobile ownership and uses. The location characteristics have interestingly countervailing effects on car ownership and vehicle use. On the one hand, doubling the distance to city center and being close to BRT corridors make households less likely to own cars. On the other hand, they increase vehicle use and this *direct* impact on energy use is stronger. As a result, in both "location" scenarios, the net change in per household weekly travel energy is positive with a magnitude similar to the "doubling neighborhood size" effect. Similar countervailing effects can be found for motorcycle ownership. Overall, the impacts of 2-wheeled vehicle ownership is smaller than that of non-"superblock" neighborhood typologies, yet greater than that in the neighborhood "changing location" and "size doubling" scenarios. Finally, Table 7-13 shows the greatest impact on household travel energy use comes from having a company car, probably because we set "no-company-car" as the "baseline" scenario and thus the estimated marginal effect indicates the expected energy consumption of a company car, which is a lot.

Figure 7-1 shows estimated energy use effects of various potential policy scenarios using a more standardized measure as percentage gains in terms of energy reduction. Similar calculation approach is followed as for estimating marginal effects. Again, eliminating the availability of a company car or a private car has the greatest savings of travel energy use, followed by the neighborhood typology changes from the "superblock" to all the others. It is interesting to see that literally halving household income would not save as much energy as policy interventions in the built environment would.

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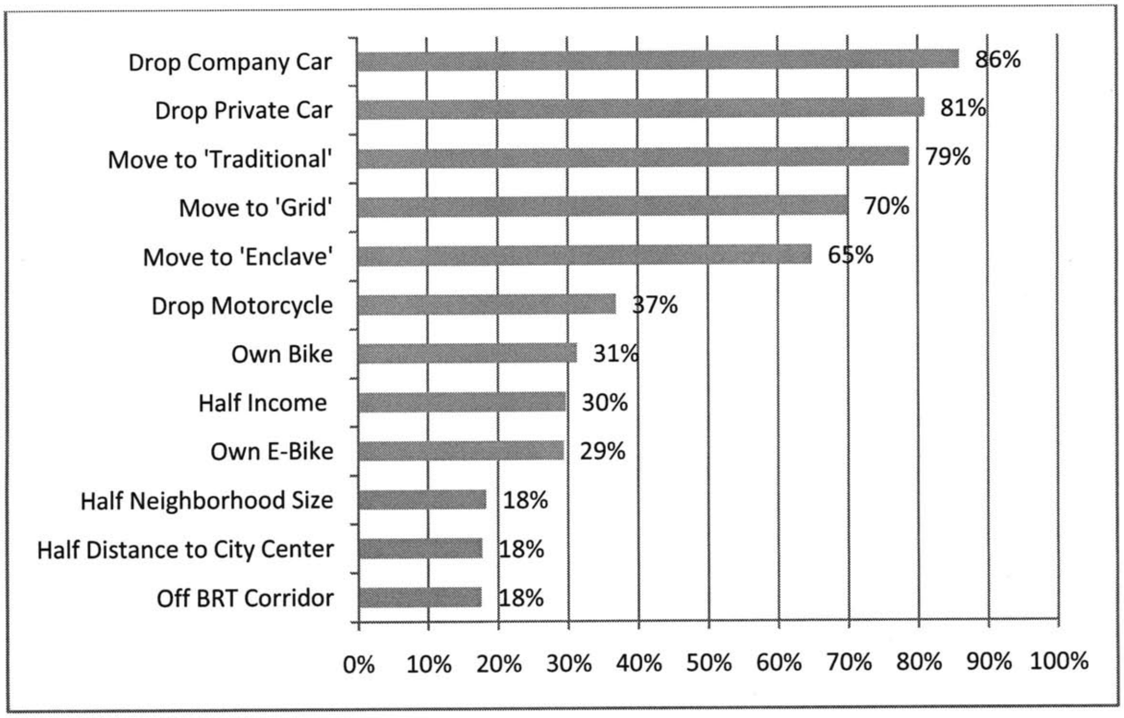
neighborhood size and typology in the model will address this but unfortunately it cannot not included in our case because the limits of variance in our sample on these two variables.

Figure 7-1 Expected Household Travel Energy Use Reductions of Hypothetical Measures



7.3 Sub Instrumental Models on Household Weekly Travel Distance by Mode

In this section, we explore the relationship between neighborhood characteristics and distance traveled by different. This potentially helps us to better understand the more nuanced effects underlying the estimated effects on total household travel energy use/GHG emissions. That is, we attempt to shed light on whether the apparent impact on energy use comes from reduced auto use, reduced transit use, increased walking, some combination, etc.

All models follow the two-stage instrument modeling approach with LOGIT+OLS and LOGIT+TOBIT both employed. Theoretically, the LOGIT+TOBIT model is better than the LOGIT+OLS model given that our dependent variables of trip distance for each mode (except walking) are heavily censored at zero.

Results using LOGIT+OLS and LOGIT+TOBIT are summarized in Table 7-14 and Table 7-15, respectively. In general, the effects of the variables revealed by the two models are consistent in terms of their significance and direction, although for the same variable, the result from the TOBIT model tends to suggest a greater magnitude of effect. Not surprisingly, the type of vehicle owned (e.g, auto) dominates that vehicle category use (e.g., auto distance traveled).

Other household attributes (including travel preferences) seem to be much more relevant in the use of transit, bike and walking than other vehicle uses. Yet we do not know why exactly it is the case.

With respect to the effect of neighborhood form, results in both models show that all non-"superblock" neighborhood typologies have significant impacts on use of car and transit, and walking; they do not affect motorcycle, E-bike or bike uses. Specifically, households in the "grid" and the "enclave" drive less and ride less transit in exchange of more walking, which implies substitution effects. The "traditional" neighborhood typology, however, reduces travel distance of all three modes including walking, suggesting it is the most self-contained. In addition, compared to the "enclave" and the "traditional" neighborhood types, the "grid" has a weaker effectiveness on reducing car travel- it even becomes ambiguous based on results in the OLS model. This reflects that the "grid" neighborhood, on the one hand, offers good access to transit and walkable streets; on the other hand, it provides more direct routes for cars which make driving attractive.

Regarding the location effects, it is worth noting that the proximity of BRT corridors does not affect transit use, a consistent finding in both models. The reason is perhaps that while households have better transit service there, they may ride the BRT frequently or travel longer distances to obtain more benefits at destinations.

We also identify some location effects that are inconsistent between results from the OLS models and the TOBIT models. For example, the effect of "distance to city center" on transit use is significant and positive in the OLS model of transit use, but becomes insignificant in the TOBIT model. Similarly, the proximity to BRT corridors indicates more car use in the OLS, but not in the TOBIT model.

Finally, by comparing results with the 2nd-stage total household energy use models (see Table 7-11), we find that sub-effects of neighborhood location features revealed in the 2nd-stage OLS sub-distance-models can explain well on their overall *direct* effect on travel energy use. The 2nd-stage TOBIT sub-distance-models failed to do so: while location effects are significant in the overall energy use TOBIT model, none is significant in 2nd-stage TOBIT sub-models on energy consumed vehicle use. Since there are no precedents of applying LOGIT+TOBIT in the literature, we are not quite sure whether it is indeed a statistically appropriate. However, to address this puzzle is beyond the scope of this research. Therefore, following discussions are based only on the 2^{nd}-stage OLS models (Table 7-14) combined with the total energy use 2^{nd}-stage OLS model (Table 7-11).

Compared to the "superblock", the "traditional" neighborhood *directly* reduces total household travel energy consumption mainly by shortening household car driving and transit distance. The "grid" neighborhood, overall, can *directly* reduce household travel energy use. However, sub-effects on vehicle use are more obscure since the grid-pattern road network encourages walking, transit, and driving at the same time. Controlling vehicle ownership and other factors, households in the "enclave" neighborhoods also consume less travel energy than those in the "superblock", too. This *direct* savings mainly comes from a reduction of car use with the compensation of walking- thanks to the traffic calming measures taken. In addition to neighborhood typology, neighborhood size is also relevant to household travel energy use: bigger neighborhoods tend to consume more transportation energy consumption due to its positive effect on car driving distance.

We then turn to location effects. The distance to city center has a *direct* and positive on total travel energy consumption, mainly through its impact on a mode shift from walking to transit. Households living on BRT corridors use more energy in average because of more driving yet no less transit use. The reason may be that BRT corridors may still present advantage of driving over transit, and people are also willing to drive longer to attain more benefits at destinations further away (e.g., shopping mall).

Table 7-14 2nd Stage OLS Models on Log Transformed Household Weekly Travel Distance by Mode (Using Predicted Car Ownership: P_Car_Owned)

	Ln_car_dist		Ln_transit_dist		Ln_motor_dist		Ln_ebike_dist		Ln_bike_dist		Ln_walk_dist	
	Coefficient	t-test	Coefficient	t-test	Coefficient	t-test	Coefficient	t-test	Coefficient	t-test	Coefficient	t-test
Household Characteristics												
Ln_Income	0.065	0.83	**0.370****	3.43	0.015	0.47	**0.176****	2.68	-0.110	-1.53	-0.075	-1.15
Adult_1	-0.157	-0.99	-0.329	-1.52	-0.088	-1.42	0.268	1.47	**-0.329****	-2.26	**-0.387****	-2.92
Adult_2	ref.		ref.		ref.		ref.		ref.		ref.	
Adult_3_or_more	-0.027	-0.30	**0.524****	4.36	0.007	0.21	0.013	0.18	**0.394****	4.87	**0.411****	5.58
Child_1_or_more	0.098	1.37	**0.220****	2.25	0.007	0.26	0.053	0.95	**0.314****	4.80	**0.224****	3.76
Elderly_1_or_more	-0.063	-0.62	-0.210	-1.50	0.002	0.06	-0.091	-1.12	**-0.323****	-3.42	**0.788****	9.16
Worker_0	-0.036	-0.24	**-1.477****	-7.24	-0.071	-1.21	-0.106	-0.90	**-0.237***	-1.72	**0.430****	3.44
Worker_1	0.143	1.38	**-0.537****	-3.77	-0.052	-1.26	-0.116	-1.41	-0.128	-1.33	**0.270****	3.09
Worker_2_or_more	ref.		ref.		ref.		ref.		ref.		ref.	
P_Car_Owned	**4.237****	13.25	**-2.667****	-5.71	-0.191	-1.52	-0.025	-0.10	**-0.737****	-2.49	-0.314	-1.17
Company_car	**3.099****	12.90	-0.198	-0.60	-0.126	-1.33	-0.250	-1.32	**-0.417***	-1.89	-0.300	-1.49
Motor_1_or_more	**-0.249****	-2.07	-0.055	-0.34	**1.721****	36.39	-0.016	-0.17	**-0.311****	-2.81	**-0.315****	-3.13
Ebike_1_or_more	**-0.517****	-6.65	**-0.325****	-3.06	-0.034	-1.10	**2.226****	36.50	-0.098	-1.37	-0.072	-1.11
Bike_1	**-0.235****	-2.94	0.131	1.20	-0.012	-0.37	0.032	0.52	**0.674****	9.15	**-0.113***	-1.69
Bike_2_or_more	**-0.509****	-4.71	0.093	0.63	**-0.088****	-2.08	-0.020	-0.23	**1.254****	12.51	**-0.152***	-1.68
Neighborhood Characteristics												
Distance_to_Center	0.003	0.08	**0.098****	2.19	-0.005	-0.39	0.039	1.53	0.012	0.39	**-0.075****	-2.72
BRT_Corridor	**0.201****	2.10	0.082	0.63	-0.036	-0.97	0.122	1.63	**0.334****	3.80	**0.205****	2.55
Neighborhood_Size	0.000	-0.01	**0.008***	1.93	0.000	0.06	-0.001	-0.43	-0.001	-0.27	**0.006****	2.26
Traditional	**-0.419***	-1.85	**-0.994****	-3.17	0.035	0.39	0.012	0.07	0.202	0.97	**-0.407****	-2.15
Grid	-0.167	-0.88	**-0.755****	-2.87	0.024	0.32	0.118	0.79	0.130	0.75	**0.364****	2.28
Enclave	**-0.347***	-1.90	-0.200	-0.79	-0.062	-0.86	0.037	0.26	-0.043	-0.25	**0.281***	1.84
Superblock	ref.		ref.		ref.		ref.		ref.		ref.	
Household Attitudes												
Transit_as_Convenience	n.a		**0.272****	2.36	n.a		n.a		n.a		n.a	
I_Like_Biking	n.a		n.a		n.a		n.a		**0.377****	5.53	n.a	
(Constant)	0.039	0.08	0.546	0.82	0.070	0.37	-0.050	-0.13	**1.019****	2.29	**1.684****	4.15
No. Observations	2,421		2,421		2,421		2,404		2,421		2,421	
F	82.340		12.269		76.405		78.620		24.481		26.179	
Adjusted R^2	0.390		0.085		0.372		0.379		0.163		0.165	

Note: *p<.10, **p<.05, n.a indicates the variable is excluded to avoid multicollinearity problems.

Table 7-15 2nd Stage TOBIT Models on Log Transformed Household Weekly Travel Distance by Mode (Using Predicted Car Ownership: P_Car_Owned)

	Ln_car_dist		Ln_transit_dist		Ln_motor_dist		Ln_ebike_dist		Ln_bike_dist		Ln_walk_dist	
	Coefficient	t-test	Coefficient	t-test	Coefficient	t-test	Coefficient	t-test	Coefficient	t-test	Coefficient	t-test
Household Characteristics												
Ln_Income	**0.563***	1.91	**0.723****	3.55	-0.349	-0.43	-0.163	-0.43	-0.371	-1.37	-0.144	-1.26
Adult_1	-0.856	-1.24	**-0.787***	-1.88	-2.527*	-1.65	-0.225	-0.29	**-1.771****	-2.81	**-0.581****	-2.48
Adult_2	ref.		ref.		ref.		ref.		ref.		ref.	
Adult_3_or_more	-0.031	-0.10	**0.827****	3.76	0.586	0.81	0.306	0.86	**1.466****	4.83	**0.754****	5.83
Child_1_or_more	**0.700****	2.89	**0.366****	2.04	0.146	0.25	0.256	0.94	**1.242****	5.02	**0.451****	4.31
Elderly_1_or_more	-0.367	-0.97	-0.362	-1.41	-0.069	-0.08	-0.638	-1.46	**-1.248****	-3.49	**1.170****	8.04
Worker_0	**-1.782****	-2.56	**-2.844****	-7.26	-2.650	-1.44	-1.119	-1.53	**-1.056****	-2.01	**0.691****	3.25
Worker_1	0.030	0.08	**-0.846****	-3.23	**-1.389***	-1.72	-0.589	-1.41	-0.347	-0.98	**0.507****	3.35
Worker_2_or_more	ref.		ref.		ref.		ref.		ref.		ref.	
P_Car_Owned	**8.589****	7.92	**-5.038****	-5.79	-2.873	-0.96	-0.002	0.00	**-3.385****	-2.82	-0.619	-1.30
Company_car	**6.319****	10.10	-0.397	-0.66	-26.875	.	**-2.285***	-1.70	**-1.728***	-1.81	**-0.717***	-1.90
Motor_1_or_more	-0.724	-1.59	-0.026	-0.09	**13.790****	8.92	0.108	0.26	**-1.196****	-2.79	**-0.546****	-3.02
Ebike_1_or_more	**-1.464****	-5.43	**-0.542****	-2.79	-0.603	-0.99	**12.102****	15.28	-0.134	-0.50	-0.106	-0.92
Bike_1	**-0.728****	-2.69	0.201	1.01	-0.315	-0.48	0.030	0.09	**3.239****	10.63	**-0.219***	-1.85
Bike_2_or_more	**-1.746****	-4.43	0.139	0.52	**-2.122****	-2.25	-0.160	-0.35	**4.412****	11.87	**-0.322****	-2.03
Neighborhood Characteristics												
Distance_to_Center	-0.037	-0.36	0.128	1.55	0.098	0.26	0.175	1.30	-0.022	-0.18	**-0.171****	-3.39
BRT_Corridor	-0.043	-0.12	0.112	0.47	-1.077	-1.14	0.617	1.44	**1.120****	3.34	**0.374****	2.69
Neighborhood_Size	-0.002	-0.18	**0.016***	1.95	-0.009	-0.29	0.000	0.00	0.001	0.10	**0.012****	2.51
Traditional	**-2.769****	-3.44	**-1.949****	-3.36	1.997	0.83	-0.112	-0.13	0.538	0.67	**-0.823****	-2.42
Grid	**-1.218***	-1.89	**-1.400****	-2.88	1.860	0.96	0.385	0.48	0.401	0.58	**0.668****	2.39
Enclave	**-1.409****	-2.45	-0.427	-0.92	0.500	0.24	0.073	0.10	-0.425	-0.63	**0.438**	1.61
Superblock	ref.		ref.		ref.		ref.		ref.		ref.	
Household Attitudes												
Transit_as_Convenience	n.a		**0.491****	2.30	n.a		n.a		n.a		n.a	
I_Like_Biking	n.a		n.a		n.a		n.a		**1.523****	5.71	n.a	
(Constant)	**-6.998****	-3.98	**-2.471****	-1.98	**-10.449****	-2.02	**-11.096****	-4.61	**-3.293***	-1.94	**1.176***	1.66
No. Observations	2,421		2,421		2,421		2,421		2,421		2,421	
LR chi2 (21)	999.771		227.063		590.591		1232.170		469.460		436.059	
Log likelihood	-2579.085		-4520.676		-412.980		-1634.323		-2503.681		-3886.588	
Pseudo R^2	0.377		0.092		0.217		0.383		0.165		0.170	

Note: *p<.10, **p<.05, n.a indicates the variable is excluded to avoid multicollinearity problems.

7.4 Summary

The multivariate analysis presented in this chapter enables us to identify the apparent effect of the neighborhood on travel energy consumption (and GHG emissions) while controlling for confounding factors. I estimate single-stage base models using OLS and TOBIT to predict adjusted log-transformed total travel energy consumption (and GHG emissions). Also, to correct for potential endogeneity problems, I implement a two-stage instrumental variable modeling routine for both the total travel energy consumption (and GHG emissions) and the travel distance for each mode.

In the single-stage modeling approach, the TOBIT model performs better than the OLS model in that the TOBIT model effectively corrects the censoring problem associated with the household energy use variable in our sample. In the two-stage modeling approach, good instruments are found for car ownership, but not the 2-wheeled vehicle ownership choices. In general, the significance and signs of factors do not vary between the models of energy use and GHG emissions (except for the E-bike ownership); nor do they vary much across models taking different approaches on a specific outcome measure, either energy use or GHG emissions.

Table 7-16 presents the estimated qualitative effects of neighborhood features on household transportation energy consumption based on the models estimated in this Chapter. It shows how each neighborhood characteristic imposes both a *direct* impact on household travel energy use and an *indirect* impact through its influence on household vehicle ownership, and those two impacts may operate in the same (e.g., form typology, size) or in opposite directions (e.g., location features). The combined marginal effects via simulation suggest that 1) non-"superblock" neighborhoods could reduce net household energy use compared to many other alternative measures; and 2) neighborhoods with bigger size, being close to BRT corridors or further away from the city center increase net household energy use, although the magnitude of their impacts is somewhat minor.

Table 7-16 Qualitative Effects of Different Neighborhood Features on Car Ownership, Travel Distance and Energy Use

	Neighborhood Features					
	Traditional (ref. Superblock)	Grid (ref. Superblock)	Enclave (ref. Superblock)	Neighborhood Size	Location: Distance to CBD	Location: On BRT corridor
Vehicle Ownership						
Car	-	-	-	+	-	-
Motorcycle	+	+	+	ns	ns	ns
E-bike	+	ns	ns	+	ns	+
Bike	+	+	ns	ns	ns	+
Vehicle Use/ Travel Distance						
Car	-	ns	-	ns	ns	+
Transit	-	-	ns	+	+	ns
Motorcycle	ns	ns	ns	ns	ns	ns
E-bike	ns	ns	ns	ns	ns	ns
Bike	ns	ns	ns	ns	ns	ns
Walk	-	+	+	+	-	+
Total Energy use	-	-	-	+	+	+

Note: Signs are extracted from the results of the two-stage LOGIT+OLS models of total energy consumption, vehicle ownership, and distance traveled for each mode. ns- not significant

Literature in the west has emphasized the important role of household characteristics on car ownership, travel behavior and related energy use. In the Jinan context, the evidence is partially consistent with these findings. Here, richer households with children and more workers increase both the likelihood of car ownership and household total travel energy use. Bigger families require more energy for travel, but they may not own more cars in the Jinan context. Household tenure and employment type matter in car ownership, but not in the travel energy use, directly (they do influence energy use through vehicle ownership). Finally, household attitudes regarding transit preference and perceived value of travel time seem to have a more direct weight on car ownership than on vehicle use or energy consumption patterns. Car prestige is revealed to be negatively associated with both car ownership and travel energy. This perhaps reflects that in a rapidly motorizing society like Jinan, China, more car owners gradually regard the car only as a common travel means, while car status/prestige as a popular perception remains among people without car access yet.

8 CONCLUSIONS AND IMPLICATIONS

This thesis set out the goal of answering the question whether neighborhood features make a difference in household transportation energy consumption in urban China and, if so, to what degree. A literature review in Chapter 2 showed that direct assessment of this relationship using empirical evidence remains rare in China, and results from similar studies in developed countries show how the results vary depending on variations in research approaches and local contexts. The theoretical discussion in Chapter 3 further illustrated the inherently complex nature of the neighborhood form- household transportation energy consumption relationship, suggesting that, while a relationship between the two certainly exists, no conclusive effects should be taken for granted. Chapter 4 set up the context of Jinan, China for this empirical research and Chapter 5 introduced the research design and analytical approaches taken. Chapters 6 and 7 presented the analytical procedures and results in detail.

The final Chapter 8 is organized as follows. Section 8.1 summarizes the overall findings from the analysis in Chapters 6 & 7. Section 8.2 discusses the policy relevance of those research results. Section 8.3 raises the possibility of using our model estimates to help develop a design-proposal based energy consumption evaluation tool (the so called "Energy Pro-forma"), designed to help educate and inform urban designers. Section 8.3 describes implications for regional travel demand modeling practices and tools. Section 8.5 & 8.6 identify the limitation of the current research and some future research directions.

8.1 Empirical Findings on Household Transport Energy Use in Jinan

Although no perfect modeling technique could be identified through the analysis of our empirical data, by comparing results across a series of alternative models, we feel confident in concluding that neighborhood features significantly affect household travel patterns and associated energy use in Jinan, China. Specifically, households living in "traditional", "grid" and "enclave" neighborhoods consume less transportation energy than those in "superblock" neighborhoods. Neighborhoods closer to BRT corridors or further away from the city center apparently increase household energy use, although these impacts are somewhat minor compared to the neighborhood typology factor and partially offset by their negative effects on household car ownership.

That said, we recognize a number of confounding effects from household socioeconomic and demographic characteristics. For example, income has a diminishing-return effect on both car ownership and transportation energy use. Young households with children and more workers increase both the car ownership likelihood and household travel energy use. Household size is positively correlated with energy use, but it does not influence car ownership in the Jinan context. A household's housing tenure and employment type also matter in car ownership decision, but not in the travel energy use pattern.

Regarding the vehicle ownership effects, we found that private car ownership is a main driver of energy consumption. Interestingly, having a company car incurs even greater energy use, probably due to lower concern for usage costs and the high travel demand nature of the people equipped. Motorcycle ownership increases transport energy use. Household having two or more bikes actually consume less energy.

Finally, we identify several effects of household attitudes. Our models suggest that a household with a transit preference and low expressed value of travel time are less likely to own cars. But such attitudes do not affect the vehicle use. Results also reveal an interesting effect of the car prestige, which decreased both car ownership probabilities and vehicle uses. This seems counterintuitive at the first glimpse. A likely explanation would be that China has entered a motorized era in which more people (particularly car-owned people) perceive car as a common traveling tool, whereas people without car access feel to be less well off (thus viewing the car as a sign of prestige).

8.2 Implications for Policy Makers

8.2.1 Rethink the "Superblock" Neighborhood Typology: Learn from the Past

Although many Chinese cities like Jinan are still consuming relatively low passenger energy at the household level compared to rich western countries (see Figure 6-14), the trend of rising energy in China seems clear. A comparison of the energy consumption levels across neighborhood typologies of "traditional", "grid", "enclave" and "superblock" suggests that the spread of "superblock" neighborhoods is contributing to China's increasing urban passenger travel energy demand. We might expect that the relatively high density of Chinese neighborhoods, regardless of which type they take, will automatically lead to high travel energy efficiency. However, our study shows that despite of comparable (and high, by western standards) densities across the neighborhoods, neighborhood typology does make a difference in travel energy performance. This raises important questions about the viability of the "superblock" as an appropriate development typology for a "clean energy" city future for China.

If the "superblock" neighborhood is not attractive from an energy efficiency perspective, what neighborhood typology should we consider for future China's urban development? Instead of borrowing ideas from the west, China can in fact learn from her own history. This empirical study reveals that existing typologies from Jinan's past ("traditional", "grid" and "enclave") imply lower per-household travel energy use than the "superblock". After controlling for household characteristics, neighborhood location and even household attitudes, those old neighborhood typologies are associated with 65%-80% less travel energy use than the "superblock". The energy reduction potentials come from both less vehicle usage and lower probability of car ownership, probably due to the mixed land uses, implicit traffic calming measures, and parking restrictions. While these principles were not necessarily intended to save energy when the neighborhoods were built, they could be revisited to inspire policy makers and urban planners in making rules/regulations/guidelines and/or invent in new neighborhood typologies for urban development in future China.

8.2.2 Neighborhood Location Matters

Distance to the city center is positively related to travel energy consumption, indicating that infill development is indeed favorable from a travel energy efficiency perspective. On the other hand, central location of neighborhood increases car ownership, although not much[18], suggesting a possible policy leakage.

Another interesting implication is that building neighborhoods along transit corridors does not necessarily achieve energy reductions. In fact, our empirical analysis shows that households

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[18] e.g., closing to the city center by half could increase a household's likelihood of owning a car by 8% based on our car ownership model estimate.

living next to bus-rapid-transit (BRT) corridors consume even more transportation energy. Does it suggest we should not provide transit services on corridors at all? Apparently not- a transit corridor can indeed help households enjoy more opportunities without being more car-dependent, partly evidenced by the BRT corridor's modest and somewhat even negative effect on household car ownership in our model. Rather, the real challenge is that in China transit corridors are often designated together with highways, and it is very difficult to provide a transit system good and convenient enough so that the incentive of driving does not exceed the incentive of transit use. That said, household energy spent on transit systems may not be reduced from the corridor effect because intensive development along corridors provide increasing opportunities further away which households may want to access even at the price of longer travel.

8.2.3 Vehicle Ownership: Promote or Control?

China is experiencing rapid motorization. While most of the time people regard it as increasing car ownership, the rise of motorcycle and E-bike ownership in China is also phenomenal. Our empirical Jinan data suggest that households owning private cars and motorcycles consume more energy than non-vehicle households whereas households who own E-bike consume less, apparently due to reductions in transit and auto demand. An implication could be that it is better to encourage households to use E-bikes (of course also bikes) rather than cars, motorcycles, and even buses. Therefore, policy discouraging owning cars and motorcycles and favoring E-bike or bike growth in China might be good for reducing energy consumption. However, when GHG emissions were estimated, the e-bike ownership is further found to increase household transportation GHG emissions, as in Jinan e-bikes draw electricity from coal-generation plants. Company cars in China, a unique vehicle type quasi-owned by households, account for a strong effect on energy use at the household level among all vehicle types (including private cars). Better monitoring or more restrict company car use rules may be helpful in reducing household travel energy consumption.

8.2.4 Improve Transit Efficiency

In middle-size cities like Jinan, empirical data shows that transit energy use is currently comparable in total magnitude, though certainly not relative to passengers carried, or to passenger car energy consumption. This is in contrast to the western context in which transit use tends to be so low that the energy share by transit could be negligible. In non-"superblock" neighborhoods in Jinan, transit-consumed energy is the main source of household travel energy consumption. While educating or incentivizing individual household to buy more efficient cars is difficult, targeting on achieving more energy efficient transit systems in Chinese cities could be both realistic and cost-effective. The efficiency may come from cleaner fuel or better bus engine design, but equally effective can be improving the transit system operations (e.g., scheduling). Policies for boosting transit ridership can also make the system more energy efficient by increasing the occupancy and therefore lowering the amount of system-wide per passenger kilometer energy use.

8.2.5 Preference Shaping

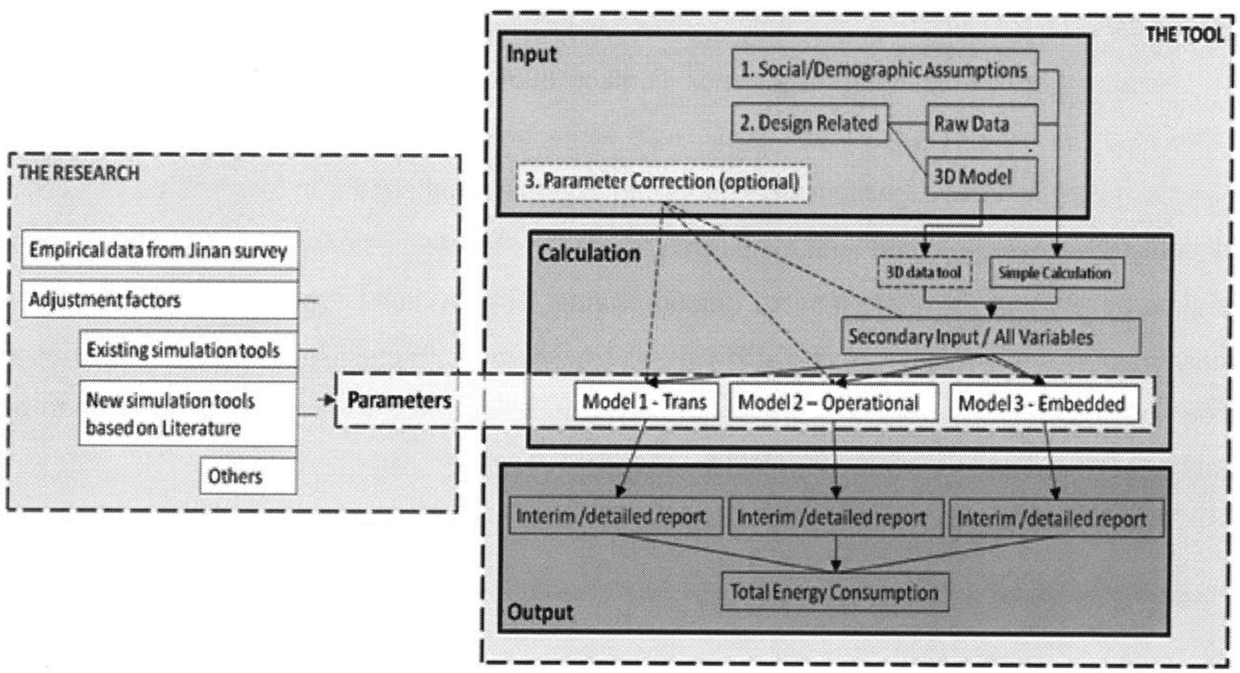
Zhao (2009) argues that shaping traveler preferences, particularly in the China context, presents significant opportunities to solve transportation problems (Zhao, 2009). Our empirical analysis in Jinan supports this argument by showing that both household attitudes toward different travel modes and people's perceived value of travel time have significant impacts on automobile ownership, a main driver of transportation energy consumption growth in China. However, our study also found that those preferences have little effect on vehicle use once controlling for ownership. This contrast in significance of the two effects seems to suggest preference shaping in China, if appropriately used, can be an effective measure to slow down the rapid motorization, but the policy window is getting smaller. Once the majority of Chinese buy cars, then further preference shaping efforts may gain little in mitigating transportation energy use or GHG emissions.

8.3 Implications for Urban Developers and Designers

As mentioned in the research context, this study is part of the "Making Clean Energy City in China" project. In addition to the tasks for collecting empirical evidences, one challenging task of the project is to create an "Energy Pro-forma" design tool to help developers and designers compare energy performance across proposed development patterns. The tool development framework is shown in Figure 8-1.

Modeling results in this thesis can provide coefficients for transportation energy use estimation, a sub-module in the "pro-forma". Specifically, one can set the "superblock" neighborhood as the baseline scenario, using empirical average annual household transportation energy consumption in the "superblock" as a default value. Designers can extract a series of neighborhood indicators (form and location) from their proposals and put them in the "pro-forma". Form indicators could then be automatically aggregated to a neighborhood typology indicator by a "neighborhood-form identification" sub-module. The derived typology value as well as location variables would then be entered as the secondary input in the transportation energy module to calculate expected transportation energy use. The efficiency gain is the ratio of the expected transportation energy use to the default "superblock" value. In the longer term, if empirical research could quantify separate neighborhood element (e.g, density) effects on travel energy use, the secondary input variables for the transportation sub-module could be replaced by more disaggregated neighborhood indicators. Similar approaches based on empirical research can be applied to estimate the other energy components (e.g., household operational energy, embedded energy) in the proposed development scenario. An output processing sub-module can then generate a series of figures and tables showing the comparison of energy performance of different components under different scenarios.

Figure 8-1 Framework of Energy Pro-Forma Tool Development



Source: based on team brainstorming and produced by Jue Wang in March, 2010

8.4 Implications for Transportation Demand Modelers

Following practice in the west, more and more cities in China have begun to develop city-wide transportation forecasting models to assist decision making on infrastructure investment and urban growth management. Conventional four-step modeling techniques deployed in the west often do not consider the built environment- travel behavior interaction, except to the extent to which land use (exogenously or endogenously, depending on the type of model used) determines the overall origin and destinations in the model. Such models are ill-equipped to capture potential micro-level impacts on travel. However, our empirical evidence of such neighborhood-level effetcs in Jinan suggests that future transportation forecasting in urban China should include neighborhood form and location factors in projecting household auto ownership and travel demand. Household attitudes towards different trip modes should also be included in the modeling framework[19]. If not, forecasts can be biased. Accompanying the need for modeling structure update is the need for more data preparation. Neighborhood information and household attitude data collection is not a trivial task for most transportation agencies in China, and they may seek help from other government departments (e.g., urban planning bureau) or even the private sector (e.g., customer research team).

Another implication for transportation demand modeling has to do with the definition of traffic analysis zone (TAZ), which is the unit of geography commonly used to calibrate and forecast aggregated travel patterns of a sub-group of urban population. . In many cities, the TAZs are defined by areas bounded with major arterials and the heterogeneity within a TAZ in terms of neighborhood form is often ignored. Incorporating neighborhood typology factors into the transportation models may prove a difficult task in the near future. Nevertheless, fine-grained geographic information is required to improve transportation demand forecasting models to be more effective in addressing the neighborhood form effects.

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[19] For detailed discussion on potential techniques for modeling improvement, see Zhao (2009).

8.5 Research Limitations

There are a number of research limitations in this thesis, including:

- *Measurement error on transportation energy use.* In estimating energy use, a) we did not account for the speed effect on vehicle operation efficiency (which could depend on the vehicle type and even neighborhood forms); b) travel distance and frequency were self-reported by the households, thus the former can be inaccurately estimated whereas the latter may be under-reported especially on those short unimportant trips; c) we did not account for long-distance travel (e.g., travel to another city by train or plane); d) higher energy efficiency of the BRT vehicles than that of traditional transit vehicles was not reflected; and e) the survey was conducted in summer when students were having summer holidays, and thus school-related trips in families with children were not reflected in our data.
- *Not a fully random sample.* We do not have it because in one of our nine neighborhood cases (Lv-Jing), surveyors could not get in and had to interview people at the gate. This may produce a different scale of error terms from observations in other neighborhoods. Our current models do not control that.
- *Aggregate neighborhood variables.* Due to the limitation of the neighborhood sampling frame, we could not distinguish effects of density, diversity and design related specific neighborhood features. Also, there may be important within-typology variation that the modeling approach is currently missing.
- *2-wheeled vehicle (2-WV) ownership variables may remain endogenous.* In our instrumental models, the instrumental variables are weak in the 2-WV ownership choice models. This does not exclude the possibility of endogeneity. Rather, the issue remains uncertain.
- *Imperfect proxies of household attitudes.* Although attitude variables in our data were found to have interesting effects on car ownership and energy use, those variables were not necessarily accurate measures of actual attitudes. On the one hand, our methodology presumes that the respondent's attitudes reflect the household's attitudes, which may not be the case; on the other hand, for a single attitude, only one related question is asked to the respondent therefore the answer may not be even reliable for representing his/her own actual attitude.

- *Inconsistency between estimation results from "LOGIT+OLS" and "LOGIT+TOBIT" sub-models on vehicle use by mode.* I was unable to explain the reason behind and justify which is correct due to time and statistical knowledge constraints. Related interpretations in section 7.3 should be cautiously taken.
- *Cross-sectional multivariate regression analysis inherently fails to identify causal mechanisms.* This is because we could not address the time-precedence concern. For example, the BRT corridor in Jinan is relatively new and we do not know whether a car-owned household have changed any of their travel patterns since the BRT system was open. If not, the corridor itself does not *cause* a reduction of car ownership or an increase of energy consumption, although the association still exists.
- *Life is more complex than the utilitarian theory.* This creates fundamental challenges to any models applied in empirical studies, since people in the real world have information asymmetry problems, behave irrationally, face peer pressures in decision-making, and the like.

8.6 Future Research Areas

An immediate next step of this research would be to enlarge the neighborhood sample size and corresponding household data via a new round survey in Jinan. More neighborhoods would allow more variance in neighborhood indicators which further allow us to 1) better understand existing neighborhood forms in China and what can be built in future; and 2) explore the effect of neighborhood typologies and form elements on household transportation energy use and emissions. Both are crucial for developing a full-version energy pro-forma tool mentioned in section 8.3. Household transport energy use estimate for revised existing typologies or even a brand new typology could then be feasible by using marginal effect of each generic form indicator. Other potential research areas include:

- *Investigating separate effects of neighborhood on transportation energy for each trip purpose in the China context.* Recall from the theoretical discussion, we expect that the neighborhood effect on commuting trips may be tempered by non-commuting travel.

- *Statistical justification on the appropriate 2-step modeling procedure*. This includes: a) identifying good instrumental variables for vehicle ownership choice models; b) improving 2-wheeled vehicle ownership model specification; c) testing alternative approach such as vehicle-bundle choice models for the first step; and d) mathematically comparing the consequences of performing LOGIT plus TOBIT models versus LOGIT plus OLS models. Meanwhile, other advanced methods (e.g., structure equations model) are worth testing.
- *Scope expansion beyond the current household transportation energy use (or emissions) measure*. For example, future research can include: a) embodied vehicle energy through lifecycle analysis; b) residential energy use; c) freight energy use; and d) the operational energy implied by non-motorized travel. Analysis of those related energy components and how they further interact with our current measure will help us obtain a fuller picture of the influence of neighborhood form on the urban transportation energy consumption and to address the policy leakage challenge. For example, people may save energy in travel but consume more residential energy via participating more in-house activities. Or, households who save energy by ordering food in fact simply transfer the energy to delivery sectors.
- *Focus even beyond the energy itself.* We should not take a narrow view by judging a "good" development pattern by only looking at its energy efficiency. Economy, equity, and quality of life are also definitely our concern about the future growth in China. As income increases, people's desire for goods will inevitably grow. It is unfair to expect Chinese people to lower their living standard for the sake of travel energy saving. Thus, ultimately, empirical research should be able to estimate the effect of neighborhood form on a more comprehensive outcome measure, such as sustainability.
- *Examining neighborhood form supply issues*. Even if the "traditional" type or a certain neighborhood typology is indeed favorable, questions remain about why it does not evolve naturally, what current implementation barriers (e.g., policy, market, technology, etc.) are, and how we can facilitate change in the future.
- *Testing more advanced data collection tools (e.g., smart phone devices)*. This will help us reduce measurement errors associated with conventional household surveys

and obtain even better and more complete travel data (e.g., over a month) with more detailed and accurate activity profile and trip making profiles.

- *Studying more Chinese cities, especially the mid-size cities.*

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