Urban Form, Daily Travel Behaviour and Transport CO_2 Emission: Micro-level Analysis and Spatial Simulation

by

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I declare that the research for these publications was solely my own work and that I am the lead author. The contribution of other joint authors was purely editorial and advisory.

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Abstract

Developing low carbon cities is a key goal of 21st century planning, and one that can be supported by a better understanding of the factors that shape travel behaviour, and resulting carbon emissions. Understanding travel based carbon emissions in mega-cities is vital, but city size, and often a lack of required data, limits the ability to apply linked land use, transport and tactical transport models to investigate the impact of policy and planning interventions on travel and emissions. Using Beijing as a case study, this thesis develops a new bottom-up methodology to provide improved transport CO_2 emission from people's daily urban travel in Beijing from 2000 to 2030. It combines spatial microsimulation approach from geography and activity travel research from the transport field and applies this in a developing country for a long period, where detailed data to undertake fine scale analysis of phenomena such as transport CO_2 emissions generated by travel behaviour is very scarce.

On the basis of an activity diary survey and demographic data from the 2000 and 2010 population censuses, this research first employs spatial microsimulation to simulate a realistic synthetic populations' daily travel behaviour and estimate their transport CO_2 emission at a fine geographical resolution (urban sub-district) between 2000 and 2010 for urban Beijing. It compares and analyses the changes in travel behaviour and transport CO_2 emissions over this decade, and examines the role of socio-demographics and change in urban form in contributing to the modelled trend. The transport CO_2 emission from people's daily travel behaviour in urban Beijing is then simulated and projected at disaggregate level to 2030 under four scenarios, to illustrate the utility of this bottom-up approach and modelling capability. The four scenarios (transport policy trend, land use and transport policy, urban compaction and vehicle technology, and combined policy) are developed to explore travel behaviour and transport CO_2 emission under current and potential strategies on transport, urban development and vehicle technology. The results showed that, compared to the trend scenario, employing both transport and urban development policies could reduce total passenger CO_2 emission to 2030 by 24%, and by 43% if all strategies were applied together. This research reveals the potential of microsimulation in emission estimation for large cities in developing countries where data availability may constrain more traditional approaches, and provides alternative urban development strategies and policy implications for CO_2 emission mitigation targets set by the national and local governments.

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Chapter 1

Introduction

1.1 Contextual background

Climate change is widely recognized as a real threat to urban development and a key global challenge of the 21st century (IPCC, 2013). An energy crisis, commonly known as “peak oil”, is further expected within the next decades (Boussauw and Witlox, 2009). How to reduce energy consumption and carbon emissions has been on the top of a number of political agendas and scientific research. While cities are responsible for 80% of global greenhouse gases, three urban sectors (industry, transport and housing) constitute the main sources of carbon dioxide emissions (Dhakal, 2009). One of the biggest sources, with the fastest growth in CO_2 emission of any sector is the transport sector (Yan and Crookes, 2009). It is estimated that cumulatively, the transport sector produced the largest increase in global CO_2 emissions from 1970-2004 and was responsible for 23% of all energy-related CO_2 emissions in 2005 (IPCC, 2007). With increasing travel demand and car usage, it is projected that transport CO_2 emissions globally will grow by nearly 50% to 2030, and by more than 80% by 2050 (IEA, 2009). Clearly, the transport sector has a key role to play in achieving the energy saving, energy diversification and carbon emission reduction goals of national governments (e.g. China’s current Five-Year Plan) and the wider international community (e.g. Kyoto protocol).

Three main factors have been shown to affect energy use and carbon emissions from urban transport: travel behaviour (e.g. trip frequency, travel distance, and modal split), urban form (e.g. land use pattern, street design), and vehicle technology (Wright and Fulton, 2005, Hankey and Marshall, 2010). The focus of national initiatives to mitigate climate change has to date, concentrated on technology fixes and economic instruments, such as improved fuel efficiency and electric vehicles, and fuel/vehicle taxation (Brand and Boardman, 2008). Although significant reduction of carbon emissions can be achieved through improvements in vehicle technology, these reductions could eventually be offset by increased car ownership and use, and traffic congestion (Chapman, 2007). Furthermore, if developing countries such as China and India follow the same path of automobile dependence as developed nations, then technological advances will be insufficient to offset the anticipated increase in motorisation and its subsequent emissions (He et al., 2013).

Consequently, the potential of urban planning in climate change mitigation has attracted much scholarly and practical attention in responding to a global low-carbon movement. It is argued that spatial patterns of urban development at city and neighbourhood-scale influence people's travel behaviour, and thus travel-induced CO_2 emissions (Grazi and Van den Bergh, 2008, Brownstone and Golob, 2009). This policy proposal of urban planning for low-carbon transport converges with recent planning ideas of new urbanism, the compact city, and smart growth, which criticise low-density sprawl, single-use zoning, and auto-oriented street design for long-distance and auto-dependent travel. Such travel patterns not only produce environmental externalities important at a local scale, such as traffic congestion and air pollution, but contribute to the externality impacts of carbon emissions, which are globally important.

Much literature provides empirical evidence on the effectiveness of urban planning in modifying individual travel behaviour (e.g. Dieleman et al., 2002; Wang and Chai, 2009), while some studies further explore the implications for carbon emission reduction (e.g. Grazi et al., 2008; Qin and Han, 2013). Scholars have found that higher population density, mixed land use and pedestrian-friendly street design correlates with fewer vehicles, shorter distance and less motorised travel (e.g. Krizek, 2003; Khattak and Rodriguez, 2005; Ewing and Cervero, 2010). These studies tend to support the advocates of new-urbanism, and compact urban design. However, theoretical debates have not been fully resolved with respect to the influence of urban form on travel behavior, especially when residential self-selection is taken into account (Bagley and Mokhtarian, 2002; Cao et al., 2007). In this regard, some scholars have argued that planning may have a smaller role in altering urban travel patterns, as residents may choose to live in the kind of neighbourhoods in line with their preferred lifestyles (e.g. Chatman, 2009). The urban form – travel associations may result from a certain residential self-selection process, in which residents select the built environment that facilitates their preferred travel patterns (e.g. Mokhtarian and Cao, 2008). The causal links between urban form and travel behaviour remain inconclusive still. Even less conclusive is the extent to which the urban form impacts on energy consumption and carbon emission from urban transport (Liu and Shen, 2011). Handy (2005) therefore argues for more research on the relationships among urban form, travel behavior and transport carbon emission, which lie at the core of developing a sustainable city.

In earlier studies, transport CO_2 emissions were estimated using aggregate data based on the total energy consumed or the size of the vehicle fleet and average vehicle kilometres travelled (VKT). Although this ‘top-down’ approach is straightforward (Dhakal, 2009; Hu et al., 2010), its application at the urban scale is often constrained by poor data, particularly a lack of reliable data on the vehicle fleet in the city, its city-wide energy use, and the average distance travelled per vehicle (He et al., 2013). Furthermore, this approach is unable to directly link travel behaviour with land use patterns or urban development policies. For example, it is known that a city's physical form (urban morphology) influences the distance people travel each day, their choice of mode, and resulting CO_2 emissions (Grazi et al., 2008). However, research on CO_2 emissions based on individual travel behaviour (and the influence of urban form) for cities as a whole has been very scarce. This is likely due to the large amount of detailed data required on travel behaviour for large populations, which is not usually available, particularly in the case of fast growing mega-cities in developing economies such as China.

China has already passed the US as the world's largest source of carbon dioxide emissions (Yan and Crookes, 2010); however, little is known about how transport CO_2 emissions from people's daily travel respond to China's changing urban form at disaggregate level. Much existing literature on urban morphology, travel behaviour, and transport CO_2 emissions predominately focuses on advanced economies such as the US or Europe. Yet urban spatial development and individuals' daily travel behaviour are very different in developing countries or transitional economies, such as China. China is still experiencing rapid urban expansion and spatial restructuring in which residents continuously find themselves constrained by institutional and spatial transformation involving marketisation of housing, residential suburbanisation, inner-city redevelopment, high job-housing spatial imbalance, and social and spatial stratification. So far, there is little research using spatial analysis and microsimulation of daily travel behaviour and the resulting transport CO_2 emissions at a fine spatial scale for urban China.

Moreover, by adopting the western idea of zoning-based land use planning, the neighbourhood-scale built environment has transformed from a more traditional mixed land use pattern in the inner city toward a mono-functional, automobile-friendly design in suburbs. As continuous urbanisation in China is expected in the next two decades (UN, 2008), urban planning and development policies are critical for China in pursuing a low-carbon model of urban development, particularly given that urban spatial structure is hard to change once developed, and thus will have lock-in effects on human activities and long-term environmental outcomes (Lefèvre, 2009). Until now, there has been little research in China on urban form, travel behaviour and transport CO_2 emissions at the disaggregate level, a scale that is important to the development of more informed land-use transport environment policy.

1.2 Research aim and objectives

The aim of this research is thus to better understand the impact of urban form, and daily travel behaviour on transport CO_2 emission in the context of rapid urbanisation and spatial transformation in China. This is achieved by spatially simulating a large population's daily travel behaviour at fine geographical scale through development of a new 'bottom-up' methodology to provide improved transport CO_2 emissions based on individuals' observed daily travel behaviour, from 2000-2030. The research provides a means to gain greater insight into the spatial variability of the CO_2 emission at micro-scale, adds new knowledge to existing transport emission research, contributes to the innovations of urban simulation, and generates empirical evidence to inform ongoing debates on policy measures needed to facilitate China’s transition towards sustainable and low-carbon urban development. There are three specific objectives to be considered in this thesis:

> **Objective One** – To comprehensively and microscopically analyse the relationships between urban form, household and individual socio-demographics and tour-based travel behaviour (*Travel Modelling*).

Tour or trip chain based travel analysis has been a feature of transport research, but has largely been the preserve of developed countries. The important associations between urban form and trip-chaining behaviour have received little attention. Therefore, the main research questions to be explored for this first objective include: (a) how do the socio-demographic attributes of households and individuals, and urban form characteristics, correlate with the tour-based travel decision process? and (b) does the urban form-travel relationship differentiate between workers and non-workers?

To address this first objective the tasks are:

1) Investigate the associations between urban form characteristics, socio-demographics, and individuals’ tour-based behaviour in Beijing, China. This will include an analysis of trip-chaining behaviour in three principle areas: tour generation, tour scheduling, and the tour interdependence effect.

2) Investigate the impacts of urban form on tour-based behaviour for workers and non-workers, respectively. Summarise the travel rules for residents with different socio-demographic attributes under various urban circumstances.

Objective Two – To spatially simulate a large population's daily travel behaviour (including travel distance and mode choice) at a fine geographical scale and estimate transport CO_2 emissions from daily urban travel at the disaggregate level over 2000-2010 (*Microsimulation Modelling*).

The research questions to be explored for the second objective are: (a) using limited data, how can the travel behaviour and associated CO_2 emissions of a large population be simulated for 2000 and 2010 in urban Beijing? and (b) what is the changing pattern of daily travel behaviour and transport CO_2 emissions during this period, and what factors drive these changes?

To address this objective the tasks are:

1) Using an activity diary survey and 2000 population census, apply a simulated annealing algorithm with important socio-demographics as constraints, to create a realistic synthetic population at the sub-district level for 2000 in Beijing.
2) Based on the underlying form-travel mechanisms, spatially simulate the synthetic population's daily travel, including travel distance and mode choice, and estimate transport CO_2 emissions from urban travel at sub-district level for 2000 in Beijing.

3) Employ spatial microsimulation to simulate a realistic synthetic population's daily travel behaviour and estimate their CO_2 emission in 2010. Compare and analyse the dynamic changes in travel behaviour and CO_2 emissions over the decade 2000-2010. Examine the role of socio-demographics and change in urban form in contributing to the modelled trend.

Objective Three – To project transport CO_2 emissions from passenger travel behaviour to 2030 under urban scenarios, to mitigate carbon emissions in the future and facilitate China's sustainable urban development (*Scenario Modelling*).

The research questions to be explored for this final objective comprise: (a) how to modify people's daily travel behaviour through transport policies, urban planning and vehicle technology? and (b) how does the change in people's daily travel behaviour (e.g. trip distance, mode share) impact upon aggregate transport carbon emission in urban Beijing to 2030?

To address this final objective the task is to:

1) Develop four scenarios on current and potential strategies to modify people's daily travel behaviour and estimate transport CO_2 emissions to 2030. Compare and analyse the results of these scenarios to find effective solutions for transport CO_2 mitigation and sustainable urban development.

1.3 Thesis structure

Chapter 2 provides a comprehensive review of relevant literature on urban form, daily travel behaviour, and transport CO_2 emissions. It first reviews the theories of compact development and the critiques of urban compaction, within the context of sustainable urban development. Following this reviews are presented of relevant empirical studies on the role of urban form in travel behaviour and carbon emission, and the potential of technology in carbon mitigation. Microsimulation research for urban analysis and transport forecasting is also reviewed.

Chapter 3 presents the overarching research design, associated modelling techniques, and data sources used in the thesis. It serves as a foundation for the subsequent empirical analysis of travel behaviour and CO_2 emission. Multiple methods are employed to address the objectives, including discrete choice modelling, spatial microsimulation, and urban scenario design. The study area, Beijing, China's capital city, is then introduced, followed by the description of the data sources used, including a travel dairy survey, land use surveys, and population census.

Chapter 4 (Objective One, task 1) investigates how socio-demographic attributes of households and individuals, and urban form characteristics, influence tour-based travel behaviour. It accounts for urban form characteristics in a series of multivariate models drawing on detailed land use data, and a travel diary survey with discrete choice models employed to analyse the trip-chaining behaviour in three principle areas: tour generation, tour scheduling process, and tour interdependence effect. The urban form – trip-chaining relationships are examined for workers (employed) and non-workers (housekeepers, the retired, etc), respectively (Objective One, task 2).

The development of a spatial microsimulation of people's daily travel behaviour and CO_2 emission is addressed in Chapter 5. On the basis of an activity diary survey and the 2000 population census, the model uses the determinants of trip-chaining behaviour, discovered in Chapter 4, as constraints and applies a simulated annealing algorithm to create a synthetic population at fine spatial scale for Beijing to spatially simulate the population's daily travel, including trip distance and mode choice at the sub-district level (Objective Two, task 1). The model then estimates transport CO_2 emission from daily urban travel at the sub-district level in urban Beijing for the 2000 base year (Objective Two, task 2).

Chapter 6 applies the method presented in Chapter 5, to provide improved transport CO_2 emission from people's daily urban travel in Beijing to 2030. Building on analysis of an activity diary survey and the 2010 population census, this chapter first employs spatial microsimulation to simulate a realistic synthetic population's daily travel behaviour and estimate their CO_2 emission at a fine geographic resolution in 2010 for Beijing (Objective Two, task 3). It also compares and analyses the changes in travel behaviour and transport CO_2 emission over the decade 2000-2010, and examines the role of socio-demographics and change in urban form in contributing to the modelled trend. The transport CO_2 emission from passenger travel behaviour is then projected to 2030 under four scenarios concerning transport policies, urban planning, and vehicle technology (Objective Three, task 1).

The final chapter, Chapter 7, discusses the limitations of the data sources, concludes the findings and innovations of this research, and suggests possible improvements and future research for scholars, as well as presenting policy implications for government.

Chapter 2

Urban Form, Travel behaviour and Transport Carbon Emission: A Literature Review

2.1 Introduction

There has been interest in how urban design promotes wellbeing and efficient living since the last century in western countries' (particularly the UK and USA) planning system. Much research exists to offer theoretical and empirical evidence on the effectiveness of urban planning in shaping individual travel patterns and reducing carbon emissions. This chapter provides a review of key literature on urban form, daily travel behaviour, and carbon emissions. Section 2.2 presents the current debate on sustainable urban development patterns, critically reviewing the theories of compact development and critiques of urban compaction. The climate change issue and research on transport CO_2 emissions are discussed in Section 2.3, including extensive reviews on the relationship between urban form and travel behaviour, as well as the potential of technology in carbon emission mitigation. Section 2.4 reviews analysis on the effects of urban form on energy use and carbon emissions from transport and buildings, followed by a review of microsimulation research for urban analysis and transport forecasting in Section 2.5. The concluding remarks are drawn in the final section of this chapter.

2.2 Cities, sustainability and urban form

2.2.1 Theories of compact development

There are general debates on urban development and sustainability worldwide, which involve a consideration of different urban forms, such as compact development, urban sprawl, and polycentricity. Different movements have been promoted to combat urban sprawl, particularly in the USA and Europe, including Smart Growth, and New Urbanism, which share much in common in terms of land use, street design and public transit development. The evaluation of these different urban forms requires comprehensive consideration of economic, social and environmental factors, which are very complicated. So far, no consensus exists on what is the most sustainable urban form, although there are growing interests in alternatives to urban compaction.

Urban sprawl, labelled as the low-density, auto-dependent spread of metropolitan areas, has been criticised on grounds of traffic congestion, air pollution, energy consumption, wasted resources, and health problems (Handy, 2005). Such concerns have contributed to the increasing momentum of the smart growth movement worldwide. Since it first appeared in the so-called "Smart Growth" legislation debate in Maryland in 1997 (Daniels, 2001), smart growth has been regarded as a new style of development able to combat urban sprawl. This term has been defined by different environmental organisations, government agencies, and research groups. Until now, there is no universally accepted definition of smart growth, but essentially it means compact, transit accessible, pedestrian-oriented, mixed use development patterns and land reuse (American Planning Association, 2002).

Ye et al. (2005) reviewed smart growth statements from ten national organisations with divergent land use agendas and forty-nine documents from two states of Georgia and Kentucky, finding that although the documents exhibited extreme variety in the meanings of smart growth, their broad conceptual definitions tended to converge. They further summarised six principal components of smart growth policies: 1) natural resources preservation, including farmland preservation, subdivision conservation, historical and ecological land preservation; 2) transportation, which aims to facilitate pedestrian and cycling, promote public transit system and reduce automobile dependence; 3) community development, which is designed to promote the population participation and the unique features of each community; 4) housing, such as providing multifamily housing and housing for special needs and diverse households; 5) planning, including comprehensive planning, mixed land use, street design, public facilities planning, alternative water infrastructure and systems; 6) economic development, including neighbourhood business, downtown revitalisation, infill development and existing infrastructure reusing. Among these six main elements of smart growth policies, there is much more agreement upon the former three elements (the importance of resource preservation, transportation choices, and community development) in various definitions of smart growth, than the housing, planning, and economic development dimensions. However, the potential conflict between economic growth and environmental protection is the main issue that the smart growth approach is intended to resolve (Ye et al., 2005).

On the whole, the transportation-land use connection lies at the centre of efforts in the United States to combat urban sprawl through smart growth strategies (Handy, 2005). Unfortunately, the relationship between transportation and land use is not a simple linear one. In September 2002, many transportation and planning professionals participated in a conference in Baltimore, Maryland, to discuss the issues, practice, and implementation of smart growth and transportation (Transportation Research Board, 2005). Their debate centred on a few key questions, including why smart growth is a transportation issue, what a smart growth transportation system looks like, and how smart growth differs with location, aiming to provide a smart transportation system to support smart growth movement.

Meanwhile, another proposition of the smart growth movement has been promoted concerning land use and design strategies, and was labelled as New Urbanism. New urbanism advocates attempt to seek a new paradigm to guarantee the public place, with its fundamental organising elements the neighbourhood, the district and corridor (Katz, 1994). New urbanists have provided specific design characteristics to reduce automobile use and create more liveable communities, by putting the activities of daily living within walking distance, accommodating a range of household types and land uses, providing an interconnected network of streets, and facilitating walking, bicycling, and public transit (Handy, 2005).

The most notable approach should be transit-oriented development (TOD) proffered by Calthorpe, which combines regional transportation and land-use strategies with detailed planning. The main characteristics of TODs include an approximate size of 80 ha, a distance from edge to centre 10 minutes' walk, a fine grain of different land uses, a mix of different houses, and a central area operating as the focus of the community's activities (Calthorpe, 1993). TOD can be further classified as "urban TOD"- located on a main transit route and suitable for job-generating and high-intensity uses or "neighbourhood TOD"- located on a feeder bus line with a residential and local-serving shopping focus. Each TOD should be a dense, tightly woven community which mixes shopping, housing and offices in a compact, walkable area surrounding a transit station, and different TODs are connected to the region through a network of light-rail and bus routes (Katz, 1994).

Traditional neighbourhood development (TND) is another well-known approach of new urbanism conceived by Andres Duany and Elizabeth Plater-Zyberk, which includes more detailed regulation and varies more in response to local conditions than Calthorpe's TOD approach. However, it is rooted less strongly in convictions about regional planning and the importance of transit, and it operates at a smaller scale (Katz, 1994). This new urbanism idea was largely supported by the British government in the final report of the Urban Task Force, which addressed many recommendations towards altering policies, aiming to establish a framework to revitalise British towns and cities (Rogers, 1999).

In general, those different approaches point to a consensus of urban compact development, which is primarily characterized as densely development centres, high population density, mixed land use, public transit priority and social interaction. Such compact city idea has been advocated by many scholars and professionals. For example, Hillman regarded the compact city as one way of responding to the challenge of "thinking globally and acting locally", for the reason that compacting the city could reduce travel distances, greenhouse gas emissions and thus help curbing global warming; and urban residents could enjoy lower transport expenditure, less pollution, lower heating costs, more self-reliance, more community activity, more cycling and walking, and better health (Jenks et al., 1996). Kenworthy (2006) also suggested that the compact city will consume less land for sprawl and save more land for open space, gardens, urban agriculture, forestry and horticulture; and with urban compaction it will promote the city to be 'greener' in its overall functioning through more use of green transport modes, traffic calming to promote greener, safer streets, less energy use and less environmental impact. In addition, Camagni et al. (2002), based on statistical analysis in the metropolitan area of Milan, further demonstrated the compact city development would be associated with specific social, environmental and economic benefits, in terms of more land preservation, lower environmental impacts, higher public transport efficiency, competitiveness and its share in the mobility market.

To conclude, the compact city development would generate many environmental, energy advantages and social benefits, like reuse of urban infrastructure, the preservation of rural land, increased accessibility, less pollution and congestion, reduced travel distance and car dependency, lower heating costs and energy consumption, social mix and interaction, concentration of local activities, urban regeneration and urban vitality (Frey, 1999). Many urban compaction policies have already been introduced in various western countries, with the purpose to promote urban regeneration, the revitalisation of town centres, the public transport services, and the concentration of urban activities (Breheny, 1997).

2.2.2 Critique of urban compaction

However, there is much criticism of urban compaction in the debate of sustainable development. Breheny, a British geographer, was a fierce critic of urban compaction. He provided a number of internal contradictions and potential conflicts of the compact city idea with other desirable policies, arguing that urban centralization undermines the desirable aim of greening the cities, contradicts British people's profound fondness for suburban qualities of life, conflicts with decentralised living enhanced with telecommunications, constrains the development of renewable energy sources like wind and solar power which cannot be used efficiently in high-density urban environments, and undermines the vulnerable rural economies threatened by a focus of activity within cities and towns (Breheny, 1992).

In addition, he further suggested the compact city idea should be subject to at least three types of tests: veracity, feasibility and acceptability (Breheny, 1995). For example, on the test of feasibility, he raised some major doubts concerning the economic, technical, and political prospects of urban compaction (Breheny, 1997). The economic doubt is that urban centralisation tends to turn around the long-established and deeply-ingrained processes of urban decentralisation, attempting to reverse the population movements from suburb to city centre. The technical doubt is that problems of achieving more use of brownfield sites and problems of contamination, access, demand and liability makes urban revival difficult. As for political doubt, it refers to the willingness of central government to commit the resources needed to bring brownfield sites into use on a large scale and the willingness of local communities to bear the consequences of greater compaction (Breheny, 1997). He also indicated that compact city policy advocating all future growth should be within existing urban boundaries seemed unreasonable.

Although there have been already many empirical studies trying to demonstrate that compact urban forms are sustainable with less energy consumption and environmental pollution, their evidences are inconclusive, and even contradictory. Hall (2001) outlined several complications concerning the relationship between energy system and urban form, pointing out density, residential parking and other land use characteristics are interrelated, and they are also associated with socio-economic factors. The sexual and cultural revolution changed people's living patterns, and household size and structure changed too, so people demanded more working places and had more complex space needs, and demands for public services became greater. Therefore, there is no clear relationship between urban compaction and energy consumption, making cities more compact should not be used as a general prescription for environmental improvement. Many people have been demonstrated to be more satisfied with rural and suburb lifestyles than city life, with high density city-living less desirable (Hall, 2001).

Meanwhile, there are other academics criticising the compact city idea in different ways. For example, by outlining the five intellectual origins of sustainability, Neuman (2005) summarized four common themes of sustainability: sustain, health, place specificity and interrelationships, and compared them with the compact city, finding that the compact city idea does not fully correspond to these themes. He further identified the compact city fallacy, concluding that the compact city is neither a necessary or sufficient condition for sustainability and the attempt to make cities more sustainable only by using urban form strategies is counterproductive; urban form should be conceived as a process towards sustainable cities (Neuman, 2005). Furthermore, while much empirical literature has concentrated on the environmental aspect of the sustainable city, Burton (2000) examined whether urban compaction promotes social equity. Based on a sample of 25 medium-sized towns and cities, she selected indicators to measure density, social equity and a range of intervening variables, and then used multivariate analyses to test the impact of higher-density urban form on 10 different social equity effects, such as access to superstores, access to green space, job accessibility, public transport use, opportunities for walking and cycling, domestic living space, health, crime, social segregation, and affordable housing (Burton, 2000). The results showed that urban compaction would have negative influences on at least four aspects of social equity, groups with lower income would have less domestic living space, less affordable housing choice, lower levels of walking and cycling, and increasing levels of crime.

Another criticism of urban compaction relates to carbon sequestration by urban greenery. It shows that urban green space can reduce net carbon emissions directly through carbon sequestration and indirectly through savings in the cooling and heating energy of buildings; with appropriate green space planning and management strategies, carbon release will be minimized and carbon storage will be maximized, thus helping mitigate the global CO_2 problem (Jo and McPherson, 1995). It is argued that if cities are built with high density, the size of urban green space will be reduced, consequently, its ability to lock up carbon emissions will be constrained as well. Besides, high-density urban development without more urban greenery seems to be less liveable and sustainable.

These arguments attempt to demonstrate that there are many disadvantages associated with urban compaction, like congestion in urban centres, contradiction to urban decentralization, conflict with the green city concept, threaten of rural economic development, reduction of living space, unpopular restrictions on movement, massive financial incentives and high degree of social control, degradation of quality of life, and social stratification (Frey, 1999). Besides, the clean-vehicle technologies, social fondness for suburban life and the development of telecommunication would make the compact city idea undesirable and unsuccessful.

2.2.3 Towards a sustainable city

In conclusion, there are both benefits and costs associated with urban compaction. Between these two extremes of the debate, there are also some compromisers, holding the opinion that the sustainable development should neither be the compact city nor urban sprawl, but some kind of 'decentralized concentration', which combines the merits of centralization with benefits of decentralization (Frey, 1999). Jenks et al., in their 1996 book 'The Compact city-A Sustainable Urban Form?', posited three main problems of the compact city debate: the claims about the sustainability of the compact city have not been proved; the feasibility or social acceptability of the compact city remains questionable; and tools to ensure successful implementation of the compact city are required (Jenks et al., 1996). As the former two questions have been paid much attention, they also discussed some concerns on the implementation issue of the compact city, for example, which agency should implement the compact city, what measures can be used to manage its effect, on which scale to tackle the compact city, and how to evaluate the outcomes. In addition, in their 2000 book 'Achieving Sustainable Urban form', they advanced this debate by offering more sophisticated analysis and testing the key elements of urban form: density, compactness, concentration, dispersal, mix of uses, housing types and so on (Williams et al., 2000). They also pointed out the relative merits of other urban forms, broadened the portfolio of options for further growth, and indicated that instead of searching for one definitive sustainable form, how to determine which forms are suitable in any given locality should be paid more emphasis and a diversity of urban futures were likely to co-exist within a single city.

Towards making the city more ecological, liveable and sustainable, Kenworthy (2006) discussed ten critical dimensions and summarized them in a simple conceptual model of the eco-city, which involved compact, mixed-use urban form, well-defined higher-density centres, priority of public transport and non-motorized modes, protection of natural environment, environmental technologies, creative economic growth, high-quality public realm, sustainable urban design, urban planning and decision-making. These ten key dimensions were organised into four critical "Sustainable Urban Form and Transport" factors, four essential factors under the heading of "Sustainable Technologies, Economics and Urban Design" and two "Overarching Process" dimensions relating to planning and decision-making for sustainable cities.

Until now, although much discussion has been devoted to the question of what form and structure would make the city more sustainable, their conclusion is confused, equivocal, and even contradictory. As the sustainable city issue is very complex, more debate is needed to precisely define the form and structure of the compact city, or to indicate the degree of compaction of the urban fabric and the degree of centralization or decentralization, which is missing in the previous discussion. In this research, the focus is on one aspect of the debate on urban development: how urban form influence people's daily travel behaviour and transport CO_2 emissions, and what form would make the residents travel less, walk more, emit less CO_2 and make the city more sustainable? In the following sections, an extensive review of literature is provided on urban form, daily travel behaviour, and transport carbon emissions.

2.3 Climate change and transport CO_2 emissions

2.3.1 Overview

Climate change is widely recognized as the key global challenge of the 21st century. The Fourth Assessment Report from the International Panel on Climate Change marked that elevated levels of greenhouse gas (GHG) emissions have led to a 0.6^{o}C increase in the global average surface temperature since 1900, which will increase an additional 1.8-4.0^{o}C by 2100 if current emission trends are not altered (IPCC, 2007). CO_2 is an important heat-trapping GHG, comprising more than 85% of total GHG emissions (IPCC, 2007). World CO_2 emission from the consumption of fossil fuels is predicted to increase from about 25,000 billion metric tonnes in 2003, to more than 40,000 billion metric tonnes by 2030, with an average rate of 2.1% per year (IEA, 2006). Moreover, with the increasing concentration of GHG in the atmosphere, global warming has become arguably the dominant issue of our time, which may induce many serious environmental problems, such as extreme weather and natural disasters, and these can greatly impact the sustainability of cities and regions all over the world (Stern, 2007). For this reason, what we should do about climate change has gained political and popular global attention.

At the international level, while strong conflicts remain, there is a general agreement about what steps need to be taken to reduce greenhouse gas emissions (Hamin and Gurran, 2009). Through international agreements, most notably the Kyoto protocol, and the resulting carbon trading schemes such as the European Union Emission Trading Scheme (EUETS), governments have sought to slow and eventually cap future global increases in greenhouse gas emissions (Jaroszweski et al., 2010). However, due to weak actions at an intergovernmental level, carbon emissions continue to rise so that we risk exceeding the concentration limits the IPCC predict, which will result in major impacts. There is inertia in the system so climate change would continue even if emissions were brought below 1990 levels. The costs of implementing mitigation measures now are far less than the costs of dealing with the impacts later (Stern, 2007).

Many studies show that the global increases in CO_2 concentration are due primarily to fossil fuel use and land use change (Poudenx, 2008, Jo et al., 2009). Human activities, in particular those involving combustion of fossil fuels, produce GHG that affects the composition of the atmosphere (Wee-Kean et al., 2008). Land use change due to urbanisation and other activities is also affecting the physical and biological properties of the earth surface and subsequently affecting the regional and global climate (IPCC, 2001). In addition, population and economic growth are the major driving forces behind increasing CO_2 emissions worldwide over the last two decades. In brief, these agreements and studies have drawn the worldwide attention on the concept of low carbon, and a lot of low-carbon projects at the national level have been carried out in various countries.

In 2003, the UK government published a white paper on energy with the title 'Our Energy Future, Creating a Low Carbon Economy', which drew international attention to the concept of a low-carbon economy. Subsequently, the first legally binding national CO_2 emission reduction plan was passed, set out in the 2008 Climate Change Act (DTI, 2003; Parliament, 2008). In 2007, the Japanese government expanded the concept of a low carbon from the economic field to the social field, and also promoted the concept of a low-carbon society (Liu et al., 2009). However, as the most significant increase in energy consumption and CO_2 emission is taking place in cities, the concept of a low-carbon city has also gained popularity around the world. Since 2008, more than half the world's population lived in cites, and their GHG emissions make up 80% of the global emissions (Stern, 2007). Moreover, the world urban population was projected to grow at an average rate of 1.9% per year and expected to rise to about 5 billion (60.2% of world population) by 2030 (Popul, 2002).

Therefore, cities, as the main living and working places for human beings, have become critical contexts for reducing CO_2 emissions.

Since the most significant increase of energy consumptions and CO_2 emissions is taking place in cities, it is necessary to focus on the urban sectors to deal with such issues. Much research demonstrates that, from the perspective of end use, the main sources of carbon dioxide emissions come from three sectors: industry, transport and housing (Dhakal, 2009). Among these urban sectors, transportation is one of the largest and fastest growing sectors of CO_2 emissions (World Bank, 2010). The transportation sector produced the largest increase in global CO_2 emissions during 1970-2004 and was responsible for 23% of energy-related CO_2 emissions in 2005 (IPCC, 2007). It is projected that CO_2 emissions from transportation will grow by nearly 50% by 2030, and by more than 80% by 2050 (IEA, 2009). The rate will be even higher in developing countries and transitional economies partly due to rapid increases in household incomes and car ownership (IEA, 2006). In China, CO_2 emissions from the transportation sector grew at an annual rate of 8.6% during 2000-2008, reaching 630 million metric tonnes by 2008 (Qi, 2011). As shown above, it is not surprising that the topic of ‘transport and climate change’ has received much attention in the scientific literature.

Some researchers argue that urbanisation, increasing incomes, more social and leisure time and the diversity of activities have led to substantial increase in passenger transport demand while increasing urban infrastructure construction (Yan and Crookes, 2009). Three main factors (Figure 2.1) are said to affect carbon emissions from urban transport (Wright and Fulton, 2005). These are individuals’ travel behaviour (such as trip frequency, mode choice, travel distance), urban form (such as land-use patterns, street network design, etc) which will affect travel behaviour, and carbon technologies concerning the carbon content of each fuel and the fuel efficiency which will affect the carbon emissions per vehicle miles travelled.

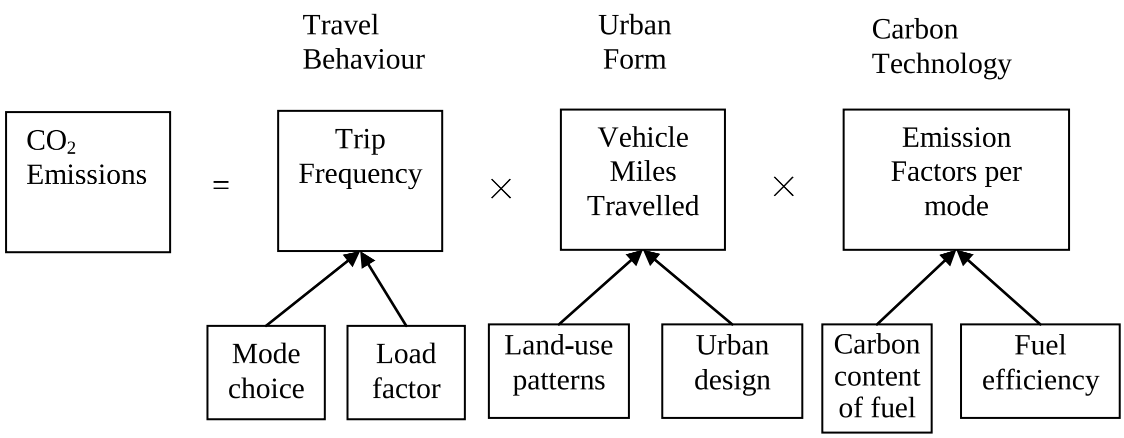

Figure 2.1: Factors affecting transport CO_2 emissions

Accordingly, there are three options which can be used to reduce transport emissions: 1) low-carbon fuels or other energy carriers, which reduce the life cycle emissions per unit of energy, 2) more-efficient vehicles, which reduce energy consumption per vehicle kilometres travelled (VKT), and 3) VKT reductions, through options such as public transit, energy-efficient urban form, and non-motorised travel such as walking and biking (Hankey and Marshall, 2010; Mitchell et al., 2011).

The first two options, concerning introducing low-carbon fuels and new technologies to increase fuel efficiency so that people can continue driving cars but with less CO_2 emissions, could be named ‘sustainable mobility’, while the solution to redesign our cities and regions so that there is less need to drive or drive shorter distance and more efficiently is known as ‘sustainable urbanism’ (Cervero and Murakami, 2010). In general, reducing urban transport CO_2 emissions will require the combination of those solutions concerning travel behaviour, urban planning and carbon technologies.

2.3.2 The role of urban form on travel behaviour

Much literature provides empirical evidence on the effectiveness of urban planning in individuals' travel behaviour since or before the 1990s. These studies can be divided into several categories, for example, by travel purpose (work travel vs. non-work travel, etc.), analytical approach (simulations vs. regressions, etc.), research scale (macro level vs. micro level), measures of urban form (dummy variables of neighbourhood type vs. concrete measures of density, diversity, and design features, etc.), or the nature and level of data (Crane, 2000). Such classifications can be useful for the understanding of its history and progress. Here, the literature is reviewed in approximately chronological order, dividing it into three stages (Figure 2.2): early stage (before 1990), mid stage (1990s), and late stage (after 2000). However, we will pay more attention to the recent research, especially that post 2000, as the early research has been extensively reviewed elsewhere (Cervero and Seskin, 1995; Handy, 1996; Ewing and Cervero, 2001) and recent studies are much more diversified, sophisticated and promising.

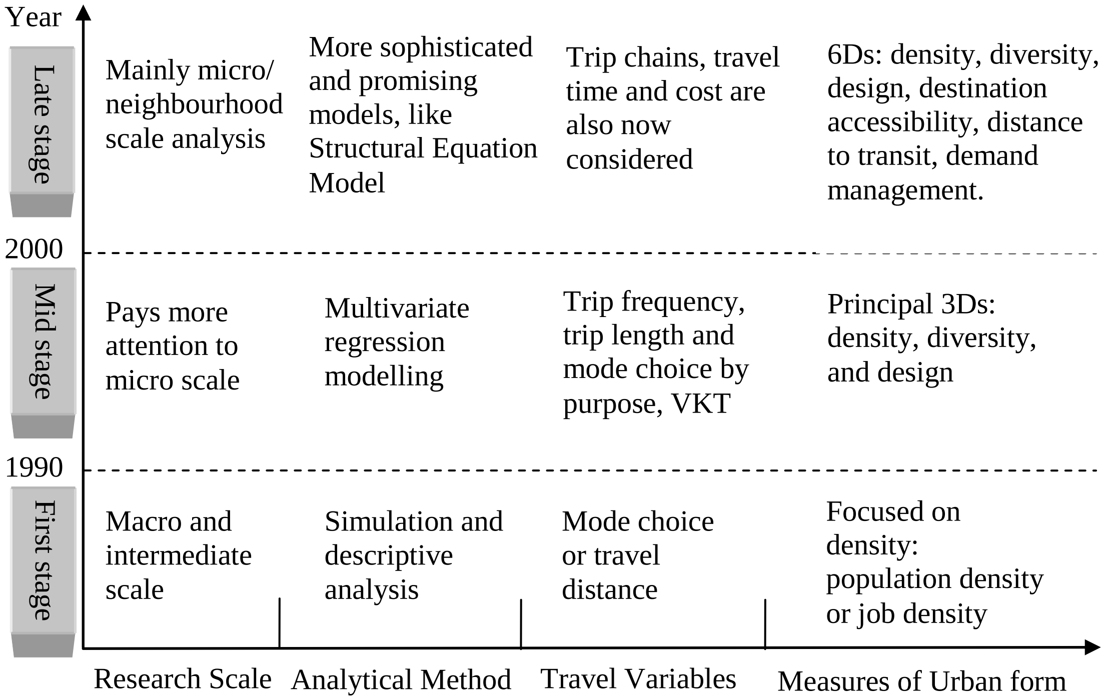

Figure 2.2: Literature summary (references are exemplified in the text below)

2.3.2.1 First stage: literature pre-1990

Past studies, especially those before 1990, were mainly aggregate in nature focused on the macro or intermediate scales, adopting the city, metropolitan area or corridors and activity centres as the analytical unit to investigate the relationship between urban form and travel patterns. Partly because of the absence of empirical data concerning land use and travel variables, many organizations used travel-demand forecasting models to simulate the effects of alternative land-use scenarios on aggregate travel behaviour (Cervero and Seskin, 1995). As this research assumed certain relationships between urban form and travel patterns, and then used these assumed relationships to predict the implications of different urban development scenarios, such simulation studies did not empirically test the relationship between urban form and travel behaviour (Handy, 1996). For the most part, they only provided some general insights into the potential effects of different urban developments on average travel patterns; therefore, this kind of studies was of limited value (Handy, 1996).

Another characteristic of research in this stage was that, density, such as population density, or job density, was mainly used as the measure of urban form. These studies usually compared the differences of urban densities and average travel variables, or energy consumption between various cities, regions or even countries. One of the best known studies was by Newman and Kenworthy (1989), who evaluated the associations between physical planning factors and gasoline use per capita for 32 cities worldwide, finding that land use parameters, such as population density, and job density, have strong correlations with gasoline use. In particular, the relationship between gasoline use and population density was an exponential curve, which implied that major fuel savings would happen when urban density increased to the range of 12 to 14 people per acre (Newman and Kenworthy, 1989). Although this work has been widely cited, it has also been criticized, notably for the lack of statistical control for other factors which may also influence fuel consumption and fuel price (Gordon and Richardson, 1989).

In general, these first stage studies only provided strong correlations between urban form and travel patterns, and did not demonstrate causal relationships between variables. While not accounting for the household and individual socio-economic attributes, such as household size, income, or car ownership, the high correlations between physical planning and gasoline use may not be true. Besides, density, the simple measure of urban form, has also been challenged, for the reason that it may mask the impacts of other urban form measures on travel variables and energy use, such as land use mix, street network design, accessibility to various facilities, and so on.

2.3.2.2 Middle stage: literature in the 1990s

The previous research attempted to predict travel patterns for given urban development scenarios. Research in the 1990s attempted to understand how travel behaviour might be influenced by land use planning and urban design (Crane, 2000). These studies pay more attention to micro-level analysis of neighbourhood-scale land use characteristics rather than only measuring macro-level urban forms such as city-scale population density. By using activity diary data and disaggregate approaches, these studies better capture the associations between land use parameters and individual travel behaviour. For example, comparing residents' travel characteristics for work trips between some neighbourhoods in the San Francisco Bay Area, Cervero (1996) found that walking and bicycling modal shares and trip rates tended to be much higher in transit-oriented neighbourhoods than in the paired auto-oriented neighbourhood. Using regression models to explore the relationship between neighbourhood type and transit modal shares, he also found that both residential densities and neighbourhood type have significant positive effects on transit commuting.

Cervero and Kockelman (1997) put forward three principal measures of the built environment as the original 3Ds: density, diversity and design, which have been widely adopted in later land use-travel research. Using 1990 travel diary data and land use records of 50 neighbourhoods in the San Francisco Bay Area, they found that these three principal urban form measures had significant impacts on individuals' travel behaviour. People living in neighbourhoods with higher density, mixed land use, and pedestrian-oriented designs tended to travel fewer vehicle miles and relied less on automobiles, especially for non-work, home-based trips. Their findings seemed to support the claims of new urbanists and others that compact, mixed-use, pedestrian-friendly designs can 'degenerate' vehicle trips, reduce vehicle kilometres travelled (VKT) per capita, and encourage non-motorized travel (Cervero and Kockelman, 1997).

On the contrary, based on five diverse neighbourhoods in the San Francisco Bay Area in the same year, Kitamura et al (1997) also examined the effects of land use variables and attitudinal characteristics on travel behaviour. They found that the attitudinal variables explained the highest proportion of the variation in the data and were more strongly associated with travel behaviour than were land use characteristics, and further indicated that land use policies promoting higher densities and diversities may not alter travel demand effectively unless residents' attitudes are also changed.

Using travel diary data for a sample of 769 individuals in the southern California, Boarnet and Sarmiento (1998) examined the link between land-use patterns at the neighbourhood scale and non-work trip generation by automobile. While applying an ordered probit model and instrumental variables regressions to control for individuals' socio-demographic attributes and residential location choice, they found the land-use variables to be statistically insignificant in the influences of non-work travel behaviour. They therefore suggested that the issues of geographical scale and residential location choice should have more attention when drawing conclusions about the relationship between travel behaviour and land-use characteristics. Research in this period attempted to investigate the influences of residents' attitudinal variables which may confound the impacts of urban planning on travel behaviour. However, this research remained limited, partly due to the lack of individuals' subjective data.

To conclude, research in the 1990s, compared to those in the first, pre 1990's stage, made great progress in examining the relationship between urban form and travel behaviour, largely because they worked with observed behaviour, showing how people behaved in different neighbourhoods, and used multivariate statistical models in an attempt to explain this behaviour (Crane, 2000). The measures of urban form were also extended to several dimensions, giving potential for greater explanatory power. Developing this last point, Stead and Marshall (2001) exemplified nine aspects of urban form which may influence travel behaviour, including distance from urban centre, mixing of land use, provision of local facilities, proximity to transport networks, and ranging from regional strategic planning down to specific local and neighbourhood planning issues. They also suggested that these land use variables are interrelated and that this would add further complexity to the analysis of relationship between urban form and travel behaviour.

Ewing and Cervero (2001) conducted a review of 73 empirical studies of land use-travel demand relationships, mainly from the 1990s. They divided these studies into five categories according to urban form measures, with studies that addressed: neighbourhood and activity centre designs, land use variables, transportation network variables, urban design variables, and composite indices. While comparing and summarizing the relationships between the built environment variables and travel variables modelled, they further tended to generalize the impact of the built environment on vehicle trips and vehicle miles travelled by using elasticity measures for the application of public policy making and sketch planning. However, some urban form variables remained relatively poorly investigated and the residential self-selection problem (see below) was largely not addressed in these studies, hence causal links between urban form and travel behaviour remained uncertain.

2.3.2.3 Late stage: literature after 2000

Whereas research in the 1990s was mainly focused on case studies from the USA, studies post 2000 became common elsewhere. Based on data from the Netherlands National Travel Survey, Dieleman et al. (2002) applied multinomial logit models and regression models to explore the impacts of urban form factors and micro-level household attributes on modal choice and travel distance, respectively. They found that the two sets of factors were of nearly equal importance in explaining individuals' travel behaviour, although these relationships could be significantly modified by trip purpose, especially for distances travelled for shopping and leisure activities. Schwanen et al. (2001, 2004) also provided some Netherlands experiences of the relationship of urban form to travel behaviour by using data from the 1998 Netherlands National Travel Survey and evaluating several national spatial policies.

Whilst the land use – transport literature remains dominated by developed country studies, studies of developing countries, including China, emerged post 2000. Using data from a travel survey of four selected neighbourhoods in Shanghai, Pan et al. (2009) examined the influence of urban form variables on individuals' travel behaviour. The results showed that residents of pedestrian-friendly neighbourhoods tended to travel shorter distances, have fewer motor vehicles and were more likely to choose non-motorized modes, which suggested that land use planning and urban design have important short- and long-term effects on motorization and travel behaviour. Based on a household interview survey in Beijing in 2001, Wang and Chai (2009) used structural equation modelling to examine the impact of job-housing relationships on transport mode and travel distance for work purpose. They demonstrated that residents living in the *Danwei*[1] system had shorter commuting trips and higher usage of non-motorized transport modes than those living in commodity housing neighbourhoods, indicating that *Danwei* neighbourhoods with a higher land use mix, better public transit accessibility, and more pedestrian-friendly street design have positive effects on travel behaviour. However, although China is experiencing rapid urban expansion and profound urban spatial transformation, such research remains very scarce and there remains little empirical evidence explaining the causal links between neighbourhood-scale urban form and urban travel behaviour in China.

Land use-transport studies have to date largely adopted the trip as the basic unit when analysing the relationship between urban form and travel behaviour. More realistic may be the use of the 'tour' or 'trip chains', defined as the travel from home to one or more activity locations and back home again. Tours (trip chains), can link individuals' multiple trips together, including the outbound and return trips and all the stops made along the way, and offer a means of better explaining an individuals' travel behaviour. By using tours as the basic unit for analysis, tour-based modelling can match more closely the way in which travel decisions are actually made, and so will more likely capture true behavioural causality (Frank et al., 2008). As a result, several studies post 2000 have attempted to model tour-based travel behaviour. Using data from the Puget Sound Transportation Panel (PSTP) in the United States, Krizek (2003) adopted multiple regression models to examine the relationship between

[1] *Danwei* used to be the basic unit of economic, social, and spatial organization in socialist Chinese cities. It not only provided a workplace for employees, but also a comprehensive package of welfare and services. Further details see Chapter 3.

neighbourhood access and number of tours, tour frequency by purpose, and distance for simple maintenance tours, respectively. He found that households living in neighbourhoods with higher accessibility were more likely to make more tours with fewer stops per tour, and they tended to travel shorter distance for maintenance activities, such as shopping, appointment or personal errands; while neighbourhood accessibility seemed to have little influence on households' propensity to take complex tours for any purpose.

Chen et al. (2008) also demonstrated the importance of using the tour as the analysis unit to model travel behaviour. Using data for the New York Metropolitan Region, they employed a simultaneous two-equation system to examine the impacts of the built environment, especially the population and employment density at home and workplace, on mode choice decisions in home-based work tours. The results showed that the built environment variables did influence tour-based travel choice, in particular, employment density at workplace was found to exert more influence than residential density at home, which provided new evidence for urban planning and policy making. Frank et al. (2008) applied discrete choice models to investigate the effects of travel time, costs, and urban form variables on individuals' mode choice and tour complexity for home and work related travel in the Central Puget Sound region. They indicated that travel time was the most important factor in travel choice decision-making while land use variables were found to significantly influence the tour complexity for any type modelled. However, partly because of the difficulties of tour classification and tour complexity, studies using a tour-based travel framework have faced difficulties in drawing general conclusions on the role of urban form in tour-based travel behaviour.

Multivariate regression models have often been used to test the impacts of urban form on travel behaviour, with most studies treating urban form variables as exogenous, assuming that urban form is determined by forces such as planning, government subsidies, and developers' decisions, which were often beyond the control of individual residents. This approach, however, has been criticised by some researchers (e.g. Cao et al., 2006) for not considering the residential self-selection process while testing the land use-travel behaviour relationships. For instance, even though residents may have little power to shape urban forms, they may choose to live in the kind of neighbourhoods in line with their lifestyles. This residential sorting process, if not statistically controlled, will confound the estimation of the effects of urban form upon travel behaviour, because, if variation in the built environment leads to households spatially sort themselves according to their travel preferences, then those preferences will be highly correlated with built environment characteristics (Chatman, 2009). In other words, the associations between urban form and travel behaviour can either imply changes in travel choices in response to urban form, or it may result from a certain residential self-selection process, in which residents select the built environment that facilitates their preferred travel patterns. If the latter is the case, planning may have a smaller role in altering urban travel patterns and mitigating environmental outcomes.

Therefore, researchers started to include individual's attitudinal variables towards urban form and travel preferences into their models to control for residential self-selection in their investigation of causal links between urban form and travel behaviour. For example, Khattak and Rodriguez (2005) surveyed and compared two different neighbourhoods in North Carolina. Using two-stage regression models to control for demographic characteristics of households and residential self-selection, they found that households in the neo-traditional neighbourhood travelled shorter distances, made fewer external trips and made more walking trips than those in conventional suburban neighbourhoods. Chatman (2009) applied a variant reported-attitudes approach to account for the residential self-selection process, provided evidence that households seeking travel access were less responsive to the built environment, and residential self-selection did not bias estimates of the effects of the built environment on travel behaviour very much. By applying the seeming unrelated regression equations model (SURE) to investigate the underlying causal link between the built environment and non-work trip frequency by different modes in Northern California, Cao et al. (2009) also found that neighbourhood characteristics influenced individuals' travel decisions, especially for non-motorized travel frequency, even when residential self-selection was accounted for.

By contrast, there is other research which had different findings, including inverse results. For instance, using structural equation modelling, Bagley and Mokhtarian (2002) found that travel behaviour was largely impacted by attitudinal and lifestyle variables, not the built environmental variables, which had often been overestimated by the new urbanism supporters. Based on a self-administered survey of 1,368 respondents conducted in six neighbourhoods in Austin in 1995, Cao et al. (2006) applied two separate negative binomial models to investigate the influence of the built environment and residential self-selection on pedestrian behaviour, finding that residential preference plays an important role in individuals' travel choices, and pedestrian shopping trips are more likely to be explained by residential self-selection variables. Furthermore, they also conducted similar research for 547 individuals from different types of neighbourhoods in Northern California. Using a structural equation model, they examined the causal link between urban form and travel demand, while controlling for residential preferences and travel attitudes derived from quasi-longitudinal data. The outcomes showed that self-selection and built environment both had a significant influence on travel behaviour, and accessibility might be the most important factor in reducing automobile use (Cao et al., 2007).

Other research with different approaches to those described above also provides useful explanations on the relationship between urban form and travel behaviour. For example, while focused on a special group of homemakers, Chen and McKnight (2007) tested this controversial relationship, finding that the effect of the built environment is an order of magnitude less than socio-economic variables and the inter-relationship between different types of activities and associated travel is very important for such studies. From the perspective of three different levels, including the block group, the individual and the trip analysis, Fan (2007) investigated the relationship between the built environment, coupled with traffic and weather conditions, travel behaviour and time allocation. Her evidence showed that land-use planning had important influences on individual travel behaviour, but that this land use-travel connection was differentiated based on activity context, such as activity type and time of day. Bartholomew and Ewing (2009) used a multi-level model to test how far compact growth scenarios were predicted to reduce VKT based on a wide range of scenario planning analysis, finding that VKT in 2050 will be reduced by 17% below compact growth scenarios assuming a continuation of existing trends.

Ewing and Cervero (2010), conducted a meta-analysis of the associations between the built environment and travel demand, based on reviewing large quantities of literature existing before 2009. They further quantified the effect sizes of various urban form measures by computing individual and weighted average elasticities, trying to provide suggestions for governments in the application of land-use planning and urban design (Ewing and Cervero, 2010). In their paper, ‘six Ds’ have been summarized as important dimensions of urban form to moderate travel demand, in comparison with the original ‘three Ds’, with demographics, the seventh D, controlled as confounding factors in travel studies. These six Ds of urban form measures include density, diversity, design, destination accessibility, distance to transit, and demand management.

To conclude, whilst much research provides empirical evidence and insights into the role of urban planning in influencing individual travel behaviour, this evidence base is heterogeneous and so remains inconclusive with respect to the causal links between urban form and travel behaviour. Also, it is clear that literature on urban spatial structures and travel behaviour predominately focuses on advanced economies, particularly of the US and Europe. Thus, application of policy lessons drawn from these places, to developing countries where the underlying context may be very different, is potentially highly problematic. This means that efforts to develop carbon sensitive transport policy and plans for countries like China, require land use-transport studies that aim to better understand travel behaviour within the specific local context.

2.3.3 The carbon mitigation potential of technology

Technology is widely regarded as a critical tool to reduce transport carbon emissions, particularly in terms of fuel type and vehicle fuel efficiency. For example, UK policy promotes advanced vehicle technologies such as plug-in hybrids and full battery electric vehicles which are viewed as key to achieve the government’s stated 2050 target to reduce CO_2 emissions by 80% from 1990 levels (Anable et al., 2012).

Technological choices have been addressed by transport emission researchers for many years, with “bottom-up” system models like MARKAL1 and the TIMES integrated assessment used to explore the impact of technology innovation and adoption in abating carbon emissions (Labriet et al., 2005; Loulou and Labriet, 2008). By considering the transport sector within a model of the worldwide energy system, Hankey and Marshall (2010) related energy choices in the transport system to some key choices made elsewhere in the energy supply system, and suggested it was important to develop new technologies for supplying renewable energies such as electricity or hydrogen with zero emission to fight climate change. Moreover, under the continuous pressure of environmental regulation, particularly the Zero Emission Vehicle (ZEV) mandate introduced by the Californian Air Resources Board, more efficient engine technologies have also been developed for low emission vehicles, such as electric, fuel cell, and hybrid vehicles. Oltra and Saint Jean (2009) analysed the advantages and disadvantages of these alternative engine technologies, and showed the potential for decarbonisation under various technology scenarios.

Although developing new vehicle technologies and increasing fuel efficiency has been seen as a central instrument to reduce both energy consumption and CO_2 emissions in the transport sector, these reductions will eventually be offset by increased car ownership, car usage, trip frequency, travel distance, and traffic congestion (Mitchell et al., 2011). Theoretical and empirical studies about rebound effects raise many doubts concerning the effectiveness of such technologies (Greene, 2012; Matiaske et al., 2012). The rebound effect refers to the increased energy services consumption by end-consumers due to the introduction of new technologies and energy efficiency improvements. Such basic economic and behavioural responses tend to offset the environmental benefits of technology choices. In particular, these counterproductive effects are estimated to be prominent in the transport sector. Matiaske et al. (2012) used the German Socio-Economic Panel data to examine the extent to which higher fuel efficiency of cars affects additional travel, and discovered fuel efficiency had a positive effect on the kilometres driven, meaning that with higher efficiency people tended to drive longer distances, which indicated a big rebound effect operated. Goerlich and Wirl (2012) introduced a theoretical framework to link the crucial issues of fuel demand, technical efficiency and quality of cars, and used Australia as the case study to demonstrate that more efficient automobiles encourage consumers to expand service demand as well as the demand for quality (larger and more powerful cars). Based on the analysis of six European countries, Ajanovic and Haas (2012) investigated the impact of fuel intensity on overall fuel consumption and on the demand for vehicle km driven in car passenger transport, and found a high rebound effect as well. They concluded that adopting the technical standards as the only policy instrument would have limited success.

Therefore, in order to respond adequately to the environmental challenges, it is likely that technological improvements should be augmented with some fundamental changes in the day-to-day patterns of human activity (Anderson et al., 1996). Despite significant reduction of carbon emissions due to improvements in technology and fuel efficiency, these reductions will eventually be offset by increased car ownership, car usage, and traffic congestion, which constitute perhaps the most pressing environmental threat of the current age. If developing countries such as China and India follow the same path of automobile dependence as developed nations, technological advances are very unlikely to offset such a monumental increase in motorisation and its subsequent emissions. The resulting emissions from millions of new vehicles will simply overwhelm the reductions achieved through improved fuel efficiency and propulsion technologies (Wright and Fulton, 2005). In addition, even if technology could theoretically provide the required reduction in CO_2 emissions, this would be a difficult, expensive and a long term solution with many risks (Chapman, 2007). On the contrary, improvements to urban spatial organization and land use patterns are considered a cost-effective tool that reduces carbon emissions from transportation by encouraging low-carbon travel (Grazi and Van den Bergh, 2008; Brownstone and Golob, 2009). This is particularly important for developing countries that still experience rapid urban spatial expansion, because urban spatial structure is hard to change once built up, and thus will have lock-in effects on long-term environmental outcomes (Lefèvre, 2009). Therefore, all these technological efforts need to be supported by improvement of the physical characteristics of urban form so that its destructive environmental impact is minimized; and it is essential to research the relationship between urban form, travel behaviour, and thus CO_2 emissions.

2.3.4 Summary

To combat climate change and facilitate low-carbon development, it is critical to have a better understanding of factors that shape travel behaviour, and resulting carbon emission. A large amount of literature has investigated the relationship between urban form and travel behaviour using various data collection techniques and analytic models, which attempts to demonstrate that higher population density, mixed land use, and pedestrian-friendly street design correlates with fewer private vehicles, shorter distance and less motorised travel. However, researchers have yet to resolve the debates regarding the complex effects of urban form on daily travel behaviour, mainly due to the residential self-selection issue. Moreover, most prior studies use trips as the basic unit of research, with little attention devoted to tour based analysis, which better reflects the interrelated decision process of individuals' daily travel behaviour.

Meanwhile, various technological approaches have been researched separately to mitigate transport carbon emission, such as introducing new clean fuels and improving fuel efficiency. Although it is a critical tool, the technological development alone cannot deliver the significant reductions in transport CO_2 emission. It should be combined with fundamental changes in the daily travel patterns of residents. Furthermore, existing literature predominantly focuses on developed countries, while Chinese cities have been largely absent from such research. As China's urban spatial development and individuals' travel behaviour are often different in advanced economies such as US or Europe, lessons learnt from studies of developed countries cannot uncritically be applied to China. More efforts should be made to better understand the travel behaviour in the context of rapid urbanisation and spatial restructuring in urban China.

2.4 Urban form, energy use and carbon emissions

2.4.1 Urban form and transport CO_2 emission from passenger travel

Presently, the techno-economic analytical approach has principally been employed to examine the influence of fuel taxation, price elasticity and fuel efficiency on transport energy consumption and carbon emissions at the aggregate level in dealing with climate change mitigation (Dahl, 2012; Sterner, 2012). However, some studies include the effects of urban form or land-use strategies too. For example, using

TRESIS (Transportation and Environment Strategy Impact Simulator), an integrated model designed to analyse a variety of land use, transport, and environmental policy strategies or scenarios for urban areas, Hensher (2008) evaluated the influence of several policy instruments, such as fuel efficiency, a carbon tax, variable user charges, and improvements in public transit on passenger travel distance and CO_2 emissions in the Sydney metropolitan area. The results showed that technology (i.e. fuel efficiency improvements) and pricing instruments (a carbon tax or a variable user charge) offered more attractive prospects than land-use strategy (i.e. public transport improvement) in terms of CO_2 emission reduction, as well as in the aspect of government financial outcome. Similarly, Brand et al. (2012) introduced a newly developed and more sophisticated forecasting model, the UK Transport Carbon Model (UKTCM), to analyze the impact of different policy scenarios on energy demand reduction through life cycle carbon emissions and external costs. The results showed that electric vehicles tended to be the most effective single strategy for reducing emissions. Nevertheless, in terms of prioritizing policy interventions, an integrated policy approach that considered both demand and supply side strategies were far more effective than any single policy intervention.

By contrast, there are some other studies which focus on the influence of urban form variables on household travel behaviour and transport carbon emissions at the disaggregate level. For instance, based on the analysis of 1998 Dutch housing survey data, Grazi et al. (2008) examined the impact of urban density on commuting behaviour and the travel-induced CO_2 emissions. Applying an instrumental variable approach (IV) to account for endogeneity of residential location, they found that locations with higher density tended to lead to lower car based carbon emissions, and so concluded that spatial planning policies deserved more attention in climate change debates because of their contribution to reducing carbon emissions. Boussauw and Witlox (2009) also investigated the relationship between spatial structure and energy consumption for commuting travel behaviour. Using 2001 census data for Belgium, they developed a commute-energy performance (CEP) index to illustrate the urban differences of transport energy consumption in Flanders and Brussels, and demonstrated that the home-work distance was a very important determinant for the commuting energy performance, whilst mode choice was much less important. Moreover, residential density and proximity to the main road and rail network had an influence on commuting travel and energy performance, but this influence varied significantly in different locations, such as suburban areas or central business districts.

Conducting a major survey with a sample of 456 individuals in Oxfordshire, Brand and Boardman (2008) described an innovative methodology and evaluation tool for profiling annual greenhouse gas emissions from personal daily travel across all transport modes within a 12-month timeframe. They aimed to find out the extent to which individual and household travel activity patterns, choice of transport mode, geographical location, and socio-economic and other factors impact on greenhouse gas emissions. The results showed that air and car travel dominated overall emissions, and the emissions amongst the population is highly unequally distributed, with the top 10% of emitters responsible for 43% of emissions and the bottom 10% for only 1%. Moreover, they further profiled the GHG emissions across all modes of personal passenger travel for non-business-related travel activity, and discovered there was a '60-20 emission' rule (with the highest 20% of emitters producing 61% of emissions) across different units and scales of the analysis. They also adopted a multivariate regression model to demonstrate that income, working status, age and car ownership are significantly related to overall emissions, while factors related to accessibility, household location and gender are not (Brand and Preston, 2010).

Based on the 2001 National Household Travel Survey (NHTS) data, Liu and Shen (2011) applied SEM to examine the effects of urban form variables on household travel and transport energy consumption in the Baltimore metropolitan area, finding that urban form did not have a direct effect on VMT or energy consumption, but its indirect effect was significant and negative, which indicated urban form influenced household travel and energy use through other channels, like speed or vehicle ownership. However, this result can be challenged for at least two reasons. Firstly, population density is used as the only urban form variable in the SEM; as urban form should be measured by many dimensions, such as diversity, design, accessibility, etc, only employing population density to represent urban form is far from enough. Secondly, urban form variables are hypothesized as the exogenous variables in their SEM, which is also questionable. Because of the interactions between urban form, travel behaviour, and transport energy consumption, the urban form variables should be included as the endogenous variables in the SEM in order to better capture the real relationship between urban form, household travel and energy use while accounting for the residential self-selection process.

Such doubts can be illustrated by comparing it with similar literature. Using the same 2001 US NHTS data, Brownstone and Golob (2009) also applied SEM to investigate the impact of residential density on vehicle usage and energy consumption in California. While treating urban form as the endogenous variables in their model to account for residential self-selection, they found that residential density had directly and totally significant and negative effects on household vehicle usage and energy consumption, and this total effect could be decomposed into two paths of influence: household vehicle mileage and type choice.

To conclude, these empirical results have provided mixed evidence of the influence of urban form on travel behaviour and transport carbon emissions. Until now, few researchers have empirically investigated the causal link between urban form and transportation energy use and carbon emissions, and this causal link remains unclear and inconclusive. Therefore, more empirical research involving more sophisticated and comprehensive quantitative models and detailed behavioural data are needed to examine the relationship between urban form and transport CO_2 emissions (Liu and Shen, 2011).

2.4.2 Building energy use and life-cycle carbon emission

The urban form-energy relationship is more complicated than implied by the preceding discussion, as in addition to the transport energy requirements, urban form can influence residential building energy use too. Owens (1984) made the first attempt in the UK to explain the influence of urban form on energy demand for different end uses, such as transport and building sectors, and addressed the potential for planners to guide the evolution of sustainable built environment with an energy-constrained consideration. Moreover, the form of the built environment may also be a significant factor in determining the feasibility of various technologies of energy supply and distribution (Owens, 1984). She later demonstrated that spatial variables could be related to energy needs and energy efficiency at various scales of urban development, the most significant interactions occurring through travel and transport requirements and through energy use in buildings, mainly for space heating. These different scale spatial variables included built form, orientation, siting, layout, density, interspersion, shape, size, regional structure, etc. (Owens, 1992b).

Not surprisingly, it is meaningful to consider the energy consumption of the residential sector, which typically accounts for a large share of energy demand. For instance, building energy use accounts for over half of the total energy consumed and an equivalent proportion of pollution generated in the UK; in the European Union this figure is 41%, and in the US 36% (Steemers, 2003). Nationally, it accounts for 16-50% of that consumed by all sectors, and averages approximately 30% worldwide (Swan and Ugursal, 2009). Therefore, it is important to explore the relationship between urban form and residential building energy use.

Taking the UK as an example, energy used in housing is mainly to provide four services: space heating, hot water, lighting and appliances. The residential energy demand is dominated by space heating, which on average accounts for 60% of the total energy, and it is the space heating that will be most affected by urban form, with the remaining consumption being largely determined by occupant needs (Steemers, 2003). As for space heating, detached houses have been demonstrated to require more energy than flats, with terraced housing or low-rise flats resulting in significant reductions in energy demand at the neighbourhood scale; density and land-use mix can affect the economic viability of large-scale Combined Heat and Power (CHP) at the urban scale (Owens, 1992a).

Ratti et al. (2005) pointed out that building energy performance was a very complex function which was dependent upon: (1) urban geometry, (2) building design, (3) systems efficiency, (4) occupant behaviour; and these four points were under the control of different actors in the building sector: urban planners and designers in (1), architects in (2), system engineers in (3) and occupants in (4). Based on use of digital elevation models (DEMs), they attempted to explore the effects of urban texture on building energy consumption and provided energy simulations for different urban areas. Ewing and Rong (2008) put forward a conceptual framework linking urban form to residential energy use via three causal pathways: electric transmission and distribution losses, energy requirements of different housing stocks, and space heating and cooling requirements associated with urban heat islands. By using various national data sources and multiple regression models, they examined the impact of urban sprawl on residential energy use through housing stock and UHI effects, demonstrated that both single-family detached houses and big houses lead to higher residential energy use, which indicated support for compact development strategies.

By contrast, there are empirical studies which show different and contradictory conclusions. For example, based on the survey of energy usage in a UK home, Wright (2008) demonstrated that there were only weak correlations between energy use and urban form variables across all types of dwelling, and households tended to have a much stronger influence on energy use than did built form. Howard et al. (2012) constructed a model to estimate the building sector energy end-use intensity for space heating, hot water, and electricity for space cooling in New York City. This indicated that such end use was primarily dependent on building function, not on construction type or the age of the building.

In addition, as far as the methodologies are concerned, Swan and Ugursal (2009) provided a comprehensive review of the various modelling and techniques applied in the building energy use analysis, and broadly divided them into two categories: top-down and bottom- up. The top-down approach treats the residential sector as an energy sink and regresses the building energy consumption as a function of top-level variables such as macro-economic indicators, energy price, and general climate. This approach is not concerned with individual end-uses and is mainly used for supply analysis based on long-term projections of energy demand by accounting for historic aggregate energy values (Swan and Ugursal, 2009). In contrast, the bottom-up approach estimates the energy consumption of a representative set of individual houses to regional and national levels, and consists of two distinct methodologies: the statistical method (e.g. regression, conditional demand analysis, neural network) and the engineering method (e.g. population distribution, archetype, sample). Such bottom-up techniques have advantages in examining the relationship between urban form and residential energy use, because it calculates the energy demand of end-uses based on representative survey data of individual houses by taking into account multiple detailed micro-level variables. However, partly because survey data is limited due to collection difficulties and cost, the strict requirements of a selected sample, the subjective descriptions of occupant behaviour, and the seasonal differences of energy use, the bottom-up building energy use analysis is often compromised (Swan and Ugursal, 2009).

As spatial proximity can allow cost-effective re-use of waste heat streams and facilitate the introduction of combined heat and power and district heating systems, Steemers (2003) described three form factors which could be managed to increase density: by increasing building depth, by increasing building height or reducing spacing, and by increasing compactness. He further demonstrated that high housing density in the UK can be achievable and beneficial for energy conservation. However, some authors argued that high density housing would increase energy demand due to restrictions on natural ventilation and light, more energy intensive construction and constrained opportunity for solar heating systems (Owens, 1984; Hui, 2001); while others maintained that even though low density living provided opportunities for energy efficient buildings with solar gain, it was at the cost of high transport energy demand due to long travel distance and motorized mode choice (Holden and Norland, 2005). This paradox seems to suggest the possibility of a density at which total energy use (transport plus building) is at a minimum; and it is important to understand its simultaneous effect on energy use in both transport and building sectors and analyse it in its entirety, if urban form is to be used as a policy tool to reduce energy use and carbon emissions (Mitchell, 2005).

Using land-use-transport interaction models, a residential dwelling type model, and transport and emission models, Mitchell et al. (2011) estimated and evaluated carbon emissions from transport, dwellings, and commercial buildings to 2031 for different spatial strategies for three English regions of decreasing size. They found that urban form was a relatively weak instrument in reducing carbon emissions and that comparatively, economic and technological instruments were more powerful in decreasing carbon emissions than urban form. When taking into account both the transport and building sectors, and estimating carbon emissions in 66 major metropolitan areas across the United States, Glaeser and Kahn (2010) discovered that there was a strong negative association between carbon emissions and land-use regulations; carbon emissions were much lower in cities than in suburban areas, and the city-suburb gap was particularly large in older areas.

In general, the energy estimated from the building sector in the above literature refers to operational energy. This means the energy used for heating, cooling, lighting and appliances; however, embodied energy, which indicates the energy used for the construction and fabrication of products used to construct a building, the energy used on-site for the assembly of the building, and the energy embodied in upstream inputs to these processes (Troy et al., 2003). Embodied energy is also an important component, and is considered by some researchers, although compared to literature on operational energy use, studies on the embodied energy use are rare. Weisz and Steinberger (2010) examined the effect of urban form, urban building stock, and urban consumption patterns on urban energy and material use, pointing out socio-economic variables, especially household income, strongly correlated with embodied energy and material use.

By calculating the primary embodied energy and operational energy consumption from both the buildings and transport sectors in six case study areas in Australia, Troy et al. (2003) attempted to capture the full energy impacts of different built forms. They suggested that embodied energy consumption might be more significant than previously thought and the full energy analysis could be used as a development control tool in the planning system. Similarly, Norman et al. (2006) also provided a relatively complete understanding of urban density effects on overall energy use and greenhouse gas (GHG) emissions from construction materials for infrastructure, building operations, and transportation. By applying an economic input-output life-cycle assessment model, they compared the energy use and GHG emission associated with high-density development close to a city core versus low-density development at the suburban periphery, finding that low-density development is more energy and GHG intensive than high-density development on a per capita basis.

To conclude, as building energy use is a complex function of many interactive factors, it is very difficult to determine the exact marginal effect of urban form on residential energy use by controlling for all other factors (Rickwood et al., 2008). The effect of urban form on residential energy use is still equivocal.

2.4.3 Summary

While there is growing emphasis on the potential of urban planning in climate change mitigation, empirical literature is still insufficient and debates over the relationship between planning parameters and carbon emissions are yet to be fully resolved. Prior studies either focused on automobile travel while paying little attention to CO_2 emission from other transportation models (e.g. subway, bus, motorcycle), or failed to consider the travel purposes for transport carbon emission. Moreover, most existing urban form-energy literature focuses on advanced economies, while only a few recent studies (e.g. Qin and Han, 2013) explored the correlations between different types of neighbourhoods and household carbon emissions in the Chinese context of rapid urbanisation and spatial restructuring. The results showed that neighbourhoods with high density, mixed land use and high accessibility to public transit tend to have lower domestic and transport carbon emissions.

As urban form might have complex and interrelated impacts on energy use and carbon emission from building and transport, it is important to consider the sectors of building and transport together in the urban form-energy relationships. However, as there are some limits in this thesis, and practical constraints including a lack of building energy data for the study area, the major research objectives remain focused on investigating the urban form-travel relationships with respect to transport carbon emissions. There will be a reflection on the building energy issue in the concluding chapter of this thesis.

2.5 Microsimulation for urban analysis and transport forecasting

2.5.1 Overview

Microsimulation is a computing process which uses simulation techniques for reproducing or forecasting a dynamic and complex system by taking micro-level units such as individuals, households and firms as the basic units of analysis (Merz, 1991; Guo and Bhat, 2007). Spatial microsimulation was developed in the field of economics (Orcutt, 1957), and has since been applied extensively in the fields of geography (Birkin and Clarke, 1988; Ballas and Clarke, 2000; Wu et al., 2008) and social sciences (Brown and Harding, 2002; Rakowski et al., 2010). For example, using the 1991 UK Census Small Area Statistics (SAS) and British Household Panel Survey (BHPS), Ballas et al. (2005) applied the deterministic reweighting method to spatially and dynamically simulate the entire population of Britain to 2021 at the small area level. Such microsimulation can be performed for a range of heterogeneous subgroups at different spatial scales, and represents a useful tool for addressing policy-sensitive problems, generating long-term forecasts and evaluating government policies (Miller et al., 2004; Mannion et al., 2012).

In the transport field, problems of congestion, air pollution, and energy consumption have raised interest in the microsimulation of travel since the 1990s (Goulias, 1992; Kitamura et al., 2000). Various models of urban travel behaviour are increasingly developed and applied in a microsimulation framework, and these models share common objectives to replicate the temporal, spatial and modal decisions that lead to observed activity-travel patterns of residents (Miller and Roorda, 2003; Miller et al., 2004). For example, the MIDAS (microanalytic integrated demographic accounting system) was developed as a new travel demand forecasting model which attempted to combine dynamic models of travel behaviour with socio-demographic and economic microsimulation (Goulias, 1992). Using simple logit models to determine household transition probabilities, MIDAS aims to simulate life changes in the household members' socio-demographic attributes dynamically, and then use these endogenously generated attributes to forecast household car ownership and mobility. Other microsimulation models include RAMBLAS (regional planning model based on the micro-simulation of daily activity patterns), which was developed to predict the spatial distribution of individuals' activities and related traffic flows in the Eindhoven region in the Netherlands (Veldhuisen et al., 2000).

In a review paper, Hunt et al. (2005) provided a detailed evaluation of several frameworks of operational and comprehensive microsimulation systems designed for urban modelling purposes, such as ITLUP, MEPLAN, and UrbanSim. However, there are two comprehensive and noteworthy microsimulation modelling systems which have been developed for the purposes of disaggregate analysis and travel demand forecasting. These are of interest to this thesis and will be summarised below.

2.5.1.1 UrbanSim

UrbanSim is a dynamic urban simulation system that was developed to simulate the development and interaction of land use, transportation and environment operated in several American metropolitan areas (Waddell et al., 2003). It is a comprehensive and operational urban simulation system which includes various urban actors (e.g. households, businesses, developers, governments) and represents their interactions in the real estate market and the dynamic processes of urban development (Waddell, 2002). Its purpose is to respond to emerging issues of urban sprawl, traffic congestion, housing affordability, and resource consumption, and further facilitate the metropolitan planning organizations and urban planners to evaluate the long-term outcomes of alternative transportation and land use policy scenarios (Noth et al., 2003).

UrbanSim consists of a software architecture for implementing models and a set of interacting model components which represent the major actors and choices in the urban system (Waddell, 2002). The major concern of UrbanSim is on the interactions of household and employment mobility and location choices which are simulated in a disequilibrium urban market. Based on parcel-level land-use data from the Eugene-Springfield, Oregon metropolitan area, Waddell (2000) simulated the interaction between demand and supply of real estate by the residential and housing market components of the developed UrbanSim model which operated on an annual time schedule.

However, the daily activity and travel patterns are handled as external inputs in UrbanSim and still under development. Individuals' travel patterns were simulated and examined with internal household choices of housing and job location, and vehicle ownership in an interdependent framework (Waddell et al., 2010). Whist tour analysis improves understanding and prediction of travel behaviour, as discussed above, UrbanSim uses the 'trip' – rather than the 'tour' – as the basic unit for travel demand analysis, and this system does not account for transport CO_2 emissions in the framework.

2.5.1.2 CEMDAP

CEMDAP (comprehensive econometric microsimulator for daily activity-travel patterns) is a static and operational microsimulation system for activity-based travel demand modelling and forecasting developed at the University of Texas at Austin in the US (Bhat et al., 2004). It is a software implementation of a set of econometric models that represent the whole decision-making processes and provides the complete daily activity-travel patterns for individuals and households by putting various land use characteristics, socio-demographic attributes and transportation services into the system (Bhat et al., 2004). CEMDAP consists of five kinds of econometric models, including regression, hazard duration, multinomial logit, ordered probit, and location choice. Each model corresponds to one or more activity/travel decisions of an individual or household, and these models can be broadly grouped into two systems: the generation-allocation model system and the scheduling model system (Pinjari et al., 2008).

Moreover, considering that out-of-home mandatory activities, such as work or school, impose constraints on participation in other types of activities and may have a significant influence on the decision-makers to pursue and schedule other activities, the CEMDAP modelling system firstly and respectively simulates the activity-travel patterns of workers as well as non-workers with different frameworks (Guo et al., 2001). In this system, a worker's day has been partitioned into five periods (the before-work period, home-to-work commute, work-based period, work-to-home commute and after-work period) and an activity-travel pattern for workers is represented by a three level structure: stop, tour, and pattern. The non-workers' daily activity-travel pattern is simply characterized by a sequence of home-based tours

(Bhat et al., 2004). However, only considering morning commute and evening commute may be not appropriate for all the workers with different socio-demographic attributes under different urban circumstances, as some of their work commute patterns may include more than two commuting decisions on a typical weekday, especially in the Chinese context of rapid urbanization and spatial transformation.

2.5.1.3 Summary

To conclude, great efforts have been made to develop various microsimulation modelling systems for urban policy-related analysis and transport forecasting purposes, particularly in developed countries. While UrbanSim focuses on the interactions of household and employment mobility and location choices, its travel forecasting framework is still under development and uses the trip as the basic unit of analysis. With respect to the system particularly designed for the disaggregate activity-travel demand forecasting purposes, CEMDAP represents a comprehensive and promising system which integrates household activities, land use patterns, regional demographics, and transportation networks in an explicitly time-dependent framework. However, these modelling systems have rarely considered the spatial dimension of travel behaviour; and in the CEMDAP system, its "morning commuting + evening commuting" analysis does not cover the travel patterns relevant to Chinese residents, as will be shown in the tour analysis in Chapter 4.

Moreover, while these microsimulators are developed to generate synthetic travel patterns using Monte Carlo simulation, they demand large samples of travel data to derive the required conditional or transition probabilities, and these microsimulation systems rarely account for transport CO_2 emissions in their framework. Therefore, more comprehensive, disaggregate, and operational microsimulation modelling system should be developed to simulate individuals' daily travel behaviour and estimate their associated transport CO_2 emissions effectively and dynamically.

2.5.2 Microsimulation in developing countries

Whilst transport problems are serious in transitional countries and in the developing world, microsimulation of travel has to date remained the preserve of developed economies (Yagi and Mohammadian, 2010). There are several possible reasons for this lack of microsimulation application to the transport problems of developing countries. First, there is a general lack of expertise in the technique, and model development is challenging requiring a high level of programming skills. Second, there is little publicly available software suited to transport microsimulation problems; those models that do exist, such as the ILUTE and CEMDAP discussed above, have a rigid design and generally require large samples of very specific data sets (Geard et al., 2013).

A third explanation is a lack of data at an appropriate scale. Microsimulation addresses individuals, households, or firms as the basic analytical unit (Merz, 1991), and requires detailed information at the micro scale. However, large micro scale datasets are generally lacking in many, and particularly developing, countries. In China, there is no national travel survey or published governmental large sample of detailed travel information (Pucher et al., 2007; Long et al., 2011). Even for the population census conducted every ten years, the Chinese government only publishes a selection of demographic tabulations at relatively coarse geography (i.e. the district or city level). Confidentiality issues also mean that at finer scales information that is collected is not disclosed, constraining the use of microsimulation techniques further.

However, attempts have been made to get around this data problem elsewhere: for example, using the 1990 population census and the USA Public Use Microdata Sample, Beckman et al. (1996) applied iterative proportional fitting (IPF) to generate a synthetic baseline population of individuals and households so as to estimate future travel demand. Using the 1991 Sample of Anonymised Records and Small Area Statistics samples, Ballas and Clarke (2001) synthesised a household micropopulation of Leeds UK, using the IPF technique. They used this synthetic population to perform 'what-if?' economic policy analysis at small-area level, estimating the geographical impact on patterns of employment and income from major changes (jobs lost or created) in the local labour market. In a recent study, Lovelace et al. (2014) also presented a spatial microsimulaiton to analyse people's daily commuting patterns at different levels in the UK, providing insight into spatial variability of commuting behaviour and its relationship with socio-demographic attributes (e.g. income, type of car, number of children). A critical review on current methods to generate synthetic spatial microdata using synthetic reconstruction or reweighting techniques can be found in Hermes and Poulsen (2012).

Microsimulation has been widely used in western countries to provide a better understanding and estimation of a large population's daily travel behaviour. However, there is little research on the spatial microsimulation of urban transport CO_2 emissions at a fine spatial scale for developing countries, where the dominant approach remains econometric modelling drawing on small sample surveys, and at an aggregate or a coarse scale for both past and prospective emission (Dhakal, 2009; Yan and Crookes, 2009). Long et al. (2011) developed a multi-agent model for the analysis of urban form, residential commuting energy consumption and environmental impact at the inner-city scale. They also proposed an Agenter (i.e. agent producer) approach to disaggregate lots of heterogeneous agents with non-spatial attributes and spatial locations using aggregate data and small-scale surveys, for future microsimulation or agent-based modelling analysis (Long and Shen, 2013). However, the daily travel behaviour and concomitant CO_2 emission of a large population has rarely been investigated by spatial microsimulation at a fine geographical scale, and no such work has been conducted for developing countries where travel behaviour may differ substantively from that represented in models of western countries.

2.5.3 Discussion

Spatial microsimulation uses individuals or households as the basic analytical unit, and represents a useful tool for generating disaggregate forecasts over a long period (Ballas et al., 2005). On the basis of some synthesising techniques, such as deterministic reweighting, conditional probability or simulated annealing, microsimulation models can synthesise much individual-level data for large populations by combining surveys and census data. It can also perform static what-if simulations to explore the impacts of alternative policy scenarios on the synthetic population for a base year, and perform future-oriented 'what-if' simulations by updating the basic microdata set over a long period (Ballas and Clarke, 2001). For an appraisal of the strengths and weaknesses of the three established synthesising techniques see Harland et al (2012).

Generally, simulated annealing algorithm has been demonstrated to provide the most promising results in the generation of synthetic microdata at different geographical scales. It has some major advantages over the deterministic reweighting and Monte Carlo sampling, such as the inclusion of the Metropolis Algorithm which allows both forward and backward steps in its search for an optimal population configuration. It evaluates the goodness of fit statistic simultaneously against all of the constraint variables, and generates a realistic representation of the observed population while maintaining the rich variety of attributes contained in the survey sample population. However, most prior simulation studies or modelling systems applied deterministic reweighting or Monte Carlo sampling to create synthetic populations, which could generate more errors. Therefore, in this thesis, the simulated annealing algorithm is adopted to create the spatial microdata at fine geographical scale, and a new microsimulation modelling system, i.e. the Flexible Modelling Framework (FMF), is used to facilitate the spatial microsimulation analysis in urban China. Further details on the microsimulation techniques can be found in Section 3.3.

2.6 Conclusion

Much research has been conducted to provide evidence on the factors that shape travel behaviour, and resulting carbon emissions, with the intention of developing low carbon cities, a key goal of 21st century planning. Understanding travel based carbon emissions in mega-cities is vital, but city size, and often a lack of required data, limits the ability to apply linked land use, transport and tactical transport models to investigate the impact of policy and planning interventions on travel and emissions. China has already passed the US as the world's largest source of carbon dioxide emissions (Yan and Crookes, 2010), it is important to provide improved understanding of form-travel relationships, and estimation of transport CO_2 emission to inform spatial development policy and mitigate carbon emissions. This thesis therefore aims to develop a spatial microsimulation of daily travel behaviour and transport CO_2 emission in the Chinese context, and provide a basis for urban planning and transport policy evaluation. The overall research design, including the modelling techniques, study area, and data sources, are provided in detailed in the next chapter.

Chapter 3

Methodology

3.1 Introduction

This chapter introduces the overall research design, including research methods, study area, and data sources used in the thesis. As noted in previous chapters, whilst transport problems (e.g. energy consumption, air pollution, traffic congestion) are generally more serious in transitional countries and in the developing world, research on urban form, travel behaviour and CO_2 emission has largely focused on advanced economies, particularly those of the USA and Europe. However, urban spatial development and individuals' daily travel behaviour are often different in developing countries and transitional economies (Pan et al., 2009; Qin and Han, 2013); hence lessons learnt from studies of developed countries cannot uncritically be applied to developing nations. This includes those experiencing rapid urban development, like China, where improved understanding of form-travel relationships and estimation of transport CO_2 emission are needed to inform spatial development policy.

Figure 3.1 illustrates the overall research design of the thesis, which consists of three major analytical parts. Multiple data sets and modelling techniques are used to address the different research objectives. Specifically, using an activity travel diary survey and land use data, the thesis first investigates how socio-demographic attributes of households, individuals and urban form characteristics correlate with tour-based travel decisions. This analysis aims to determine the important predictors of people's daily trip-chaining behaviour. As people's choices of tour frequency, tour pattern are a discrete multi-dimensional choice issue, discrete choice models (e.g. ordered logit, multinomial logit) are the most appropriate methods and are thus employed to investigate the relationships among urban form, socio-demographics and trip-chaining behaviour.

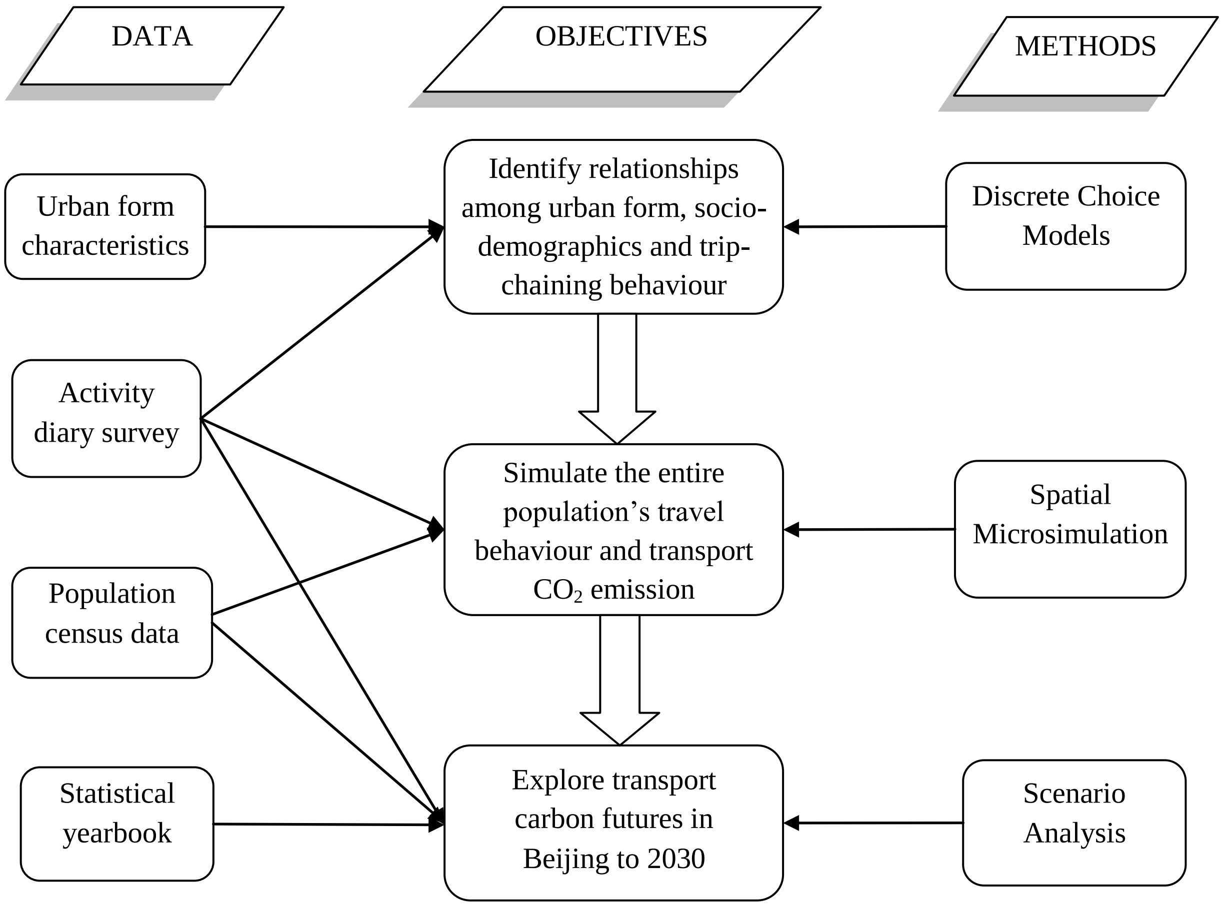

Figure 3.1: Research design

The next major analytical part involves simulating transport CO_2 emission from people's urban travel, which is addressed through the development of spatial microsimulation of people's daily travel behaviour, drawing on the analysis of trip chain behaviour described above. Using the activity diary survey and population census data at the sub-district level, a simulated annealing algorithm is applied to create a realistic synthetic population at fine spatial scale in urban Beijing. The constraints in the spatial microsimulation model are socio-demographic attributes of households and individuals, which are important predictors of people's daily travel behaviour found in the first empirical analysis. The population's daily travel, including travel distance and mode choice are then spatially simulated at the sub-district level, and the transport CO_2 emissions from people's daily urban travel are also estimated at the disaggregate level over the decade 2000-2010.

Finally, in the last empirical analysis, the transport CO_2 emissions from passenger travel behaviour are projected to 2030 using scenario analysis. On the basis of the population microsimulation, travel diaries and the aggregate parameters in the statistical yearbook (and city plans and Five Year Plan), this part develops four scenarios (transport policy trend, land use and transport policy, urban compaction and vehicle technology, and combined policy) to explore travel behaviour and transport CO_2 emission under current and potential strategies on transport, urban development and vehicle technology. The analysis of these scenarios will lead to a better understanding of the role of various factors on daily travel behaviour and total CO_2 emission, and provide alternative urban development strategies and policy implications for CO_2 emission mitigation targets set by the national and local governments.

Compared with existing research, this research design facilitates a more detailed assessment of travel behaviour at the disaggregate level, provides an improved estimate of transport CO_2 emissions based on individuals' observed daily travel behaviour, and allows the effect of different policies, strategies or technologies to be more realistically evaluated. In addition, whilst transport CO_2 is the focus of the thesis, the methodology presented could also be useful in estimating emissions of other pollutants relevant to local air quality (e.g. CO, NO_x), or identifying geographical areas where congestion may become more serious in future.

Below, Section 3.2 presents the discrete choice modelling for trip-chain analysis. Section 3.3 briefly reviews three established simulation techniques for population synthesis, before selecting the most appropriate algorithm for the spatial microsimulation models. Section 3.4 provides the scenario design for exploring transport carbon futures. The geographical research area (i.e. urban Beijing) is described in Section 3.5, followed by an introduction to the multiple data sources used in the thesis. The concluding remarks are drawn in the final section of this chapter.

3.2 Trip-chain modelling

3.2.1 Overview

In the first empirical analysis (Chapter 4), this thesis uses discrete choice models to analyse people's daily trip chains and their relationship with socio-demographics and urban form. Compared to traditional trip-based travel analysis, the new models adopt tours (or trip chains) as the basic unit of analysis within a theoretical activity-based framework. Tours link individuals' multiple trips and stops, take into account the linkages between travel behaviour and activity participation, and provide a clearer explanation of the inter-related decisions that link trips. Analysis of tours can thus improve understanding and prediction of travel behaviour, capturing more precisely urban form–travel relationships, and so contribute towards better transportation systems, travel demand management policies and land use strategies (Wallace et al., 2000; Lee et al., 2009).

Trip-chaining analysis reflects considerable progress and growing significance in examining travel decision making within the space-time constraints and the integration of land use models with transport models. It has led to the development of a series of comprehensive econometric models for trip chain analysis. The econometric modelling typically involves using equations to explore individuals' daily travel decision-making process, as well as to examine relationships among travel patterns, land use, and socio-demographic characteristics of individuals and households (Bhat and Singh, 2000). Until now, different kinds of econometric models have been used in travel analysis, including instrumental variable models, sample selection models, discrete choice models, structural equations models and longitudinal designs (Mokhtarian and Cao, 2008).

Each model has its own advantages and disadvantages, and is used for different purposes. When it comes to the relations between travel behaviour and activity participation and predicting the probabilities of various decision outcomes, discrete choice models are the most appropriate method, as the household and individual choices of residential location, vehicle ownership, tour frequency, tour patterns, etc, are a discrete multi-dimensional choice issue (Waddell, 2002).

3.2.2 Discrete choice models

Typically, discrete choice models, which are suited to model choices between alternatives that are mutually exclusive, refers to the development of a class of econometric models known as random utility maximization (RUM) based on discrete choice theory (Waddell, 2002). In discrete choice models, the decision makers, e.g. households and individuals, are assumed to make rational choices when faced with multiple choices that offer different utilities, and a rational decision maker usually selects the alternative offering the highest utility (McFadden, 1973). Therefore, the household and individual multi-dimensional choices have been widely treated with a model structure that allows for joint and conditional discrete choices which are dependent on a large number of discrete or continuous explanatory variables (Waddell, 2002). The most widely applied model structures in the land-use and transport studies are the ordered logit and multinomial logit models.

Before introducing ordered and multinomial logit, models for binary outcomes are briefly introduced here, as they are the most basic types and provide a foundation for the complex models. Binary dependent variables have two values, typically coded as 0 for a negative outcome and 1 as a positive outcome. In the linear probability model (Long and Freese, 2001):

$$\Pr(y = 1 \mid \mathrm{x}) = \mathrm{x}\beta + \varepsilon \qquad (3.1)$$

where x represents the independent variables, β means the coefficients to be estimated, and ε refers to the random error. Using the equation above, the predicted probabilities can be greater than 1 or less than 0, which is problematic. In order to constrain the prediction of probabilities (Pr) to the range 0 to 1, it transforms the probability into the *odds*:

$$\Omega (x) = \Pr (y = 1 \mid x) / \Pr (y = 0 \mid x) = \Pr (y = 1 \mid x) / [1 - \Pr (y = 1 \mid x)] \tag{3.2}$$

which indicates whether something happens ($y = 1$) relative to whether it does not ($y = 0$), ranging from 0 to ∞. The log of the odds, or *logit,* ranges from - ∞ to ∞:

$$\ln \Omega (x) = x\beta \tag{3.3}$$

Ordinal and multinomial logit models are equivalent to the simultaneous estimation of a series of binary outcomes. The main difference between ordered and multinomial logit model is that the former is based upon cumulative response probabilities while the latter is based upon the response probability for each category or outcome. Specifically, the ordered logit model is a generalisation of the multinomial logit, and is useful for explaining ordinal discrete choices where individuals have systematic unobserved preferences, with proximate covariance in the stochastic utility components (Small, 1987). In the ordered logit model, it defines the odds that an outcome is less than or equal to m versus greater than m given values of x:

$$\Omega_{\leq m|>m} (x) = \Pr (y \leq m \mid x) / \Pr (y > m \mid x) \quad \text{for } m = 1, J - 1 \tag{3.4}$$

The log of the odds is assumed to equal:

$$\ln \Omega_{\leq m|>m} (x) = \tau_m - x\beta \tag{3.5}$$

where J refers to the number of ordinal categories, τ_m represents the cut points or thresholds. However, when the dependent variable is a categorical outcome, multinomial logit (MNL) models are adopted, which can be defined as:

$$\ln \Omega_{m|b}(x) = \ln [\Pr (y = m \mid x) / \Pr (y = b \mid x)] = x\beta_{m|b} \quad \text{for } m = 1 \text{ to } J \tag{3.6}$$

where b is the base category or the comparison group and J refers to the number of categories.

Using tours (or trip chains) as the basic unit of analysis within an activity-based theoretical framework, discrete choice models are adopted to investigate relationships among urban form characteristics, socio-demographic attributes and individuals' trip-chaining behaviour for a typical weekday in Beijing. The trip-chaining behaviour is focused in three principle areas: tour generation or frequency, tour scheduling (type and order of stops made), and tour interdependence mechanisms. As the tour frequency variable is an ordinal outcome, ordered logit models are used to investigate the effect of socio-demographics and urban form on tour generation choices. Multinomial logit models are then employed to explore the tour scheduling process, as the variable of tour pattern is a categorical outcome. Further details on trip-chaining analysis are provided in Chapter 4.

3.3 Microsimulation techniques

3.3.1 Overview

Spatial microsimulation is another modelling technique used in this PhD thesis. The microsimulation models simulate virtual populations in given geographical areas, so that the characteristics of these populations are as close as possible to their 'real-world' counterparts (e.g. Ballas et al., 2007). The microsimulation method offers many advantages, including data linkage, flexibility of scale changes, efficiency of storage, and update and forecast (Clarke, 1996). With respect to travel analysis specifically, microsimulation represents an effective disaggregate modelling technique which can replicate the process of complex travel systems and thus generate better estimation of real-world travel behaviour (Bhat et al., 2004). Compared to the traditional four-stage approach in transport studies, there are three major advantages of microsimulation: 1) technical advantage related to computational savings in the calculation and storage of large multidimensional probability arrays; 2) advantage in the explicit modelling of various decision-making chains and time-space constraints on travel behaviour; 3) the variability of microsimulation outcomes which can yield full information about the distributions of the travel demand statistics rather than single deterministic estimates or average values (Vovsha et al., 2002).

The spatial microsimulation method typically involves three major procedures: 1) the construction of a microdata set from samples and surveys. 2) Static what-if simulations, in which the impacts of alternative policy scenarios on the population are estimated: who would benefit from a particular local or national government policy? Which geographical areas would benefit the most? 3) Dynamic modelling, to update the agents' characteristics on the basis of mathematical models or rule-based models and create future-oriented scenario simulations (Ballas et al., 2005). The first procedure can also be defined as static spatial microsimulation. This involves the reweighting of an existing microdata sample (which is only available at coarse levels of geography), so that it would fit small area population statistics tables (Ballas et al., 2006). Generally, there are three established techniques for creating synthetic populations, including deterministic reweighting, conditional probability (Monte Carlo sampling), and simulated annealing (Harland et al., 2012). These three methods are briefly reviewed below, before selecting the one that is most appropriate to this research.

3.3.2 Deterministic Reweighting

The most common deterministic reweighting approach is based on iterative proportional fitting (IPF) and uses a simple equation to iteratively calculate new weights for the existing microdata to match known small area distributions (Hermes and Poulsen, 2012). For example, using household survey data and small area statistic tables, the main principle of the deterministic reweighting algorithm is to apply different weights iteratively to the survey population for each constraint step by step, while maximising the goodness of fit between the model distributions and the census tabulations. This method has been widely used in microsimulation models, such as evaluation of social policies and healthcare research. The reweighting process can be defined as (Ballas et al, 2005):

$$n_i = w_i \times s_{ij} / m_{ij} \tag{3.7}$$

where n_i is the new weight for individual i, j is an attribute of the individual, w_i is the original weight for individual i, s_{ij} is the element of population census table (e.g.

small area statistics table) for individual i and attribute j, and m_{ij} is the element of the survey data table for individual i and attribute j.

Normally, the initial weight for each individual is 1 and their final weight is fractional. Starting with reweighting the first constraint, the process then moves sequentially to the next variable, replacing the initial weight with the newly generated one. This process is repeated through each remaining constraint until to the last one, multiplying each new weight in the equation produced in the previous step. Since the last constraint would fit perfectly, it is necessary to put the constraints in order, with the last to be fitted the one which accounts for the most variation in the outcome variable of interest (Anderson, 2011). After reweighting all constraints once, the process then loops back to the first constraint and the process is repeated using the weight produced by the last constraint in the first iteration. It is suggested that 10 iterations are sufficient to produce stable weights that reduced the error to a point where it converges (Anderson, 2011).

This method can be operated easily and rapidly, and it produces the same result every time. However, this method is sensitive to the configuration of constraints and generates more errors if the geographic areas are characterised with different distributions, as it assumes all areas are homogenous. Some researchers have improved on this deterministic approach. For example, Smith et al (2009) conducted a cluster analysis to divide all areas into several groups in which the geographic areas are most similar in terms of population constraints, and ran the reweighting algorithm to create area-specific synthetic populations. This effectively reduced the errors which resulted from the assumption of homogeneity. Moreover, Lovelace and Ballas (2013) present a new method 'truncate, replicate, sample (TRS)' to overcome the problem of non-integer weights produced by the IPF technique, which offers more flexibility, efficiency and accuracy than alternative approaches to integerisation.

3.3.3 Conditional Probabilities

The conditional probabilities method is based on the synthetic reconstruction procedure first introduced by Birkin and Clarke (1988). This technique builds up the synthetic populations with one attribute each time, based on its conditional probabilities derived from the sample data. The characteristic of each attribute (e.g. male or female) is stochastically added to each individual in line with the associated constraining tables (Harland et al, 2012). This involves a sequentially random distribution process rather than iteratively deterministic reweighting, commonly known as Monte Carlo sampling. For each small area, a synthetic record is created for each individual, with each attribute added in turn against its conditional probability (Birkin and Clarke, 1988):

$$p(x) = p(x_1) \times p(x_2 / x_1) \times p(x_3 / x_2, x_1) \times \ldots \times p(x_m / x_{m-1}, \ldots, x_1) \qquad (3.8)$$

As shown above, with the number of constraints increasing, the conditional probabilities become more complicated. Moreover, defining the order of the constraint variables is very important. Since the latter probability of attributes is dependent on the former constraints, it is reasonable to order the constraints in such a way that the most significant predictor of an outcome comes first and the least important variable comes last. Alternatively, it also makes sense to start with constraints which are relatively evenly distributed between the categories, like gender and age, rather than ethnicity or qualifications (Harland et al., 2012). For example, the sequential procedure of synthetic reconstruction might begin with creating a set of household heads to whom are assigned a spatial location, gender, age and marital status by Monte Carlo sampling from known aggregate distributions from the census datasets (Williamson et al., 1998).

However, if the sample population is not available to derive the underlying probabilities, iterative proportional fitting (IPF) can be applied alternatively to estimate the compound probability distributions. This technique involves combining joint probabilities and requires many repetitions to derive a fitted distribution, that is, it provides maximum likelihood estimates for the full conditional probability distributions from partial ones (Birkin and Clarke, 1989; Ballas and Clarke, 2000). The details about the mathematical properties and the theory of IPF can be found in prior studies (e.g. Norman, 1999).

As the conditional probabilities technique involves random distribution and stochastic selection, it produces different results each time the model is run. It is necessary to run the simulation many times and derive the average estimation. This method is widely used in microsimulation studies, as it builds the model easily, it does not necessarily require a sample population, and it can combine different sources of microdata sets. Nonetheless, this approach might be not capable of handling numerous variables or when a large number of estimated cross-tabulations are required (Voas and Williamson, 2000).

3.3.4 Simulated Annealing

Simulated annealing is a refinement over the basic combinatorial optimisation approach – hill climbing. In the hill climbing algorithm, a combination element to be replaced and a possible replacement element are randomly selected. If the replacement element improves the overall performance of the combination, that is reducing the error of the model, the replacement is made; otherwise, other elements are randomly selected for evaluation. This process is repeated until no further improvement to the selected combination can be made. The main disadvantage of the hill climbing method is that it cannot go backwards and it may easily become trapped in suboptimal peaks, rather than getting the most optimal solution (Williamson et al., 1998).

Simulated annealing is superior to hill climbing, as it overcomes the latter's drawbacks by relaxing its basic assumption - only replacement elements that lead to reduced error are accepted. For the simulated annealing technique, in order to allow the algorithm to go backwards from suboptimal solutions, some replacement elements which lead to worse performance (i.e. increase in error) are also accepted, if they satisfy some criteria. That is, the choice of whether or not to accept a 'worse' combination element in place of a 'better' one is determined by an equation, as shown in Williamson et al (1998):

$$p(\delta E) = exp(-\delta E/T) \tag{3.9}$$

where δE represents the potential change in combination performance, and T refers to the maximum level of performance degradation acceptable for the change of one element in a combination.

Initially, the threshold of a simulated annealing algorithm is set to equal the maximum change in combination performance likely to be induced by replacing an old element with a new one. As replacement elements are randomly selected and evaluated, those improving combination performance are automatically accepted, while those degrading performance are only accepted if $p(\delta E)$ is greater than a randomly generated number between 0 and 1. As shown above, the smaller the value of δE (increase in error), the greater is the likelihood of potential replacement being made. On the contrary, the smaller the value of T, the smaller is the change in performance likely to be accepted (Williamson et al., 1998).

Moreover, the simulated annealing algorithm evaluates the goodness of fit statistic simultaneously against all of the constraining tables, and it is thus not affected by the configuration of constraint variables. The simulated annealing algorithm randomly selects the synthetic population from the sample population optimising to reduce the Total Absolute Error and provides the best possible match to the real life population in each geographic zone. The weight for each individual in the sample population can be 0 representing exclusion or any number up to the total population count representing the number of times a particular individual has been selected in a specific geographical zone. This is very different from the decimal value in the deterministic reweighting process. As expected, the great strength of this method is that it incorporates the Metropolis Algorithm (Harland et al., 2012) allowing both backward and forward steps in the search for the optimised combination of sampled population, which the deterministic reweighting or conditional probability method cannot do. Figure 3.2 illustrates the operating process of the simulated annealing algorithm.

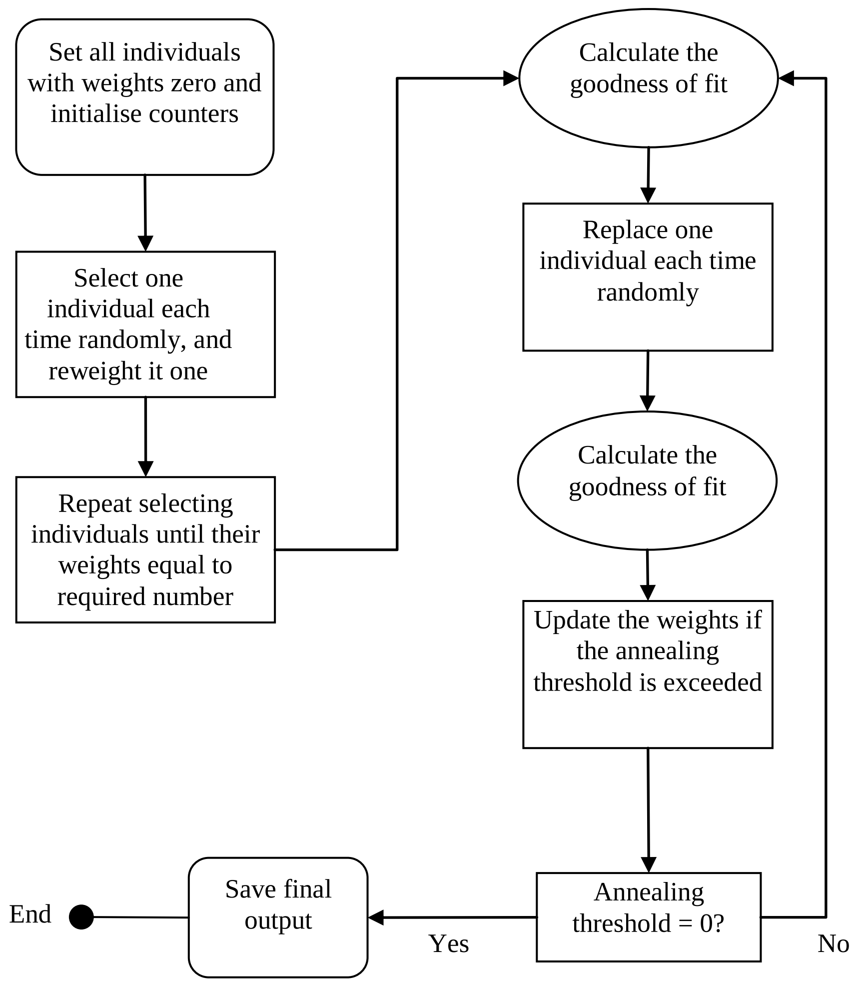

Figure 3.2: The operating mechanism of simulated annealing algorithm

Birkin and Clarke (2011) suggested that simulated annealing is 'the most popular – and probably the most effective – method for the creation of reweighted spatial micro-data'. Some prior studies also demonstrated that the simulated annealing technique generates the most consistent and accurate populations over various spatial scales (e.g. Williamson et al., 1998; Harland et al., 2012). For instance, using the study area of Leeds (UK) Metropolitan District Area (MDA), Harland et al (2012) compared the performance of these three methods over varying spatial scales, and found that simulated annealing consistently produced the best outcome with little misclassification when fitting constraints. Moreover, using the simulated annealing algorithm, the generated population dataset is a realistic representation of the observed population aligning closely to the constraint totals while maintaining the rich variety of attributes contained in the survey sample population. This method is well suited to spatial microsimulation problems requiring attribute enrichment while simultaneously ensuring close constraint matching. It deals with the data constraints best in this research. Therefore, we adopt the simulated annealing algorithm to create realistic synthetic populations at fine spatial scale (i.e. the sub-district level) over the period 2000-2010; for further details see Chapter 5 and 6.

3.4 Scenario design

The third and final major analytical part of the thesis is the exploration of travel carbon emission futures for Beijing, under a range of scenarios reflecting possible development trajectories, and planning and policy interventions. Scenario design usually involves a range of "what if?" questions to define some possible future conditions. The typical scenario planning process compares alternative future planning scenarios to a trend scenario, which is often referred to as the Business As Usual scenario (Bartholomew and Ewing, 2009). The general approach for scenarios in urban and transport modelling is to model the process over a recent past time period and then (after calibration and validation) project that into the future (typically 20-50 years ahead), with the scenarios reflecting the states (or combination of states) that the independent variables in the models could take. This method could incorporate the most important and uncertain factors in the analysis, identify the most plausible conditions in the future, and evaluate the impact of trends and possible management strategies.

Following the spatial microsimulation of carbon emission over 2000-2010 (which serves as a baseline), the transport CO_2 emission from passenger travel behaviour is projected to 2030 under four scenarios. These scenarios aim to explore the impact of current and potential strategies on transport CO_2 emission from people's future travel behaviour. All four scenarios incorporate dynamic changes in Beijing's population, and also incorporate combined measures on transport policies, urban development and vehicle technology, which are important influences on travel behaviour and carbon emission. These four scenarios comprise: transport policy trend, land use and transport policy, urban compaction and vehicle technology, and combined policy.

In contrast to prior studies which estimate transport CO_2 emissions using aggregate vehicle population statistics, this scenario analysis presents a new 'bottom-up' methodology to simulate and project transport CO_2 emissions at fine spatial scale using disaggregate travel attributes. An average per capita CO_2 emission for passenger transport under the four scenarios to 2030 is calculated. This is calculated from mode share by trip frequency by travel distance and mode specific CO_2 emission factor, as:

$$AverageCO_2 = \sum MS_j \times ATF \times ATD_j \times EF_j \qquad (3.10)$$

where MS_j refers to the mode share by vehicle type j (j = bicycle, bus, subway, car, taxi, and other), ATF represents the average trip frequency on a typical workday (per person per day), ATD_j is the average trip distance by vehicle type j, and EF_j the emission factor associated with the vehicle type j.

Total CO_2 emission from people's daily travel is also calculated. It is by the total population (i.e. the projected full population in eight urban districts in 2020 and 2030) multiplied by the average CO_2 emission, as:

$$TotalCO_2 = \sum MS_j \times (ATF \times TP_t) \times ATD_j \times EF_j \qquad (3.11)$$

where TP_t refers to the total population in year t (t = 2020 or 2030). This method develops a realistic set of spatially resolved passenger transport CO_2 emission futures, examines how changes in people's daily travel behaviour (e.g. trip distance, mode share) may impact upon transport carbon emissions, and evaluates the impact of current and potential strategies on transport, urban development and vehicle technology; for further details see Chapter 6.

3.5 Case study

China's major cities (Figure 3.3) including its mega-cities, such as Beijing, provide particularly interesting cases for studying the role of urban spatial organization in climate change mitigation in the context of rapid urban restructuring. China has already passed the US as the world's largest source of carbon dioxide emissions (Yan and Crookes, 2010), and its unprecedented urbanization continues to add to these emissions. It is projected that the urban population of China will grow to over 800 million by 2020, with the urbanization rate rising from 44.9% in 2007 to 56-58% in 2020 (Chinese Society for Urban Studies, 2009). Meanwhile, rampant spatial expansion drives up demand for commuting and non-work travel (Pan et al., 2009; Wang and Chai, 2009). With stronger travel demand coupled with increased automobile ownership, urban transportation is likely to contribute a larger share to urban carbon emissions in China in the next decade. This trend raises great concerns over its possible ramifications for the environment, transportation, and climate change (Chen et al., 2008; Creutzig and He, 2009).

Figure 3.3: China and its large cities (urban population > 2.5 million in 2012)

From these large and rapidly growing cities, Beijing, China's capital, is selected as our case study. Beijing is representative of the rapid urbanization and economic growth of urban China, driven by changes in lifestyle and spatial structuring, and with increasing energy consumption and carbon emissions (Feng et al., 2013). Beijing also offers, for China, good access to required datasets, and, as the capital, any analysis will be of particular interest to policy makers.

Beijing has undergone rapid urban expansion since the 1980s, and the urbanised area has increased 168% in the decade since 1998 (National Bureau of Statistics of China, 1999, 2009). Driven by urban land reform, housing reform and economic restructuring, the industrial decentralisation and residential suburbanisation process accelerated in the 1990s (Zhou and Ma, 2000). High-tech industry zones and housing were established mainly in the suburbs, but employment opportunities arising from the redevelopment of industrial land for tertiary industries remained in the inner city, resulting in a job-housing spatial mismatch (Zhao et al., 2010; Wang et al., 2011). Meanwhile, public transport in urban Beijing developed greatly from 2000 to 2010, and there are now 14 subway lines comprising 336 km of track, and 713 bus lines served by 21,548 buses (Beijing Statistical Bureau, 2011). Beijing has a zonal structure formed by concentric arterial ring roads, connected by radial expressways and light rails (Wang et al., 2011). People have become increasingly dependent on automobiles, especially private cars, with private car ownership doubling to three million over the period 2004-2009 (Beijing Statistical Bureau, 2010) with a concomitant rise in traffic congestion and pollution, now pressing problems in the city area.

The rapid urban expansion has been accompanied by urban sprawl on Beijing's fringe, characterised by low density development with little mixed use

(Zhao, 2010). Compared to western cities, traditional urban space in Beijing and other Chinese cities was characterized by mixed land use, proximity to services, and pedestrian friendly street design. In the inner city districts of Beijing are historical *hutong*-courtyard[2] neighborhoods, built before 1949 and characterized by high-density, low-rise courtyard housing (Figure 3.4-A). Usually, several families share a big *hutong* courtyard together, which is crowded. Work unit compounds are the legacy of Chinese socialist urban space (Wang and Chai, 2009), where employees of work units (*danwei*) worked and lived in the same compound and enjoyed on-site services and welfare provided by work units (Figure 3.4-B). The *danwei* used to be the basic unit of economic, social, and spatial organization in socialist Chinese cities (Chai, 1996; Bray, 2005). Work units not only provided a workplace for employees, but also a comprehensive package of welfare and services including housing, dining, health care, schools, grocery, and leisure facilities. *Danwei* employees not only worked but also lived in the work unit compounds that they belong to, and could enjoy job-housing proximity and on-site services. However, since the 1980s, the social welfare functions were gradually removed from *Danwei* and the *Danwei* was transformed from a multi-functional work unit to mere workplace for its employees. In 1998, the government officially removed the housing provision for employees function from *Danwei* and new employees of *Danwei* have since had to buy or rent dwellings on the housing market (Wang and Chai, 2009).

Also, during the reform era (since the 1990s), western planning ideas, such as zoning-based land use, were introduced to urban planning practice in China. Most suburban neighborhoods built thereafter in Beijing adopted a market-based model of commodity housing development and followed the model of single-use, large-lot

[2] *Hutong* is a traditional living block built in the city centre before 1949.

residential development, and auto-oriented street design (Figure 3.4-C). Moreover, affordable housing projects initiated since the late 1990s were often located in the urban fringe with the aim to reduce land-related development costs and to decentralize inner-city urban population (Figure 3.4-D). Nonetheless, traditional *hutong*-courtyards and work units have not disappeared in the post-reform urban space but still occupy primary locations of the city. The neighbourhoods have urban form characteristics that differ in terms of density, land use mix, design (e.g. housing height, road width, street connections), and public transit accessibility. The co-existence of different neighbourhoods causes a complicated urban landscape and makes it possible to examine effects of land use on travel behaviour and simulate transport CO_2 emissions.

A	B
C	D

A – A *hutong*-courtyard neighbourhood in the inner city
B – A work-unit compound of a government agency within the third-ring road
C – A commodity-housing neighbourhood located in northwest suburb
D – An affordable housing (*jingji shiyong zhufang*) neighbourhood in the northern urban fringe in Beijing

Figure 3.4: Four types of urban neighbourhoods in Beijing

Beijing can be divided into three broad zones: central urban, inner suburban and outer suburban (Zhao et al., 2010). The central urban zone (Figure 3.5) comprises the urban districts of Dongcheng, Xicheng, Chongwen and Xuanwu[3], located in the inner city and representing the traditional business districts. The inner suburban zone includes the districts of Chaoyang in the northeast (where the Beijing International Airport is located and where a new business district with an agglomeration of overseas investment enterprises is emerging), Haidian in the northwest (where the

[3] In 2010, the Beijing government adjusted the administrative division in the central urban zone. Chongwen and Dongcheng districts were merged into new Dongcheng district, while Xuanwu and Xicheng districts were merged into new Xicheng district. Other sub-districts remain the same.

research institutes, universities, and hi-tech firms are found), Fengtai in the southwest (where a major development zone was established to introduce domestic and foreign investment), and Shijingshan in the far west (where Beijing's major heavy industrial enterprises are located) (Wang and Chai, 2009). These two zones of central urban and inter-suburban accounted for 63% of the all households in 2000 (National Bureau of Statistics of China, 2000), with the inner suburban zone experiencing most of the post 1980s urban expansion. The outer suburban area refers to the remote counties and villages in the Beijing municipality.

Figure 3.5: Beijing and its urban districts

The area of each urban district is large and varies considerably, from 16 km^2 to 470 km^2, with a population range of 0.35 to 2.29 million respectively. However, at a finer spatial scale, each sub-district has a similar geographical area and population (approximately 8 km^2 and 54,000 residents on average). This thesis uses the smaller geographical scale, the sub-district[4] (*jiedao*) principal administrative unit in Beijing, as the basic geographical unit in the microsimulation research (see Chapter 5). It also focuses on the central urban and inner suburban zones to represent only urban Beijing. This comprised 146 sub-districts in 2000, many located in the Chaoyang and Haidian districts (Figure 3.5).

3.6 Data sources

3.6.1 Activity diary survey

An activity diary survey, conducted in Beijing in 2007, was used in this research. The survey was designed and implemented by the behavioural geography research group in Peking University in 2007 (of which I was an active member), with the intention of developing an improved understanding of the population's travel behaviour (noting the absence of any publicly available travel survey data). The survey adopted a two-stage sampling process. First, ten representative neighbourhoods were selected on the basis of location, year of construction, building type, housing tenure structure, and land use characteristics (Table 3.1). The purpose was to cover the range of historical and institutional features in Beijing's urban neighbourhoods, as well as a spread of location and spatial measures. Two traditional neighbourhoods – Jiao Dao Kou (JDK) and Qian Hai Bei Yan (QHBY) – are located within the second ring road in the central urban zone (Figure 3.6). Four work unit compounds were selected: San Li He (SLH) and He Ping Li (HPL) are located between the second and third ring roads, and

[4] Beijing has 16 districts and counties, each of which includes dozens of sub-districts, the basic administrative unit. For each sub-district census data is collected for neighbourhoods which comprise the *jiedao* (in urban areas) and *xiangzhen* (rural town) elsewhere.

Tong Ren Yuan (TRY) and Yan DongYuan (YDY) are located south of the third ring road and northwest of the fourth ring road respectively. Four inner suburban neighbourhoods were selected, including two commodity housing neighbourhoods - Fang Zhou Yuan (FZY) and Dangdai Chengshi Jiayuan (DCJ), and two affordable housing neighbourhoods –Wang Jing Hua Yuan (WJHY) and Hui Long Guan (HLG). Among them, Hui Long Guan is located furthest away from the city centre (Figure 3.6).

Table 3.1: Basic characteristics of ten surveyed neighbourhoods

Abbr. of communities	Years of construction	Building types	Type of residents	Valid samples
JDK	Pre-1949	Single-story bungalow	Transient, older or low income population	115
QHBY	Pre-1949	Single-story bungalow	Transient, older or low income population	103
YDY	1970-80s	Multiple-story apartments	Employees of universities and their families	100
TRY	1970s - 90s	Multi-story or high-rise apartments	Employees and retirees from various factories	132
SLH	1950-60s; 1990s	Multi-story or high-rise apartments	Employees and their families from various government agencies	96
HPL	1950- 60s, 1990s	Multi-story or high-rise apartments	Employees and their families from various stated-owned enterprises	99
DCJ	Early 2000s	Multi-story or high-rise apartments	White-collar or private entrepreneurs with high income	91
FZY	Late 1990s - Early 2000s	High-rise apartments	White-collar or private entrepreneurs with high income	117
WJHY	Early 2000s	High-rise apartments	Young or middle-aged residents with middle-to-low income	133
HLG	Late 1990s	Multi-story apartments	Young or middle-aged residents with middle-to-low income	133

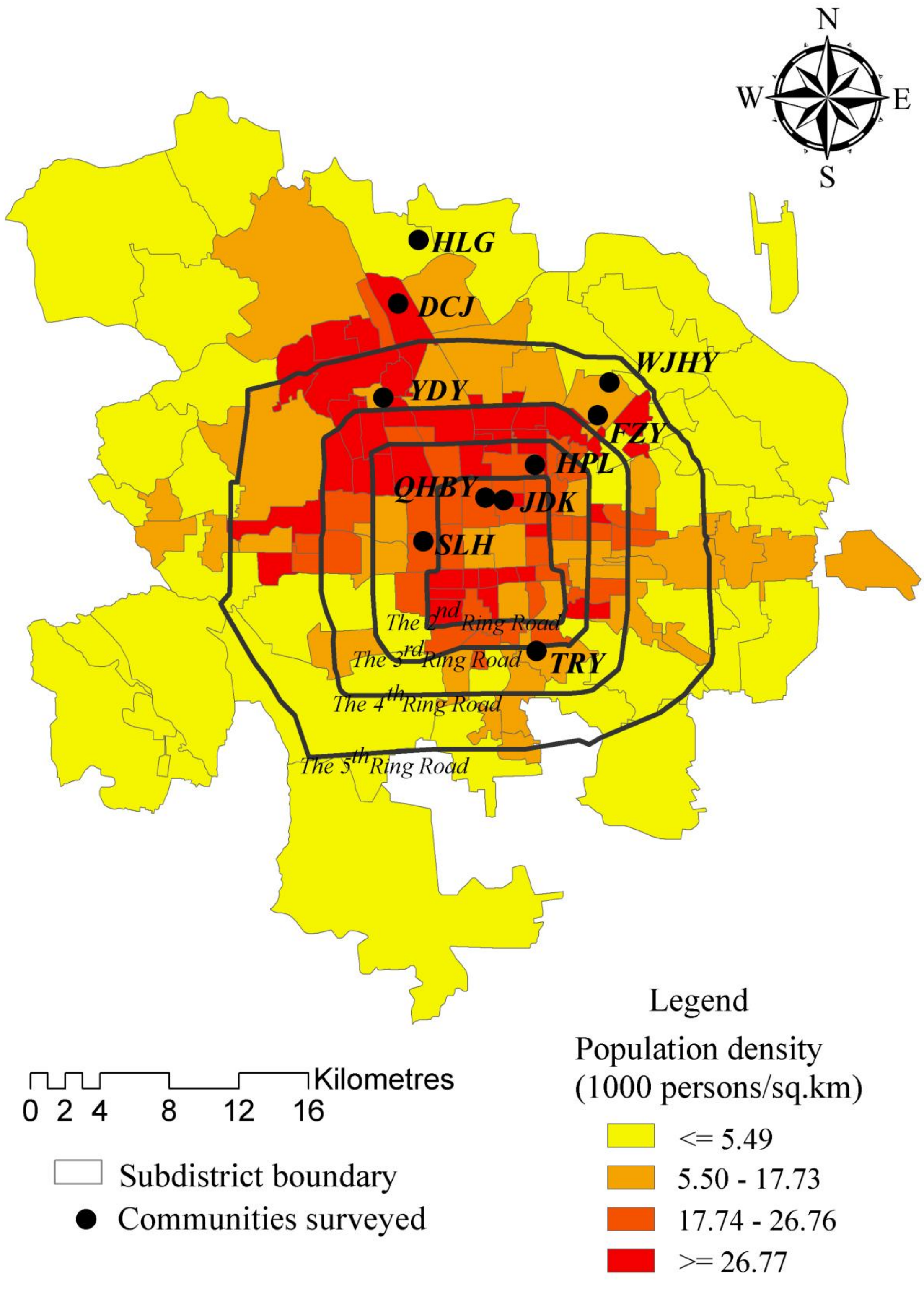

Figure 3.6: Surveyed neighbourhoods and population density in Beijing's sub-districts

Second, 60 households in each neighbourhood were randomly selected to complete a self-administered questionnaire, with each household member aged sixteen or above providing information on household and individual socio-demographic attributes, commuting, shopping and leisure activities, as well as a continuous activity-travel record of a Sunday, representing a weekend, and a Monday, representing a weekday. In total 1,119 individuals from 520 households returned the questionnaire with valid answers (an 86.7 percent response).

3.6.2 Land use data

GIS-based spatial analysis was used to derive multi-dimensional measures of neighbourhood-scale land use characteristics at both residence and workplace using data from government sources. Population density, derived from the Fifth Population Census of China in 2000, is shown in Figure 3.6, by quartile, for the main sub-districts (or *jiedao*) of urban Beijing. Most of the sub-districts within the fourth urban ring road are characterised by a high population density, in contrast to the lower density towards the periphery (excepting some north western sub-districts located near the fifth ring road which belong to the Haidian district, recognised as another sub-centre).

Primary data to quantify retail employment density, service facility (e.g. hospital, bank, post office, library, stadium, and restaurant) density and accessibility were derived and geo-coded from the 2001 Basic Economic Unit Census developed by the Beijing Statistical Bureau. This database contains information on the locations and attributes of c.200, 000 economic units, which refer to any companies, factories, shops, restaurants, hospitals, banks, and so on. Figure 3.7 illustrates, by quartile, the distribution of workplaces for employed residents and the retail employment density at their workplaces, measured as the number of retail employees per thousand residents within a 1 km radius, a variable often considered a proxy of land use mix (Krizek, 2003). It shows that most of these residents worked within the fifth ring road (with density highest within the fourth ring road), although there is evidently an additional lower density cluster north of the fifth ring road.

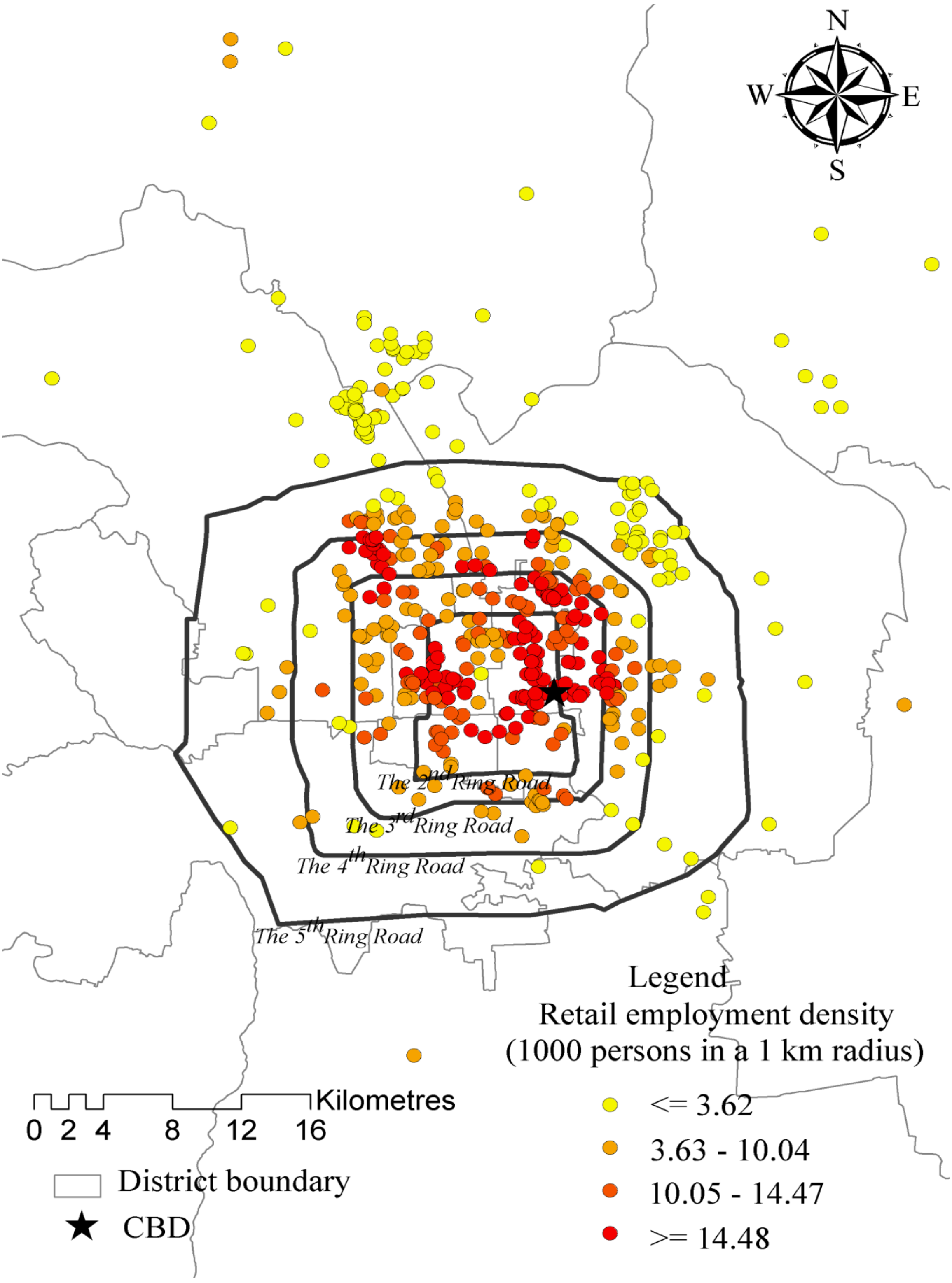

Figure 3.7: Retail employment density at workplaces within a 1 km radius

Table 3.2 compares some of the urban form characteristics of the ten surveyed neighbourhoods. *Hutong*-courtyard neighbourhoods and work unit neighbourhoods are more traditional not only because they were built prior to the market reform in 1978 and were located closer to the centre of the city, but also because they are typified by higher population density, mixed land use, proximity to retail and services, availability of public transit, and pedestrian-friendly streets (Table 3.2). For instance, all work-unit neighbourhoods in the survey are within 1 km from a subway station, whereas *hutong*-courtyard and work unit neighbourhoods are much closer to densely city centre, and have higher retail employment density and leisure facility accessibility.

Table 3.2: Urban form characteristics of ten surveyed neighbourhoods

Surveyed communities	Types of neighbour-hoods	Population density* (1000 persons / km^2)	Distance to the nearest subway station (km)	Retail employment in 1-km radius (1000 persons)	Distance to the nearest leisure facility (km)
JDK	*Hutong*-Courtyard	27.460	1.033	21.909	0.647
QHBY	*Hutong*-Courtyard	18.986	1.243	13.920	0.113
YDY	*Danwei* Compound	15.896	0.586	5.175	0.123
TRY	*Danwei* Compound	13.733	0.187	9.897	0.082
SLH	*Danwei* Compound	26.259	0.856	28.257	0.632
HPL	*Danwei* Compound	20.949	0.442	16.806	0.714
DCJ	Commodity housing	44.785	0.979	4.097	3.072
FZY	Commodity housing	2.166	2.266	4.734	0.171
WJHY	Affordable housing	8.947	2.309	1.423	1.143
HLG	Affordable housing	2.147	0.934	0.005	5.330

* 1000 persons/km^2, based on sub-district or *jiedao*.

In contrast, commodity housing and affordable housing neighbourhoods, built since the 1990s, tend to follow the western planning model, dominant up to the turn of the century, of mono-functional land use and auto-oriented street design. These neighbourhoods tend to have lower population density (with only one exception) and lower land use mix measured by retail density (Table 3.2). Hui-Long-Guan is a typical example of single-use, large-lot residential development, one of the many suburban neighbourhoods developed as a "sleeping town" in order to decentralize population from the central city. Residential use accounts for 85% of its land area, with 12% for retail and leisure services and only 3% for transportation and other facilities (Chinese Society for Urban Studies, 2009: 728).

3.6.3 Population census

Other data sets used in this thesis are the fifth population census of Beijing conducted in 2000 and the sixth population census in 2010 by the national government. The census has a stratified sample covering all districts, counties and villages in Beijing, with four sub-survey types with differing data collection regimes. All people are required to answer the short census form, which contains basic information on the household and individual socio-demographic attributes, such as gender, age, registration, education, and housing area. A 10% sample of the population in each sub-district was randomly selected to complete the long census form, which requires additional information on demographic and economic attributes, including employment, occupation, housing tenure and household expenditure. A deaths questionnaire and an annexed table are designed to assist in estimating mortality and the temporary resident population respectively. The analysis used the 10% population sample as it comprises most socio-demographic attributes, as shown in Table 3.3. The 2000 population census sample includes a total of 721,894 residents aged 15 or over in the 146 *jiedao* sub-districts in urban Beijing, while the 2010 census sample includes 1,006,036 residents.

Table 3.3 summarises key socio-demographic attributes in the 2007 activity diary survey and 2000 population census. People aged 14 and below are not included in the activity dairy survey. However, for people aged 15 and above both data sets contain common socio-demographic attributes, including gender, age, education, employment, and occupation. Household-level attributes, average housing area and housing tenure, also appear in both datasets, while the presence of children and car ownership are only available in the travel survey data. The travel survey also contains information on daily travel behaviour, such as travel purpose, trip frequency, travel distance, mode choice, start and end time, which is not reported by the population census.

Table 3.3: Key socio-demographic attributes in population census and travel survey

Variables	**Population census data**		**Activity Diary Survey**	
Individual-level	***Categories***	***Count***	***Categories***	***Count***
Gender (0-14)	Male	47086	Not available	
	Female	43270		
Gender (15+)	Male	379227	Male	503
	Female	342667	Female	523
Age	0-4	23517	Not available	
	5-9	26552		
	10-14	40287		
	15-19	76471	16-18	28
	20-24	85727	19-29	163
	25-29	78961		
	30-34	77452	30-39	280
	35-39	84848		
	40-44	76254	40-49	226
	45-49	65755		
	50-54	39593	50-59	217
	55-59	29079		
	60-64	35799	60+	112
	65+	71955		
Education (6-14)	illiterate	29589	Not available	
	Primary school	40237		
	Junior high school	20273		
	Senior high school and above	257		
Education (15+)	Primary school and below	91561	Primary school and below	19
	Junior high school	223108	Junior high school	101
	Senior high school	217302	Senior high school	262
	College	80595	College	222
	University and above	109328	University and above	422
Employment (15+)	Employed	500782	Employed	746
	Jobless	71415	Jobless	49
	Retired	138759	Retired	195
	Other	10938	Other	36
Occupation (15+)	Students	78294	Students	42
	Workers in government and public institutions	181548	Workers in government and public institutions	344
	Workers in factories, service companies and other	240940	Workers in factories, service companies and other	360
Total	Individuals (0-14)	90356	Individuals (0-14)	0
	Individuals (15+)	721894	Individuals (15+)	1026

Table 3.3/cont.

Variables	**Population census data**		**Activity Diary Survey**	
Household-level	***Categories***	***Count***	***Categories***	***Count***
Housing area (m^2/capita)	<=12	43957	<=12	88
	13-19	57554	13-19	84
	20-29	53788	20-29	150
	30-39	41086	30-39	98
	40+	57681	40+	83
Housing tenure	Self-built	32152	Self-built	20
	Buy commodity housing	4078	Buy commodity housing	104
	Buy affordable housing	4309	Buy affordable housing	82
	Buy public housing	93509	Buy public housing	155
	Rent public housing	91653	Rent public housing	107
	Rent commodity housing	18882	Rent commodity housing	20
	Other	9483	Other	15
Presence of child (0-5)	Not available		Yes	104
			No	399
Presence of child (6-12)	Not available		Yes	63
			No	440
Car ownership	Not available		Yes	186
			No	317
Total	Households	254066	Households	503

3.6.4 Beijing Statistical Yearbook

The Beijing Statistical Yearbook has been published by the government annually since 1978. The Yearbook contains much information on population, economy, energy, environment, finance, public services, industry, transport, buildings and so on. Usually, the indicators in the Yearbook, such as total population, GDP, per capita GDP, per capita disposable income, birth rate, death rate, vehicle ownership, etc, are only published at the city level or district level.

3.7 Conclusion

This chapter presents the overarching research design, modelling techniques, and data sources used in the thesis, which serves as a foundation for the subsequent empirical analysis of travel behaviour and CO_2 emission. To comprehensively analyse and dynamically simulate the integration of urban form, daily travel behaviour and transport CO_2 emission in urban China, multiple methods are employed to address the different objectives, i.e. discrete choice modelling for trip chain analysis, spatial microsimulation for population's transport CO_2 emission, and scenario analysis for transport carbon futures. These methods are highly appropriate tools for the research in question; they are complementary and work well together. Using this set of tools, we can comprehensively investigate the relationships among socio-demographics, urban form and trip chains, provide improved transport CO_2 emissions based on individuals' observed daily travel behaviour, and effectively evaluate the impact of different policies, strategies or technologies on transport carbon emissions in the future.

This is addressed using multiple data sources, such as travel diary survey, land use data, and population census. Some temporal mismatch between the multiple data sources utilized in the thesis is acknowledged; however, the most systematic datasets available for scholarly research in China have been obtained, particularly related to some of the geo-coded data sets and population census at the sub-district level. China has no national travel survey, and the Beijing municipal government travel surveys are only published at an aggregate level due to confidentiality issues with the more individual level data. Whilst the 2007 travel diary data is a relatively modest data set considering the scale of Beijing, it does represent the latest and best data available, and comprises complete activity-travel records for over 1,000 individuals, which remains a suitable data set from which to understand trip chain behaviour. The combination of micro and macro-level data sources is reasonable given the limited access of Chinese scholars to officially collected datasets. Further details on the three empirical analyses are provided in Chapters 4 – 6.

Chapter 4

An Analysis of Trip Chains and Their Behavioural Determinants

4.1 Introduction

A tour or trip chain is defined as the travel from home to one or more activity locations and back home again. Using tour or trip chain as the basic analytical unit, this chapter investigates how socio-demographic attributes of households and individuals, and urban form characteristics, at both residence and workplace, influence tour-based daily travel behaviour. The approach taken accounts for urban form characteristics in a series of multivariate models drawing on detailed land use data, and a travel diary survey with discrete choice models employed to analyse the trip-chaining behaviour in three principle areas: tour generation or frequency (number of tours taken on a workday), tour scheduling process (the number of stops, their type, and order), and tour interdependence effect (how the characteristics of one tour type may influence other tours an individual may take). As the employed residents have great work related spatio-temporal constraints and their working activities may have significant influences on the decisions to pursue and schedule other non-work activities (Bhat et al., 2004), the impacts of urban form and socio-demographic attributes on tour-based daily travel behaviour are examined for the employed residents (workers) and the unemployed residents (non-workers), respectively.

This chapter, investigating the determinants of individual's daily trip-chaining behaviour, serves as a basis for the following work (Chapters 5 and 6) that seeks to develop a spatial microsimulation model to forecast the daily travel behaviour and estimate the transport CO_2 emission of a large synthesised population in a Chinese mega-city. Below, an empirical analysis of urban form and trip chains in Beijing is developed. Section 4.2 presents an analysis which considers the characterisation of trip chains that residents in Beijing make, and the role of neighbourhood type in tour behaviour. Then an ordered logit modelling of tour generation analysis is presented in Section 4.3, followed by multinomial logit modelling of tour schedule, and an analysis of interdependence in Section 4.4. Conclusions on the role of socio-demographics and urban form on trip-chaining behaviour in Beijing are drawn in the final section.

4.2 Characterisation of trip chains

4.2.1 Tour frequency

Tour generation or frequency, i.e. number of tours made during the day, is the first and foremost decision to be made on a typical workday. In this chapter, the Monday activity-travel records are used to yield a sample of 1,026 individuals who participated in at least one out-of-home activity, and who generated a total of 1,437 home-based tours. Table 4.1 lists the tour frequency profile by selected individual socio-demographics. Male, household head and the employed residents have a higher proportion of one tour generation than their counterparts, especially for the employed residents. Partly due to their working constraints, most workers tend to generate only one tour on a typical workday while non-workers are more likely to generate two or more tours. Similarly, the percentages of two or more tours are also lower for the male and household head, as they have diverse responsibilities within a family and face different spatio-temporal constraints on activity participation. This further illustrates how tour frequency varies according to socio-demographic attributes. The majority of residents generate only 1 or 2 tours on a typical workday in Beijing, while less than 10% generate 3 tours or more.

Table 4.1: Tour frequency by socio-demographics

Tour Frequency	**Gender**		**Household Head**		**Employment**		**Total**
	Male	**Female**	**Yes**	**No**	**Employed**	**Unemployed**	
1 tour	360	341	433	268	569	132	701
(%)	*(71.57)*	*(65.20)*	*(72.77)*	*(62.18)*	*(76.27)*	*(47.14)*	*(68.32)*
2 tours	107	140	131	116	142	105	247
(%)	*(21.27)*	*(26.77)*	*(22.02)*	*(26.91)*	*(19.03)*	*(37.50)*	*(24.07)*
3 tours	33	37	28	42	33	37	70
(%)	*(6.56)*	*(7.07)*	*(4.71)*	*(9.74)*	*(4.42)*	*(13.21)*	*(6.82)*
4 tours	3	5	3	5	2	6	8
(%)	*(0.60)*	*(0.96)*	*(0.50)*	*(1.16)*	*(0.27)*	*(2.14)*	*(0.78)*
Total	503	523	595	431	746	280	1,026
(%)	*(100)*	*(100)*	*(100)*	*(100)*	*(100)*	*(100)*	*(100)*

To better understand the role of urban form on tour frequency, the number of tours taken by the employed residents in each of the ten surveyed neighbourhoods is compared. Figure 4.1 illustrates that the propensity to take tours does vary across neighbourhoods, differentiated by retail employment density (measured as the number of retail employees per thousand residents within a 1 km radius). For example, people resident in *hutong*-courtyard (e.g. JDK) and *danwei* compound (e.g. YDY, SLH, HPL) neighbourhoods take an average 1.4 tours per person per day, while those in commodity (DCJ, FZY) and affordable housing (WJHY, HLG) neighbourhoods take less than 1.2 tours per person per day. This shows that people living in high-density or mixed land-use neighbourhoods tend to take more tours on a typical workday.

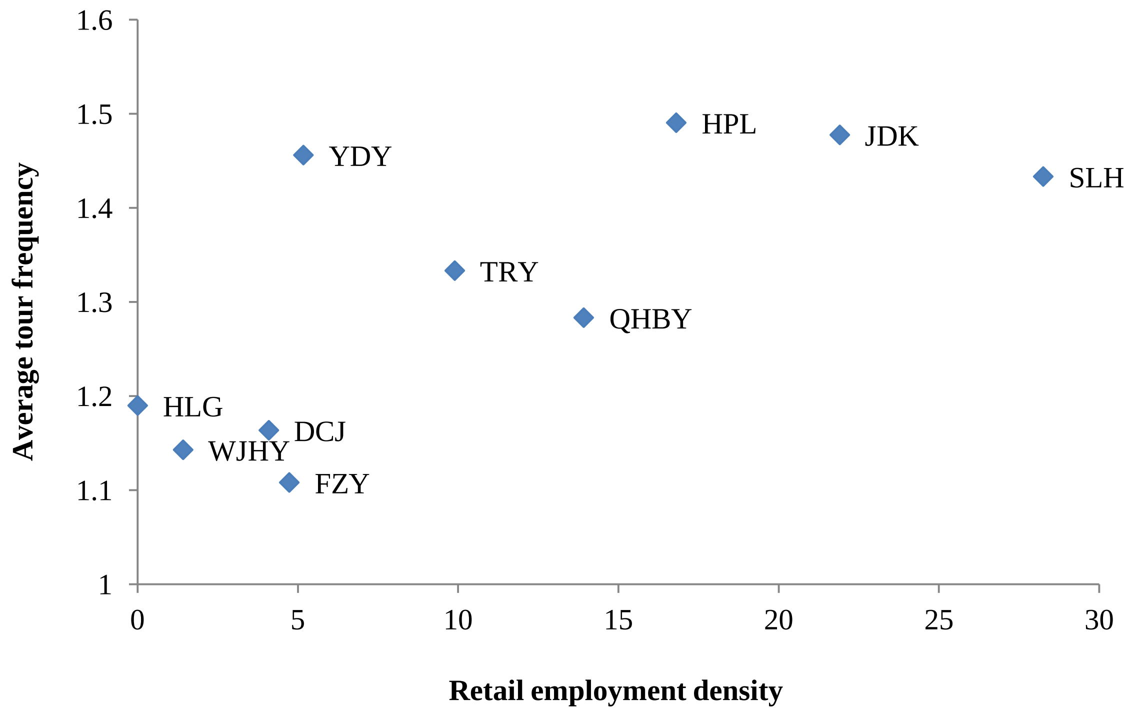

Figure 4.1: Tour frequency across neighbourhoods by retail employment density

4.2.2 Tour classification

In prior literature, trip chains or tours, which sequentially link outbound and return trips and all intermediate stops, have been classified using different methods. For example, based on the combination of simple and complex tours with three different activity purposes (work or study, household-sustaining activities, and recreation) within each tour, Krizek (2003) derived nine tour types (e.g. simple work, complex maintenance only, complex work and discretionary only). On the basis of the primary purpose of each tour, Frank et al. (2008) divided all tours into three simple types: home-based work tour, home-based non-work tour and midday work-based tour.

This study adopts the home-based tour as the basic unit of research to better reflect the interrelated decision process of an individual's daily behaviour, and classifies the home-based work and non-work tours into eight types respectively, according to the trip sequence and activity purposes (Table 4.2). The single-purpose work tour of H-W-H (Home-Work-Home), is the most common type accounting for nearly half of all the 882 work tours, a very similar proportion observed elsewhere (Chen et al., 2008). The other half comprises multi-purpose tours with non-work activities assigned before, during, or after work and their combinations. Here, tour type H-W-X-W-H (where W represents a work or work related activity, and X any non-work activity) is most common, indicating people participate in non-work activities during work near their workplace on a typical weekday. Conversely, tour types H-X-W-X-H and H-X-W-X-W-X-H are uncommon (c. 1%), suggesting few people participate in multiple non-work activities associated with a home-based work tour.

Table 4.2: Tour classification

Home-based Work Tour			**Home-based Non-work Tour**		
Tour type	Freq.	Percent (%)	Tour type	Freq.	Percent (%)
H-W-H	439	49.77	H-L-H	197	35.50
H-X-W-H	29	3.29	H-S-H	139	25.05
H-W-X-W-H	225	25.51	H-F-H	52	9.37
H-W-X-H	68	7.71	H-P-H	66	11.89
H-X-W-X-W-H	36	4.08	H-O-H	28	5.05
H-X-W-X-H	9	1.02	H-2 stops -H	52	9.37
H-W-X-W-X-H	68	7.71	H-3 stops -H	16	2.88
H-X-W-X-W-X-H	8	0.91	H-4 stops -H	5	0.90
Single-purpose	439	49.77	Single-purpose	482	86.85
Multi-purpose	443	50.23	Multi-purpose	73	13.15
Total	882	100	Total	555	100

Note: W represents work or work-related activity; X represents any non-work activities; L represents leisure activity; S represents shopping activity; F represents family obligation, including taking care of old people and children, etc; P represents personal business, like eating out, going to hospitals, etc; O represents other non-work activity.

Of the home-based non-work tours (Table 4.2), most are single-purpose, with only c. 13% being multi-purpose. The non-work activities are: leisure (L), shopping (S), family obligation (F), personal business (P) and other (O). Among the single-purpose non-work tours, H-L-H dominates (36%), followed by H-S-H (25%) indicating workers go shopping and particularly engage in leisure activities for non-work tours on a typical workday. Family obligation and personal business are also important non-work activities accounting for 21% of the non-work tours. The multi-purpose non-work tours comprise three types according to tour complexity (number of stops), but collectively account for only 13% of all non-work tours, most having two stops.

To understand the role of urban form on tour types, an analysis of tour complexity (number of stops) by neighbourhood is undertaken, particularly considering how tours are affected by retail employment density and land use mix.

For example, Figure 4.2 shows the share of multi-purpose tour (i.e. H-2 or more stops-H) by the surveyed neighbourhoods. The share of multi-purpose tour type is low in the *hutong*-courtyard (JDK, QHBY) and *danwei* compound (e.g. SLH, HPL) neighbourhoods, typified by higher retail employment density or mixed land use. In contrast, the multi-purpose tour has the highest proportion in the affordable housing neighbourhood WJHY (about 70%), followed by the commodity housing neighbourhood FZY and DCJ. This suggests people living in a low-density, mono-functional environment located in the suburb tend to make more stops *en route*.

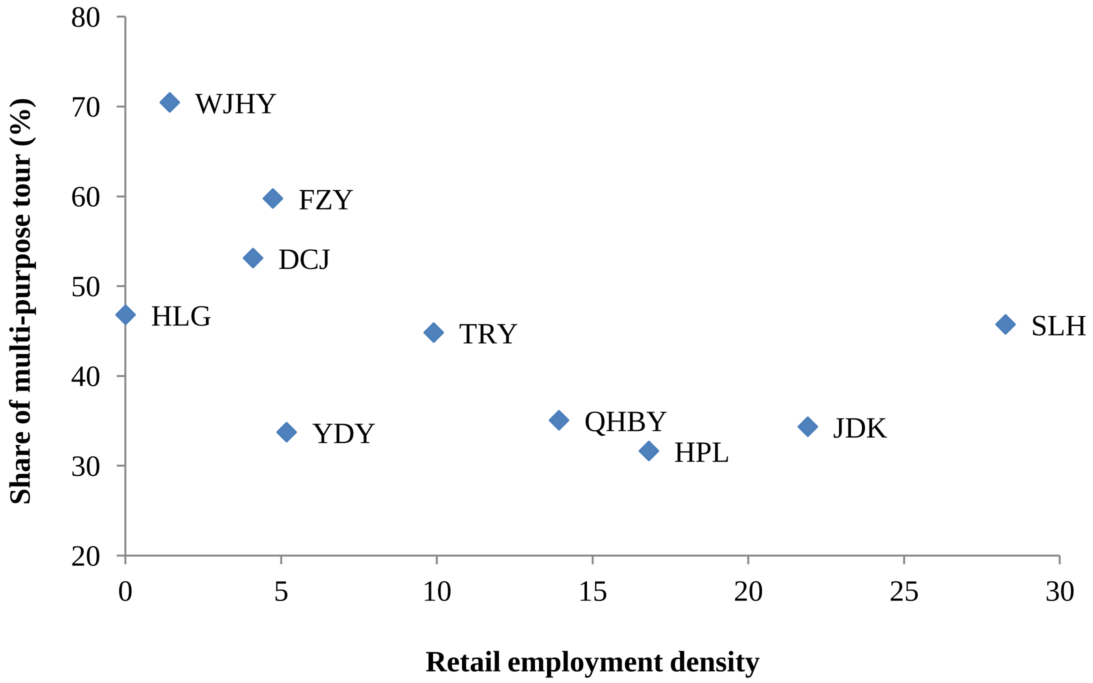

Figure 4.2: Tour complexity across neighbourhoods by retail employment density

4.2.3 Tour type choice for workers

As workers' daily activity-travel behaviour may be very different to that of non-workers, the tour-based travel decision mechanisms for workers and non-workers are examined separately. Table 4.3 presents the profile of tour type choice for workers generating one and two tours. More than 30% of workers with only one tour choose the single-purpose work tour type of H-W-H on a typical weekday, while another 34% or so choose the multi-purpose tour type of H-W-X-W-H. The proportion of any other work tour type is low (less than 6%), except the type of H-W-X-W-X-H with about 10%. Note that about 8% of workers generate only one tour which is of a non-work tour type. One possible reason may be that they need to take part in some occasional personal business (e.g. going to hospital) rather than work activities on that survey day. Another reason may be that these people, who work but at home, are telecommuting.

Table 4.3: Tour type choice for workers with one and two tours

Workers with one tour generation			**Workers with two tours generation**					
Tour type	Freq.	Percent (%)	1st Tour type	Freq.	Percent (%)	2nd Tour type	Freq.	Percent (%)
H-W-H	178	31.28	H-W-H	80	56.34	H-W-H	57	40.14
H-X-W-H	19	3.34	H-X-W-H	6	4.23	H-X-W-H	1	0.70
H-W-X-W-H	193	33.92	H-W-X-W-H	17	11.97	H-W-X-H	20	14.08
H-W-X-H	25	4.39	H-W-X-H	4	2.82	H-X-W-X-W-H	1	0.70
H-X-W-X-W-H	32	5.62	H-X-W-X-W-H	1	0.70	H-W-X-W-X-H	1	0.70
H-X-W-X-H	8	1.41	H-X-W-X-H	1	0.70	H-L-H	32	22.54
H-W-X-W-X-H	60	10.54	H-W-X-W-X-H	4	2.82	H-S-H	13	9.15
H-X-W-X-W-X-H	7	1.23	H-L-H	8	5.63	H-F-H	8	5.63
Non-work tour	47	8.26	H-S-H	9	6.34	H-P-H	7	4.93
			H-F-H	5	3.52	H-2 stops-H	1	0.70
			H-P-H	3	2.11	H-3 stops-H	1	0.70
			H-O-H	2	1.41			
			H-3 stops-H	2	1.41			
Total	569	100	Total	142	100	Total	142	100

Of the workers taking two tours, more than 50% choose the single-purpose work tour type as their first tour arrangement, while another 12% or so select the multi-purpose work tour type of H-W-X-W-H. About 19% choose the single-purpose non-work tour as their first tour type, with very few people selecting a multi-purpose non-work tour. By contrast, with respect to the second tour type arrangement for these workers, the proportion of single-purpose work tour type is high, followed by another multi-purpose work tour type of H-W-X-H. However, the proportion of single-purpose non-work tour type is also high, exceeding 40%, which indicates many workers participate in some non-work activities for their second tour arrangement if they display two tours on a typical weekday. In particular, among them, leisure activity is the most popular, as more than 20% select the tour type of H-L-H.

Table 4.4: Tour type choice for workers with three or more tours

Workers with three or more tours generation								
1st Tour type	Freq.	Percent (%)	2nd Tour type	Freq.	Percent (%)	3rd Tour type	Freq.	Percent (%)
H-W-H	25	71.43	H-W-H	24	68.57	H-W-H	12	34.29
H-W-X-H	1	2.86	H-X-W-H	1	2.86	H-W-X-H	2	5.71
H-L-H	6	17.14	H-W-X-H	5	14.29	H-L-H	14	40.00
H-F-H	1	2.86	H-L-H	1	2.86	H-S-H	6	17.14
H-P-H	1	2.86	H-S-H	1	2.86	H-P-H	1	2.86
H-O-H	1	2.86	H-F-H	1	2.86			
			H-O-H	1	2.86			
			H-X-X-X-H	1	2.86			
Total	35	100	Total	35	100	Total	35	100

Table 4.4 lists the tour type profile for workers with three or more tours. As very few workers take more than three tours on a typical weekday, the samples of three tours and four tours generation are put together and the fourth tour is disregarded if the workers take four tours. As Table 4.4 shows, the majority of these workers choose the single-purpose work tour type as their first tour arrangement, followed by the single-purpose non-work tour type of H-L-H. The proportions of any other types are very low. Similarly, with respect to their second tour type arrangement, almost 70% choose the single-purpose work tour type while another 15% participate in some kind of non-work activity after work and before going home. As far as the third tour type arrangement is concerned, about 30% of these workers choose the single-purpose work tour type, while another 60% select the single-purpose non-work tour types, especially the tour type of H-L-H, suggesting most of these workers go

shopping or participate in some leisure activities for their last tour arrangement on a typical weekday. Overall, it shows that workers with different tour frequencies choose different tour types for their different tour arrangement.

4.2.4 Tour type choice for non-workers

With respect to non-workers, Table 4.5 presents the profile of tour type choice and arrangement for non-workers with one and two tours generated. More than 50% of non-workers with only 1 tour generated choose the single-purpose non-work tour type on a typical weekday. Of them, shopping and recreation are the main activities which people like to participate in, followed by personal business. The proportion of multipurpose non-work tour type with two activities participation, i.e. H-X-X-H, is nearly 13%, while the multipurpose non-work tour type with three or more activities participation accounts for about 6% altogether. Nonetheless, 25% of non-workers with only 1 tour choose work tour type on a typical weekday, probably due to that these unemployed residents take some temporary work-related activities on that survey day, like training or study for a job, re-hired by the company or university after retirement, etc.

Table 4.5: Tour type choice for non-workers with 1 and 2 tours

Non-workers with 1 tour generation			**Non-workers with 2 tours generation**					
Tour type	Freq.	Percent (%)	1st Tour type	Freq.	Percent (%)	2nd Tour type	Freq.	Percent (%)
H-L-H	24	18.18	H-L-H	34	32.38	H-L-H	32	30.48
H-S-H	27	20.45	H-S-H	18	17.14	H-S-H	24	22.86
H-F-H	5	3.79	H-F-H	8	7.62	H-F-H	6	5.71
H-P-H	14	10.61	H-P-H	7	6.66	H-P-H	15	14.28
H-O-H	4	3.03	H-O-H	5	4.76	H-O-H	5	4.76
H-X-X-H	17	12.88	H-X-X-H	12	11.43	H-X-X-H	6	5.71
H-X-X-X-H	5	3.79	H-X-X-X-H	2	1.90	H-X-X-X-H	3	2.86
H-X-X-X-X-H	3	2.27						
Work tour	33	25.00	Work tour	19	18.10	Work tour	14	13.33
Total	132	100	Total	105	100	Total	105	100

Of the non-workers with two tours generation, more than 30% choose the single-purpose non-work tour type, i.e. H-L-H, as their first tour arrangement, while another 17% or so select the tour type of H-S-H. Only 13% choose the multipurpose non-work tour type with two or three activities participation, with about 18% selecting the work tour type as their first tour type. By contrast, with respect to their second tour type arrangement for these non-workers, recreation and shopping are still the primary activities for the single-purpose non-work tour type, with about 14% selecting personal business. The proportion of multipurpose non-work tour type is very low, about 8%.

Table 4.6 presents the tour type profile for non-workers with three tours. Nearly 40% choose the single-purpose non-work tour type of H-L-H as their first tour arrangement, with about 16% selecting the tour type of H-F-H. The proportion of H-S-H is only 9%, while that of other non-work tour types is low. Similarly, regarding their second tour type arrangement, about 30% choose the single-purpose non-work tour type of H-L-H, followed by the tour types of H-S-H and H-F-H, accounting for 14% and 12% respectively. In contrast, with respect to their third tour type arrangement, more than 50% choose the single-purpose non-work tour types of H-L-H and H-S-H, while the proportion of any other non-work tour type is very low. However, about 28% choose the work tour type as their third tour type arrangement on a typical weekday.

Table 4.6: Tour type choice for non-workers with 3 tours

Non-workers with 3 tours generation								
1st Tour type	Freq.	Percent (%)	2nd Tour type	Freq.	Percent (%)	3rd Tour type	Freq.	Percent (%)
H-L-H	17	39.53	H-L-H	13	30.23	H-L-H	12	27.91
H-S-H	4	9.30	H-S-H	6	13.95	H-S-H	10	23.26
H-F-H	7	16.28	H-F-H	5	11.63	H-F-H	3	6.98
H-P-H	3	6.98	H-P-H	4	9.31	H-P-H	2	4.65
H-O-H	2	4.65	H-O-H	1	2.33	H-O-H	2	4.65
H-X-X-H	3	6.98	H-X-X-H	3	6.98	H-X-X-X-H	2	4.65
H-X-X-X-H	1	2.33	H-X-X-X-H	1	2.33			
Work tour	6	13.95	Work tour	10	23.26	Work tour	12	27.91
Total	43	100	Total	43	100	Total	43	100

4.3 Modelling tour generation

4.3.1 Ordered logit models

Having established that tour frequency and type do vary for workers and non-workers, the next step was to determine whether tour characteristics (frequency and type) could be explained by the socio-demographic and / or urban form characteristics of the associated neighbourhoods. As the variable of tour frequency is an ordinal outcome, the ordered logit models are adopted to investigate association between urban form characteristics (at residence and workplace), socio-demographic attributes (of households and individuals), and tour generation choices for workers and non-workers, respectively.

The ordered logit model is a generalisation of the multinomial logit, and is useful for explaining ordinal discrete choices where individuals have systematic unobserved preferences, with proximate covariance in the stochastic utility components (Small, 1987). This approach allows for ordinal differences in the dependent variable (in this case, the tour frequency) with a small range of discrete choice (our travellers chose to take 1 to 3 tours) and may also more appropriately account for the actual behaviour (Bhat, 1999; Noland and Thomas, 2007). The ordered logit model is based upon cumulative response probabilities and the odds that an outcome is less than or equal to m versus greater than m given values of x:

$$\mathbf{\Omega}_{\leq m|>m}(\mathrm{x}) = \Pr(y \leq m \mid \mathrm{x}) / \Pr(y > m \mid \mathrm{x}) \quad \text{for } m = 1, J-1 \tag{4.1}$$

The log of the odds is assumed to equal

$$\ln \mathbf{\Omega}_{\leq m|>m}(\mathrm{x}) = \tau_m - \mathrm{x}\beta \tag{4.2}$$

where J refers to the number of ordinal categories, τ_m represents the cut points or thresholds, and β means the coefficients to be estimated (Long and Freese, 2001). In this case, as the options of tour generation are divided into three categories, there are only two cut points (τ_1 and τ_2) to be estimated (i.e. between 1 and 2 tours, and 2 and 3 tours). Stata software was used to estimate all the models in this analysis and the option of three tours generation was set as the reference category.

4.3.2 Tour generation modelling for workers

Table 4.7 shows model results for the employed residents with effective samples representing workers who generated at least one home-based work tour on a typical weekday. Model 1 is the null model with only two cut points to be estimated. Taking the antilogit[5] of them, we can obtain the estimated probability that a worker's tour frequency is one and the cumulative probability that a worker's tour frequency is less than three, respectively. Household and individual socio-demographic attributes (e.g. gender, age, occupation, child presence, household size) are added in model 2, followed by model 3 which adds urban form variables at both residence and workplace, and which includes population density (for the *jiedao* sub-district), retail employment density (retail employees within a 1 km radius), and service facility density (number of various service facilities within a 1 km radius). The natural log transformation is applied to these urban form variables at both residence and workplace, to make their distribution more symmetric and to mitigate the potential problem of heteroskedasticity (Anderson and West, 2006). The model indicators of Log likelihood and R^2 increase as more variables are added. All the models pass the Brant Test of Parallel Regression Assumption (Long and Freese, 2001), indicating that the models are well fitted and the coefficients are appropriately estimated.

[5] The antilogit of r equals to $\exp(r) / [\exp(r)+1]$

Table 4.7: Ordered logit models for workers

Variables	Model 1		Model 2		Model 3	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Cut point1	1.082	0.087	-1.607	0.716	0.681	1.146
Cut point2	2.943	0.173	0.561	0.719	2.876	1.153
House head			0.426**	0.212	0.424**	0.216
Female			0.357*	0.205	0.290	0.208
Age (30-49)			1.284***	0.347	1.164***	0.354
Age (>=50)			1.368***	0.386	1.250***	0.394
Monthly income			-0.439***	0.091	-0.431***	0.092
Occupation 1			-2.344***	0.885	-2.469***	0.890
Occupation 2			0.393*	0.215	0.303	0.223
Occupation 4			0.483	0.294	0.506*	0.298
Child presence			-0.505**	0.231	-0.396*	0.234
Household size			-0.126	0.123	-0.063	0.126
Commuting time			-0.534***	0.097	-0.529***	0.099
Population density at residence					0.292*	0.171
Retail employment density at residence					-0.001	0.070
Population density at workplace					-0.030	0.132
Retail employment density at workplace					-0.394	0.264
Service facility density at workplace					0.570**	0.287
Log likelihood	-483.539		-412.481		-405.841	
Pseudo R^2	0.000		0.147		0.161	

* Significant at 0.10 level, ** significant at 0.05 level, *** significant at 0.01 level. Occupation is divided into four categories. Occupation 1 refers to students and occupation 2 refers to staff members in various government and public institutions. Occupation 3 refers to workers in factories and companies, while occupation 4 refers to private-owned entrepreneurs and freelance workers. In the models, occupation 3 was set as the reference category.

Compared with the parameters in model 2, the estimates of socio-demographic attributes in model 3 vary little, which suggests the correlation of demographics and tour frequency is stable. It shows most of these socio-demographic attributes are significantly correlated with workers' tour generation choices. For example, household head, low-level income workers, private-owned entrepreneurs and freelance workers tend to generate more tours than their counterparts on a typical weekday. Distinctness is also found between various age cohorts – older people are significantly associated with a higher tour frequency, contrary to the findings of Noland and Thomas (2007). Gender difference in trip-chaining behaviour is found in many developed countries, but here there is no significant difference between men and women's tour frequencies. One possible reason for these observations is that many young couples live with their parents (partly due to very high house prices in Beijing) to form big families. Older people, including those without work or the retired, take partial responsibility for housework (shopping, child-care, family errands) instead of women workers, a rather different situation than in many developed countries.

Travel duration or commuting time is also very significantly and negatively associated with tour frequency, indicating that people tend to take fewer tours if they have to travel long periods for work activities. With respect to urban form, it shows that people living in neighbourhoods with higher population density at place of residence, or higher workplace service facility accessibility tend to leave home more often and generate more tours, which is mostly consistent with other research (Krizek, 2003).

4.3.3 Tour generation modelling for non-workers

Table 4.8 presents model results for the unemployed residents with effective samples representing non-workers who generated at least one home-based tour on a typical workday. With household and individual socio-demographic attributes added in model 2, it shows that people with high educational attainment tend to generate fewer tours than their counterparts on a typical workday. Compared to non-workers with no or low-level income (e.g. pensioners), the high-level income non-workers tend to generate more tours on a typical workday. By contrast, with urban form characteristics at residence added in model 3, some estimates of socio-demographic attributes (e.g. gender, education, and monthly income) vary little, while other attributes, like age and child presence, vary a great deal. For example, child presence is significantly correlated with non-workers' tour generation choices when accounting for urban form characteristics at residence. The non-workers with children in their households tend to generate more tours than their counterparts on a typical workday. With respect to urban form, it shows that people living in neighbourhoods with a higher population density at place of residence, or better access to a subway station tend to leave home more often and generate more tours than their counterparts on a typical workday.

Table 4.8: Ordered logit models for non-workers

Variables	Model 1		Model 2		Model 3	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Cut point1	-0.105	0.138	1.337	0.653	3.770	0.959
Cut point2	1.866	0.203	3.386	0.689	6.021	1.017
Female			-0.007	0.292	-0.013	0.301
Age(40-49)			0.586	0.689	1.012	0.727
Age(50-59)			0.365	0.520	0.968^{*}	0.571
Age(>= 60)			0.236	0.510	0.677	0.561
Education(tertiary)			-0.841^{**}	0.390	-0.842^{**}	0.408
Monthly income			0.332^{***}	0.115	0.387^{***}	0.122
Child presence			0.441	0.327	1.266^{***}	0.388
Population density at residence					0.435^{**}	0.221
Retail employment density at residence					-0.071	0.085
Subway accessibility at residence					1.184^{***}	0.342
Log likelihood	-206.978		-198.177		-185.110	
Pseudo R2	0.000		0.031		0.095	

* Significant at 0.10 level, ** significant at 0.05 level, *** significant at 0.01 level.

4.4 Modelling tour schedule and interdependence

Next, this section examines how socio-demographic and urban form attributes correlate with residents' tour schedule (the type and order of intermediate stops made) and interdependence. It firstly explores such correlations for workers with different tour frequencies separately to account for the sequence of tours taken and the tour interdependence effect for workers taking multiple tours in a day, followed by the multivariate analysis for non-workers. As the dependent variable of tour pattern is a categorical outcome, multinomial logit (MNL) models are adopted. These are the most frequently used discrete choice models, favoured for their simple mathematical structure and ease of estimation (Wen and Koppelman, 2000). Based upon the response probabilities for each category (in our case, tour type), the MNL models can be defined as:

$$\ln \Omega_{m|b}(\mathrm{x}) = \ln[\Pr(y = m|\mathrm{x})/\Pr(y = b|\mathrm{x})] = \mathrm{x}\beta_{m|b} \quad \text{for } m = 1 \text{ to } J \tag{4.3}$$

Where b is the base category or the comparison group and J refers to the number of categories.

4.4.1 Tour schedule modelling for workers taking one tour

The eight types of home-based work tours taken (Table 4.2) vary in frequency, with some of the more complex tours occurring relatively infrequently. To simplify the modelling, four tour categories are thus developed:

- The single-purpose tour (H-W-H), comprising about 34% of observed tours;
- The first pattern multi-purpose tour (H-X-W-H, H-W-X-H, H-X-W-X-H); without work-based tour (i.e. non-work activities occur before and/or after work) comprising almost 10% of observed tours;
- The second pattern multi-purpose tour (H-W-X-W-H) with work-based tour (i.e. non-work activities only take place during work) comprising 37% of observed tours;
- The third pattern multi-purpose tour (H-X-W-X-W-H, H-W-X-W-X-H, H-X-W-X-W-X-H), a more complex combination of the first and second pattern multi-purpose tours, comprising 19% of observed tours.

The most complex pattern multi-purpose tour was set as the reference outcome in the MNL models of workers taking a single tour. The results (Table 4.9) reveal that household size, gender, and monthly income are significantly associated with tour type. Compared to the reference category, workers with large families tend to take less complex tours, whilst female and high income workers have the most complicated (third pattern multi-purpose) tour. This indicates that although women have a similar tour frequency (number of tours) to men, they tend to make more stops within their tour; this supports the findings of gender differences in trip-chaining behaviour reported elsewhere (McGuckin and Murakami, 1999) and contradicts the findings (i.e. no gender difference on tour types) of Yang et al. (2007). Commuting time is also significantly correlated with tour pattern, as might be expected. As travel duration increases, people are more likely to choose simpler tours making fewer intermediate stops (relative to the reference case).

Table 4.9: MNL results for workers with one tour generation

Variables	Single-purpose tour		The first pattern of multi-purpose tour		The second pattern of multi-purpose tour	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Child presence	-0.449	0.319	-0.622	0.434	-0.117	0.309
Household size	0.293*	0.160	0.636***	0.199	0.109	0.159
Female	-0.702***	0.273	-0.366	0.372	-0.605**	0.267
Age (>=50)	-0.552	0.405	-0.350	0.563	-0.352	0.389
Occupation 2	-0.157	0.294	-0.100	0.415	0.349	0.280
Monthly income	-0.250***	0.093	-0.209*	0.124	-0.198**	0.092
Commuting time	0.527***	0.144	0.477**	0.198	0.485***	0.138
Population density at residence	0.198	0.180	0.025	0.237	0.322*	0.175
Retail employment density at residence	-0.014	0.075	0.081	0.102	-0.028	0.075
Population density at workplace	-0.160	0.165	0.190	0.213	0.095	0.160
Retail employment density at workplace	0.009	0.163	-0.475**	0.213	-0.269*	0.158
Service facility accessibility at workplace	-0.050	0.176	-0.092	0.228	-0.345*	0.186

The third pattern of multi-purpose tour is the reference case.
Log likelihood (model) = -630.48, Prob > Chi^2 = 0.00, Pseudo R^2 = 0.06
* Significant at 0.10 level, ** significant at 0.05 level, *** significant at 0.01 level.

Regarding the urban form variables, land use characteristics at both residence and workplace have significant impacts on tour pattern choices, especially with respect to the workplace built environment, which exerts more influence than the residences'. For example, people living in neighbourhoods of higher population density tend to choose simpler tours rather than the most complex (reference) category. However, where retail employment density and service facility accessibility (as average distance to service facilities within a 1 km radius) at the workplace is higher, people are more likely to take the most complex tour or make more stops *en route*. It indicates that firstly the urban form variables at residence and workplace have different impacts on tour pattern decisions; secondly, mixed land-use at a workplace with higher accessibility leads to a more complex tour pattern with multiple stops within one work tour.

4.4.2 Tour schedule modelling for workers taking two tours

With respect to workers with two tours, based on the tour type selection profile in Table 4.3 and each tour type's characteristics, their first and second tour types are also grouped into four categories respectively. As shown in Figure 4.3, their first tour types are grouped as single-purpose work tour, multi-purpose work-based tour, other multi-purpose work tour and non-work tour, which are mostly single-purpose. By contrast, their second tour types are grouped as single-purpose work tour, multi-purpose work tour, single-purpose non-work tour with leisure activities (H-L-H) and maintenance activities (H-M-H) separately.

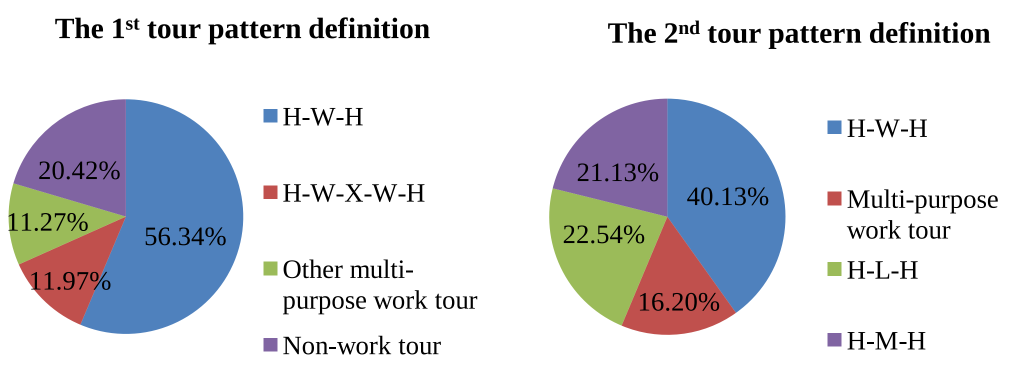

Figure 4.3: Tour pattern definition for workers with two tours generation

Table 4.10 presents the estimated results for the first tour pattern decisions. As shown below, the socio-demographic attributes of household size, gender, and age are significantly associated with first tour pattern taken. Relative to the reference case (i.e. other multi-purpose work tour), workers with a large family tend to choose the single-purpose work tour pattern as their first tour arrangement, whilst women select the multi-purpose work-based tour. Older individuals tend to participate in some non-work activities before they travel to work. Commuting time was also found to have a significant and positive effect on the first tour pattern choices. As the commuting time increases, people are more likely to begin with work activities and then participate in non-work activities close to their workplaces. However, the urban form variables are insignificant influences on the first tour pattern choices.

Table 4.10: MNL results for the first tour of the day

Variables	H-W-H		H-W-X-W-H		Non-work tour	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Child presence	0.206	0.773	-2.264	1.403	1.093	0.891
Household size	1.071*	0.554	1.055	0.695	0.979	0.620
Female	0.681	0.622	1.484*	0.851	0.757	0.730
Age (>=50)	0.878	0.863	1.461	1.098	2.180**	0.980
Occupation 2	-0.276	0.638	-1.045	0.875	-0.715	0.746
Monthly income	-0.103	0.284	-0.027	0.357	-0.223	0.328
Commuting time	-0.267	0.360	1.281**	0.532	0.365	0.417
Population density at residence	1.018	0.686	1.596	1.230	0.714	0.716
Retail employment density at residence	-0.231	0.370	-0.407	0.504	-0.406	0.380
Population density at workplace	-0.094	0.624	0.183	0.729	-0.414	0.677
Retail employment density at workplace	-0.324	0.532	-0.187	0.659	-0.473	0.581
Service facility accessibility at workplace	-0.274	0.761	-0.552	0.985	-1.045	0.829

The category of other multi-purpose work tour is the base outcome.
Log likelihood (model) = -133.77, Prob > Chi^2 = 0.01, Pseudo R^2 = 0.18
* Significant at 0.10 level, ** significant at 0.05 level, *** significant at 0.01 level.

In contrast, urban form variables at residence and workplace are significantly correlated with the type of tour taken by workers taking a second tour in the day (Table 4.11). With higher population density at workplaces, people are more likely to choose the reference tour type (i.e. H-L-H) as their second tour of the day. However, with mixed land use at workplaces, people are more likely to select the work tour or non-work tour with maintenance activities (e.g. shopping). Monthly income and commuting time are also significantly correlated with the second tour type taken, indicating people with higher income or longer duration commutes tend to participate in some leisure activities after work. There is also a significant correlation between the choice of first and second tour type. For example, compared with the multi-purpose work tour, if the workers' first tour pattern is single-purpose work tour or non-work tour, they are more likely to select the tour patterns of H-W-H, H-W-X-H or H-M-H as their second tour, rather than the base category of H-L-H. This suggests there may be a tour interdependence effect for different tour pattern choices for workers taking multiple tours in a day. This observation is tentative, and additional data are required to test this further.

Table 4.11: MNL results for the second tour of the day

Variables	H-W-H		H-W-X-H		H-M-H	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Child presence	0.617	0.828	0.748	0.914	0.225	0.785
Household size	-0.678	0.476	-0.100	0.507	-0.476	0.426
Female	-0.309	0.653	0.164	0.725	0.015	0.626
Age (>=50)	-0.408	0.856	0.815	0.891	0.190	0.840
Occupation 2	-0.227	0.717	0.087	0.793	-0.375	0.685
Monthly income	-1.256***	0.354	-1.290***	0.404	-0.576*	0.349
Commuting time	-1.959***	0.478	-1.796***	0.491	-0.763*	0.447
Population density at residence	-0.590	0.730	-1.013	0.725	-1.096*	0.664
Retail employment density at residence	-0.205	0.327	-0.081	0.318	0.229	0.287
Population density at workplace	-1.232**	0.616	-1.395**	0.671	-0.849*	0.513
Retail employment density at workplace	1.690***	0.555	1.038*	0.577	0.910*	0.500
Service facility accessibility at workplace	0.208	0.655	-0.412	0.696	0.553	0.548
The first tour pattern of single-purpose work tour	2.538***	0.801	1.607*	0.876	0.628	0.761
The first tour pattern of non-work tour	2.068*	1.064	2.088**	1.064	2.351***	0.889

The tour pattern of H-L-H is the base outcome.
Log likelihood (model) = -132.15, Prob > Chi^2 = 0.00, Pseudo R^2 = 0.29
* Significant at 0.10 level, ** significant at 0.05 level, *** significant at 0.01 level.

4.4.3 Tour schedule analysis for workers taking three tours

As the sample of workers with three or more tours generation is small (Table 4.4), MNL models cannot be used to explain these tours. Therefore, to explore this data further, different tour types were grouped into two categories: work tour (W) and non-work tour (N), most of which are single-purpose. With three tours, each taking two possible states, we have six possible tour patterns (Figure 4.4). Of these, tour pattern WWN accounts for about 60% of the three tours per day observations, indicating that most workers have two work tours, followed by a final non-work tour.

These workers are going home for lunch (as shown in the activity diaries) and then out again for work in the afternoon and non-work activities in the evening. Another 17% select a non-work tour (e.g. take morning exercise) as their first tour followed by two work tours (i.e. one H-W-H in the morning and one in the afternoon), suggesting their first tour pattern influences the decisions about subsequent tours. Thus these particular tour patterns also indicate a tour interdependence effect for different tour decisions in the scheduling process.

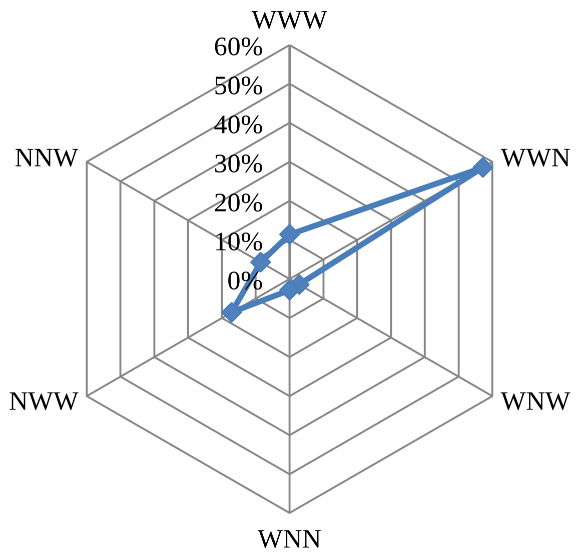

Figure 4.4: Tour patterns profile of workers taking three tours in a day

4.4.4 Tour schedule analysis for non-workers taking one tour

The eight types of home-based non-work tours taken (Table 4.5) vary in frequency, with multi-purpose tour occurring relatively infrequently. To simplify the modelling, three tour categories are thus developed:

- The single-purpose recreational tour (H-L-H, H-S-H), comprising about 52% of observed tours;
- The single-purpose business tour (H-F-H, H-P-H, H-O-H), comprising about 23% of observed tours;
- The multi-purpose tour (H-X-X-H, H-X-X-X-H, H-X-X-X-X-H), comprising 25% of observed tours.

The most common pattern single-purpose recreational tour was set as the reference outcome in the MNL models of non-workers taking a single tour. The results (Table 4.12) show that age cohorts and child presence are significantly associated with tour type selection. Compared to the reference category, older people (aged 60 and above) tend to participate in several activities within one multi-purpose tour, whilst households with child presence are more likely to choose single-purpose business tour or multi-purpose tour. Regarding the urban form variables, the modelling shows that retail employment density at residence is significantly related with tour pattern taken. As the retail employment density increases or the land use is more mixed, people are more likely to choose multi-purpose tour and make more intermediate stops within one tour.

Table 4.12: MNL results for non-workers with one tour generation

Variables	Single-purpose business tour		Multi-purpose tour	
	Coef.	S.E.	Coef.	S.E.
Female	0.213	0.607	0.101	0.578
Age (>=60)	-0.455	0.621	1.045*	0.572
Child presence	1.838***	0.669	1.388**	0.676
Education (primary)	0.092	0.623	0.892	0.593
Population density at residence	0.308	0.378	-0.329	0.376
Retail employment density at residence	-0.017	0.170	0.282*	0.167
Subway accessibility	-0.348	0.671	0.580	0.647

The category of single-purpose recreational tour is the base outcome.
Log likelihood (model) = -90.13, Prob > Chi^2 = 0.03, Pseudo R^2 = 0.11
* Significant at 0.10 level, ** significant at 0.05 level, *** significant at 0.01 level.

4.4.5 Tour schedule analysis for non-workers taking two tours

On the basis of tour type selection for non-workers with two tours generation (Table 4.5), their first and second tour types are further grouped into three categories: H-L-H, H-S-H, and other non-work tour (including single-purpose business tour and multi-purpose tour). Table 4.13 presents the results for the first tour pattern of non-workers taking two tours in a day. Results show that, compared to the reference case (i.e. H-S-H), older people (aged 60 or above) tend to participate in some leisure activities and choose the single-purpose tour of H-L-H as their first tour of the day. Households with child presence are more likely to begin with some non-work activities, like leisure, person business or family obligation, rather than shopping. Subway accessibility is also significantly correlated with the first tour pattern choice. People resident in neighbourhoods with subway station nearby are more likely to choose single-purpose business tour or multi-purpose tour as their first tour pattern of the day.

Table 4.13: MNL results for the first tour of non-workers

Variables	H-L-H		Other non-work tour	
	Coef.	S.E.	Coef.	S.E.
Female	0.145	0.695	0.139	0.699
Age (>=60)	1.191*	0.715	0.629	0.726
Child presence	3.028**	1.407	2.606*	1.427
Education (primary)	0.599	0.722	0.301	0.729
Population density at residence	0.866	0.647	0.030	0.654
Retail employment density at residence	-0.125	0.227	0.219	0.228
Subway accessibility	0.178	0.766	1.594**	0.822

The category of H-S-H is the base outcome.
Log likelihood (model) = -77.59, Prob > Chi^2 = 0.04, Pseudo R^2 = 0.11
* Significant at 0.10 level, ** significant at 0.05 level, *** significant at 0.01 level.

Regarding the second tour of the day, no significant correlations between tour type and any urban form variables at residence are observed (Table 4.14). In contrast, for the socio-demographic attributes, child presence is still significantly associated with tour type choice. It shows that, relative to the reference case (H-L-H), households with child presence are more likely to participate in some shopping activities and choose the single-purpose tour of H-S-H as their second tour of the day. Moreover, as shown below, a significant correlation between the choice of first and second tour type is also found for non-workers. For example, compared with the reference case, if the non-workers' first tour pattern is single-purpose tour of H-L-H or other non-work tour, they are more likely to select the tour pattern of H-S-H as their second tour. This suggests there may be also a tour interdependence effect for different tour pattern choices for non-workers taking multiple tours in a day.

Table 4.14: MNL results for the second tour of non-workers

Variables	H-S-H		Other non-work tour	
	Coef.	S.E.	Coef.	S.E.
Female	0.909	0.691	1.025	0.650
Age (>=60)	0.087	0.702	-0.634	0.649
Child presence	1.717*	1.033	1.324	1.045
Education (primary)	-0.091	0.728	0.110	0.671
Population density at residence	0.524	0.601	-0.292	0.567
Retail employment density at residence	-0.143	0.219	0.102	0.210
Subway accessibility	-0.155	0.893	-1.106	0.751
The first tour pattern of H-L-H	2.024*	1.206	0.903	0.813
The first tour pattern of Other non-work tour	2.750**	1.230	1.458*	0.859

The category of H-L-H is the base outcome.
Log likelihood (model) = -72.79, Prob > Chi^2 = 0.02, Pseudo R^2 = 0.18
* Significant at 0.10 level, ** significant at 0.05 level, *** significant at 0.01 level.

4.4.6 Tour schedule analysis for non-workers taking three tours

As the sample of non-workers taking three tours in a day is very small (Table 4.6), MNL models cannot be used to explain these tours. Therefore, to explore this data further, tours were grouped into only two categories: the single-purpose tour (S) and the multi-purpose tour (M). Figure 4.5 presents the tour pattern profile for non-workers taking three tours in a day. As shown below, tour pattern SSS accounts for nearly 65% of the three tours per day observations, indicating that most non-workers have three single-purpose tours of the day. Another 14% select a multi-purpose tour as their first or second tour, accompanied by two single-purpose tours. Very few people choose a multipurpose tour as their last tour of the day. These particular tour patterns for non-workers also suggest a tour interdependence effect for different tour decisions in the scheduling process.

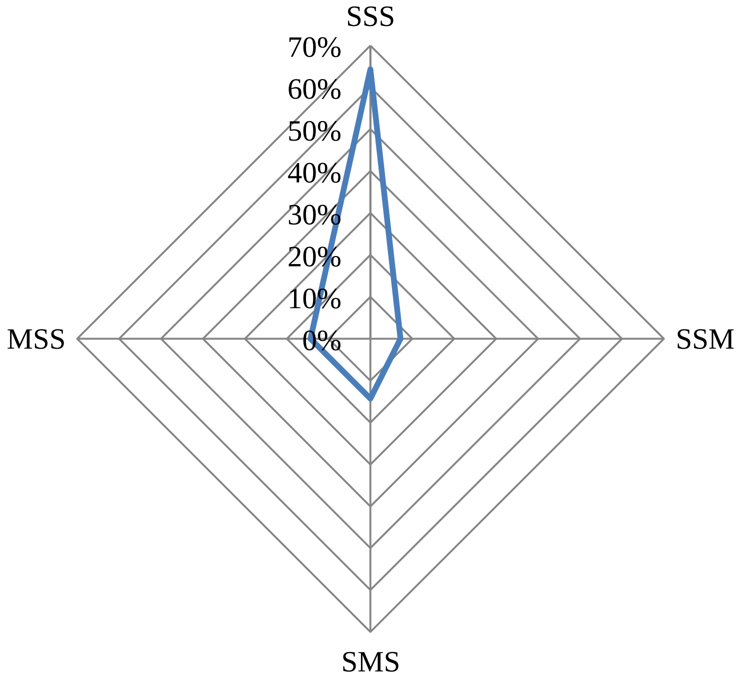

Figure 4.5: Tour pattern profile of non-workers taking three tours in a day

4.5 Conclusions

Gaining an understanding of the determinants of travel behaviour, including the role of built form, is important when attempting to address the transport problems of cities. However, such an understanding is often limited, particularly with respect to cities of transitional and developing countries, which to date have been little studied with respect to trip-chaining behaviour and especially its association with urban form. Such research is generally limited, and very scarce in developing countries, and particularly China, where the urban form characteristics and people's daily travel behaviour might be very different from developed countries. One reason for this is attributed to data availability. For example, in China, there is no national travel survey or published large samples of detailed travel information by the government (Pucher et al., 2007).

Based on detailed land use data and activity diary survey, this chapter has examined the relationships between socio-demographic attributes, urban form characteristics, and tour-based travel behaviour for workers and non-workers, respectively. The tour decision process are mainly focused on tour generation, tour scheduling and interdependence mechanism. Contrary to prior research that analysed aggregate samples, this study analysed tour behaviour at a disaggregate level, and further investigated the urban form – trip-chaining relationship for workers and non-workers, separately, taking one, two and three tours in a single day. This allows for a consideration of both tour sequence, and tour interdependence, which has rarely been considered before, and not at all for China.

Socio-demographic attributes of households and individuals correlate significantly with people’s tour-based behaviour, especially with respect to the number of tours taken. For example, workers with high income or in households with children tend to take fewer tours on a typical workday; but when they do leave home, they make more intermediate stops. Older people tend to take more tours and tend to participate in non-work activities before they travel to work, which is notably different from the findings in developed countries (e.g. Noland and Thomas, 2007). However, whilst no gender differences were observed with respect to the number of tours taken, women workers tend to make more stops within one tour, participating in non-work activities (mostly household-sustaining activities, such as shopping, child-care and family errands) *en route*. This is consistent with the results found in many developed countries (e.g. McGuckin and Murankami, 1999). With respect to non-workers, people with lower educational attainment tend to generate fewer tours than their counterparts on a typical workday. The non-workers with children in their households tend to generate more tours and participate in some family obligation activities *en route*.

Regarding the urban form variables, the prior studies illustrate the difficulty in drawing general conclusions on the role of urban form in trip chaining. For instance, using an activity-based model to analyse the effect of land use on household shopping tour decisions, Limanond and Niemeier (2004) suggested that land use patterns had virtually no impact on overall shopping tour frequencies. In contrast, Crane (1996) and Krizek (2003) found, for the USA, that urban form influenced trip-chaining behaviour, with the more accessible (high density) areas generating more tours, with fewer stops. Maat and Timmermans (2006) conducted similar European research on urban form and trip-chaining, and also found that higher densities led to more frequent tours, but that tours were more complex (tours had more stops). Noland and Thomas (2007) drew a very different conclusion, presenting evidence to show that (low density) suburban areas had a higher tour frequency with these tours being more complex than for higher density areas.

In this research, land use characteristics at both residence and workplace are significantly associated with residents' tour frequency, but differ with respect to tour complexity. For instance, higher density at residence leads to more home-based tours with fewer stops for workers, while mixed land use at workplace with higher density and accessibility leads to more stops within one work tour or a more complex tour pattern. With respect to non-workers, it finds that people living in neighbourhoods with higher density or better access to subway station tend to leave home more often and make more intermediate stops than their counterparts on a typical workday. Moreover, for residents taking several tours in a day, the models indicate that first tour type is significantly correlated with the type of tour subsequently taken, suggesting that behaviour for one tour affects that observed for others. The tour interdependence effect, revealed in this research for the first time, contributes to the relative trip-chaining analysis.

To conclude, this disaggregated analysis of trip-chaining behaviour provides a sophisticated understanding of tour-based travel decisions and an empirical basis of behavioural determinants. Following this, the next chapter develops a static spatial microsimulation to analyse the entire population's daily tour-based travel behaviour and associated CO_2 emissions at fine spatial scale for urban Beijing. While lack of detailed travel data for a large population, spatial microsimulation represents a useful tool in population synthesis, and it provides a good means to gain greater insight into the spatial variability of the emissions at micro-scale than has previously been possible. Using various relevant socio-demographic attributes (e.g. gender, age, education, employment, etc) as constraints, the next chapter firstly creates a realistic synthetic population and spatially simulates the population's daily travel, including travel distance and mode choice at the sub-district level. It also estimates the transport CO_2 emission from daily urban travel at the disaggregate level in urban Beijing.

Chapter 5

Spatial Microsimulation of Transport CO_2 from Urban Travel

5.1 Introduction

The preceding (Chapter 4) analysis of tour-based travel relationships concluded that household and individual socio-demographic attributes, e.g. gender, age, education, employment, occupation, are important predictors of people's daily travel behaviour in Beijing. Therefore, in this chapter, these significant socio-demographic attributes are used as constraints to create a realistic synthetic population (a good selection of constraints is of paramount importance in a spatial microsimulation model, see Section 5.2.2), and simulate the population's daily travel behaviour and estimate their subsequent CO_2 emission. This chapter presents a new 'bottom-up' methodology to provide improved transport CO_2 emission based on individuals' observed daily travel behaviour.

Note that one of two main approaches is usually employed to estimate transport CO_2 emission. The first is to estimate CO_2 emission using aggregate data on total energy consumed or from a consideration of size of the vehicle fleet and average vehicles kilometres travelled (VKT) per vehicle. This 'top-down' approach is straightforward and has been widely used (Dhakal, 2009; Hu et al., 2010), including in China, where on the basis of fuel consumption Cai et al. (2012) estimated CO_2

emissions from transport at national and regional levels for 2007. However, the application of this approach at the urban scale is often constrained by poor data, particularly a lack of reliable data on the vehicle fleet in the city, its city-wide energy use, and the average distance travelled per vehicle (He et al., 2013). Furthermore, this approach is unable to directly link travel behaviour with land use patterns or urban development policies. For example, it is known that a city's physical form (urban form features, such as density) influence the distance people travel each day, their choice of mode, and resulting CO_2 emission (Grazi et al., 2008).

In contrast, the second approach is to estimate emissions from less aggregate travel attributes, including trip frequency, mode choice and vehicle kilometres travelled for each trip (e.g. He et al., 2013). This 'bottom-up' method not only differentiates CO_2 emission from different types of vehicles, but also helps to understand the influence that other factors (e.g. socio-demographic or urban form characteristics) have on carbon emissions. This is useful for examining how much emissions may respond to development scenarios or strategic policy and plan interventions (noting that factors such as fuel type, speed, and road condition are also influential; Cai et al., 2012). This approach is prevalent in urban air quality (and CO_2 emission) analyses but such studies rarely address people's travel behaviour at the individual level or account for urban form. This is likely due to the large amount of detailed data required on travel behaviour for large populations, which is not usually available, particularly in the case of fast growing mega cities in developing economies such as China.

Using the understanding of travel behaviour developed in Chapter 4 (based on an activity diary survey), and the 2000 population census, this chapter employs static spatial microsimulation to generate a realistic synthetic population at a fine geographical resolution as a basis on which to model the entire urban population's daily travel, and subsequently their CO_2 emission. The method provides an alternative means to estimate transport CO_2 emission, and provides a way to gain greater insight into the spatial variability of the emission at micro-scale than has previously been possible. Section 5.2 below details how the microsimulation model is developed within a generic 'Flexible Modelling Framework' (https://github.com/MassAtLeeds/software/releases) using a simulated annealing technique and the constraint specification. Model validation is discussed in Section 5.3, followed by the travel analysis by constraints (Section 5.4). Section 5.5 presents and discusses results of the population synthesis and spatial simulation of urban travel and CO_2 emission. Discussion on the relationship between transport CO_2 emission and socio-economic indicators, and the conclusions are provided in the final section.

5.2 Building a spatial microsimulation

5.2.1 Flexible Modelling Framework: The Modelling Tool

The Flexible Modelling Framework (FMF) developed at the University of Leeds is a generic software framework to assist in the development of social science models. It incorporates a static spatial microsimulation algorithm based on Simulated Annealing and facilitates the construction of population microdata for a single time period. The FMF eases data manipulation / processing – but it does not prescribe the model attributes and their relationships. Although the software has only recently been released to the wider academic community, it has been the subject of internal development and testing at the University of Leeds since 2005. The FMF includes model evaluation options that provide a variety of fitness statistic calculations at individual cell, category and overall attribute levels.

Several spatial microsimulation algorithms are available; for an appraisal of the strengths and weaknesses of the three most commonly applied techniques see Harland et al. (2012). Generally, Simulated Annealing has been demonstrated to provide the most promising results in the generation of synthetic spatial microdata at different geographical scales (Voas and Williamson, 2000; Hermes and Poulsen, 2012; Harland et al. 2012). It has some major advantages over the other approaches, such as the inclusion of the Metropolis Algorithm which allows the algorithm to take backward steps in its search for an optimal population configuration. This ability prevents the algorithm becoming stuck in a sub-optimal solution preventing it finding the global optimal solution. However, the sensitivity of results to the stochastic element of the algorithm should be examined to ensure that this is the case and that the number of iterations and algorithm progression rate are suitable for the problem under examination, section 5.5.1 presents the sensitivity analysis for this study.

The Simulated Annealing approach is a combinatorial optimisation technique that selects an optimal configuration from a small sample population (i.e. activity diary survey in this study) constrained by observed aggregate population counts (population census). The optimisation process operates on known values common to both sample and constraint datasets. The generated population dataset is a realistic representation of the observed population aligning closely to the constraint totals while maintaining the rich variety of attributes (e.g. information on daily travel behaviour) contained in the survey sample population. As outlined by Harland et al. (2012) Simulated Annealing is well suited to spatial microsimulation problems requiring attribute enrichment while simultaneously ensuring close constraint matching.

5.2.2 Constraint specification

The microsimulation draws on an activity diary survey conducted in 2007 across urban Beijing, which includes 1,026 individuals for whom there is a valid and continuous activity-travel record for the weekday. A second data set used here is the fifth population census of Beijing conducted in 2000 by the national government. Full details of these two data sets are reported in Chapter 3. This study used the 10% population sample as it comprises most socio-demographic attributes. However, people aged 14 and below are not included in the activity dairy survey, while both data sets contain common socio-demographic attributes for people aged 15 and above, such as gender, age, education, employment, and occupation. Household-level attributes, average housing area and housing tenure, also appear in both datasets. In summary, the target population addresses a total of 721,894 residents aged 15 or over in the 146 *jiedao* sub-districts in urban Beijing in 2000 (see Figure 3.5).

To produce a successful synthetic population, the spatial microsimulation model must create a realistic representation of the population whose structure and dynamics match the profiles of real populations. Of paramount importance is a good selection of constraints, which represents the important dimensions of interest (Smith et al., 2009). Furthermore, constraint attributes must be present in both survey data and the population census. As demonstrated in preceding (Chapter 4) analysis, household and individual socio-demographic attributes of age, gender, education, employment, occupation, housing area[6], and housing tenure, are all significant influences on travel behaviour, and are variables found in both principal data sets. Therefore, this study uses their tabulations (education, housing tenure, and housing area) and cross-tabulations (age by gender, employment by occupation) at the sub-district level as constraints to generate a synthetic population of urban Beijing.

Table 5.1 presents the configuration of these seven constraints. As shown, people aged 15 and above are divided into five age cohorts; the education attribute has three categories: primary (junior school and below), secondary (senior high school) and tertiary (college and above). The employment attribute is divided into four categories comprising the employed, jobless, retired and other, while employed residents are further classified by occupation: students, workers in government or public institutions (worker TP1), and workers in factories, service companies and other (worker TP2). Of the household-level attributes, housing tenure is categorised as buy or rent; whilst the average per capita housing area of urban residents is divided into two broad categories: low (< 30 m^2) and high (>= 30 m^2).

Table 5.1: Constraints description

Socio-demographic attributes	Categories
Gender	male, female
Age	15-29, 30-39, 40-49, 50-59, 60+
Education	primary, secondary, tertiary
Employment	employed, jobless, retired, other
Occupation	students, workers in government or public institutions, workers in factories, service companies and other
Housing tenure	buy, rent
Housing area (m^2 / capita)	< 30, 30+

[6] As shown in Chapter 4, monthly income is a significant influence on people's daily travel behaviour, but this variable is not available in the population census. Instead, housing area and housing tenure are used as constraints in the microsimulation model, as these two variables partly represent the economic conditions of households, and they are significant influence on travel behaviour in prior studies (e.g. Wang et al., 2011; Ma et al., 2011).

Ensuring the survey population is representative of the general population observed in the aggregate census data is key to producing a realistic microsimulated population. This is achieved by comparing attribute combinations between the census data and the survey dataset. Theoretically, there are 720 combinations[7] of these constraints, but some are not feasible (e.g. a male aged 15-29 with retired employment status, or a female aged over 60 occupied as a student). Multiple two dimensional cross-tabulations of the seven constraints are created using the survey samples which showed that all combinations observed in the activity diary survey are sensible and represent the expected combinations identified from the census data. This indicates that the travel survey data is a good representation of the population that is to be synthetically reconstructed.

5.3 Evaluation

The evaluation of the microsimulated or synthetic population is established via goodness-of-fit testing. However, as model outputs are estimates of unknown data, we must aggregate the simulated outcomes to a suitable geographic scale and validate the tabulations and cross-tabulations for the constrained and unconstrained variables (Ballas and Clarke, 2001). There are several established goodness-of-fit statistics in use for geographical microsimulation. The most frequently used statistic is the Total Absolute Error (TAE), expressed as:

$$\text{TAE} = \sum_i \sum_j | T_{ij} - E_{ij} | \tag{5.1}$$

[7] 720=2*5*3*(3+3)*2*2, while the "(3+3)" refers to six combinations of "employment by occupation", as only the employed individuals can be further divided into 3 categories of occupation.

where T_{ij} and E_{ij} are the observed and simulated counts respectively for the cell at ij.

This goodness-of-fit statistic is easily calculated and understood, simply a count of the absolute differences, and depends on the total number of samples (Voas and Williamson, 2001). However, TAE can be misleading when used across all the categories for an attribute, and may produce a larger total population than observed (Harland et al., 2012). The Total Error (TE) statistic can instead be used to modify the raw TAE, and better calculate the misclassified population for attributes with multiple categories:

$$TE = TAE / 2 \tag{5.2}$$

Both these statistics are referred to as the Classification Error, which show the number of misclassified individuals in a cell, zone or attribute (Harland et al., 2012). Nevertheless, TAE and TE are absolute measures of misclassification and they are subject to population size, and relative measures may be preferable. Some well performing relative statistics, such as Percentage Error (PE), Cell Percentage Error (CPE) and Standardised Root Mean Square Error (SRMSE), can also be applied to evaluate simulated outputs. PE is a relative error statistic derived by TE/N*100 while CPE is derived by TAE/N*100, where N is the population of the relevant cell, zone or attribute. SRMSE is defined as:

$$SRMSE = \{\sum_i \sum_j (T_{ij} - E_{ij})^2 / m \times n\}^{1/2} / (\sum_i \sum_j T_{ij} / m \times n) \tag{5.3}$$

where m and n are the flow matrix dimensions (Knudsen and Fotheringham,1986). These relative measures are also appropriate options for validating or evaluating estimated populations (Voas and Williamson, 2000; Smith et al., 2009). As each goodness-of-fit statistic tests different aspects of the model's results and has its own advantages and disadvantages, all are applied here to provide a comprehensive evaluation of Beijing's synthetic population.

5.4 Travel analysis by constraints

Drawing on the activity diary survey, this section details the comparison of the samples' daily travel behaviour for the different constraining groups. Four dimensions of travel attribute are considered, including tour frequency, number of trips made during the day, total distance travelled, and low-carbon travel, measured as the proportion of trips by low-carbon travel modes in all trips for each group. Low-carbon travel mode refers to walking, cycling (including electronic cycles), bus, and subway. In addition, CO_2 emitted from each individual's daily travel is estimated based on a complete account of travel activities during the day, derived from the survey. This is calculated from travel distance by travel mode and mode specific CO_2 emission factor, as:

$$CARBON = \sum_{i=1}^{m} Distance_i \times Factor_i \tag{5.4}$$

where, *CARBON* refers to individual CO_2 emission from urban travel on a typical workday, $Distance_i$ is the distance travelled in trip i during the day, m the number of trips made during the day, and $Factor_i$ the emission factor associated with the travel mode used in trip i (in tonnes of carbon dioxide per person kilometre travelled).

5.4.1 Emission factor

No commonly agreed set of emission factors (EF) exists for all travel modes used in the Chinese urban context. Most studies on transportation-related CO_2 emissions are performed on aggregate levels and do not provide estimates of carbon dioxide emissions on a person · kilometre scale for each of the urban transportation modes. No official report has been published in China on CO_2 emission factors for all transportation modes on a person · kilometre scale. Thus different emission factor estimates are used by Chinese scholars (Zhao et al, 2009; Jiang et al. 2011; Qin and Han, 2013). Table 5.2 lists the Energy factor and Carbon intensity adopted in a recent Chinese study (Guo et al., 2013). From these data we can calculate a Modified CO_2 EF and a Direct CO_2 EF, respectively:

$$\text{Modified } CO_2 \text{ EF} = \text{Energy factor} \times \text{Carbon intensity} \tag{5.5}$$

$$\text{Direct } CO_2 \text{ EF} = \text{Modified } CO_2 \text{ EF} / \text{Passenger capacity} \tag{5.6}$$

The Direct CO_2 EF only addresses direct CO_2 emissions from fuel combustion by a vehicle during a trip, while the Total CO_2 EF, derived from an EU's TREMOVE baseline model, takes into account both these direct emissions plus lifecycle emissions from the manufacturing of the vehicle fuel (European Commission, 2006; cited from Grazi et al., 2008). Comparing the Direct CO_2 EF and Total CO_2 EF shows that, the EU-TREMOVE model presents quality estimations of emission factors for all urban transportation modes concerned in this study. Besides, this model includes both the direct and indirect carbon emission during the lifecycle and provides the emission factor for the most complete list of urban travel modes on a person · kilometre scale.

Table 5.2: Energy factor and CO_2 emission factor for different transportation modes

Transportation mode	Energy factor (MJ/km)	Carbon intensity (t/TJ)	Modified CO_2 EF [a)] (g/km)	Passenger capacity [b)]	Direct CO_2 EF (g/person/km)	Total CO_2 EF [c)] (g/person/km)
Car	2.962	69.3	205.3	1.4	146.4	178.6
Bus	10.680	74.1	791.4	18	43.9	73.8
Taxi	2.673	69.3	185.2	1.2	154.2	178.6
Motorcycle	0.612	69.3	42.4	1	42.4	113.6
Electric bike	0.076	--	--	--	--	69.6
Subway	--	--	--	--	--	9.1

a) EF represents emission factor; b) derived from Jiang et al. (2011); c) cited from Grazi et al., (2008)

Emission factors for the majority of vehicles in China are however expected to be increasingly comparable to those of European countries, as the dominant vehicle manufacturing technologies in China stem from Europe and the vehicle emission regulations implemented in Beijing are emulating the historical development and adoption of the EU standards (Cai and Xie, 2007; Darido et al., 2013). On January 1, 1999, the Beijing Environmental Protection Bureau (EPB) introduced emission standards for vehicles by adopting the Euro 1 standard for light-duty vehicles (Hao et al., 2006), first adopted in Europe in 1993. This first-ever emission standard implemented in Beijing resulted in a dramatic decrease in permitted emissions for new vehicles (Wu et al., 2011). The increasingly tighter Euro 2 – Euro 4 standards were introduced to Beijing between 2003 and 2008 (Table 5.3), only three years behind their adoption in Europe. These regulations have been the most important control measures on vehicle emission in Beijing, and, as a consequence of their accelerated introduction (relative to Europe) and the turnover of the vehicle fleet, fleet weighted emission factors are little different to those now observed in Europe.

Table 5.3: Summary of EU emission standards implemented in Beijing

Vehicle type	Euro 1	Euro 2	Euro 3	Euro 4
Light-duty gasoline vehicle	1999-1-1	2003-1-1	2005-12-30	2008-3-1
Heavy-duty gasoline vehicle	2002-7-1	2003-9-1	2009-7-1	--
Heavy-duty diesel vehicle	2000-1-1	2003-1-1	2005-12-30	2008-7-1
Motorcycle	2001-1-1	2004-1-1	2008-7-1	--

Nonetheless, with respect to CO_2 emission estimation for Beijing, there remains uncertainty in the aggregate emission factors, mainly due to uncertainty over the composition of the vehicle fleet, because regulated emissions vary for every vehicle dependent upon factors such as vehicle class, engine size, weight and age, and because a range of other factors mean that actual emissions may differ substantially from the regulated emission standard. For example, cold start condition, road slope and condition, and travel speed and driving style are all important additional determinants on emissions and hence actual EF for individual vehicles, and hence the fleet as a whole. Of these, speed is perhaps the most significant, as vehicles have highest emissions at very high and low speeds (e.g. a motorway, or in congested traffic respectively) (Yan and Crookes, 2010), so that vehicle specific EFs display a characteristic U shape indicative of speed dependent emission. Whilst such factors may be incorporated into microsimulation models of traffic flow, more aggregate traffic models tend to address these factors through the aggregate EFs – that is EFs are determined through observation of typical drive cycles (that include variable speeds, cold start etc). This more aggregate approach is quite suitable for the determination of CO_2 emission, whose impacts are important at the strategic scale, although it is not ideal where finely resolved spatio-temporal emission estimates are needed, as in, for example, air quality modelling.

Unlike many developed countries which release vehicle-use data regularly, China does not officially publish such data, possibly due to the restriction of data access and relatively short history of motor vehicle development (Huo et al., 2012). Therefore, the analysis presented in this chapter makes use of fleet-averaged emission factors taking no consideration of travel speed variation on CO_2 emission in 2000. However, for the projection of carbon emissions in the future (Chapter 6), reduction in fleet weighted EF is addressed, recognising the impact of the fleet turnover, as older, less efficient vehicles are retired, and replaced by new vehicles that adhere to the latest emission factor standards (e.g. EU 5 and 6 too).

5.4.2 Comparison analysis

Table 5.4 compares travel behaviour and modelled CO_2 emission for different constraining attributes. Males, young people, people with high educational attainment, the employed, and workers in companies or factories have a lower tour frequency and take fewer trips during the day. However, they generally travel further, have a lower percentage of low-carbon travel and so emit more CO_2 on a typical workday. Females, old people (aged 60+), people with low educational attainment, and the unemployed make more trips but these are generally shorter with a higher percentage of low-carbon travel and so emit less CO_2 than their counterparts.

With respect to the household-level constraints, it shows that people with a smaller home have a higher tour frequency and take more trips than their counterparts.

However, they do not travel as far, and have a higher proportion of low-carbon travel, and so generate less CO_2. Regarding the housing tenure variable, although the two groups do not show significant difference in travel characteristics, the renters generally have lower CO_2 emission than their counterparts on a typical workday. One-way ANOVA shows the difference in travel behaviour and CO_2 emission between most constraining groups is statistically significant (p value < 0.05).

Table 5.4: Mean value of travel variables and CO_2 emission by constraints

Household and individual Socio-demographic attributes		Tour frequency	Number of trips	Distance travelled (km)	Percentage of low-carbon travel	CO_2 emission (kg)
Gender	Male	1.36	3.24	23.64	80.18%	2.31
	Female	1.44	3.42	19.25	90.16%	1.46
	F value (*p*)	3.51(0.06)	3.31(0.07)	6.36(0.01)	- -	14.86(0.00)
Age	15-29	1.11	2.64	28.14	85.35%	2.10
	30-39	1.26	3.06	26.39	72.89%	2.65
	40-49	1.46	3.47	20.76	84.06%	2.01
	50-59	1.61	3.78	14.92	93.79%	1.17
	60+	1.74	4.04	11.27	96.24%	0.66
	F value (*p*)	29.67(0.00)	23.79(0.00)	12.16(0.00)	- -	9.29(0.00)
Education	Primary	1.61	3.63	14.37	97.71%	0.79
	Secondary	1.54	3.59	15.51	93.31%	1.07
	Tertiary	1.31	3.17	25.11	79.12%	2.41
	F value (*p*)	20.05(0.00)	9.58(0.00)	15.76(0.00)	- -	20.03(0.00)
Employment	Employed	1.29	3.12	25.09	81.05%	2.33
	Jobless	1.53	3.41	14.18	91.62%	0.81
	Retired	1.82	4.15	9.45	97.78%	0.42
	Other	1.33	3.17	19.60	77.19%	1.85
	F value (*p*)	38.58(0.00)	24.06(0.00)	18.25(0.00)	- -	17.05(0.00)
Occupation	Students	1.07	2.49	22.70	94.12%	1.43
	Worker TP1	1.41	3.37	19.92	83.93%	1.78
	Worker TP2	1.20	2.95	30.31	76.63%	2.95
	F value (*p*)	16.22(0.00)	12.59(0.00)	10.65(0.00)	- -	8.88(0.00)
Housing tenure	Owner	1.39	3.33	22.18	83.91%	2.03
	Renter	1.43	3.34	19.27	89.49%	1.44
	F value (*p*)	0.69(0.41)	0.03(0.87)	2.18(0.14)	- -	5.70(0.02)
Housing area (m^2/capita)	<30	1.44	3.41	19.31	89.50%	1.51
	30+	1.33	3.17	25.64	76.47%	2.61
	F value (*p*)	6.43(0.01)	5.30(0.02)	11.82(0.00)	- -	22.32(0.00)

Note: As the percentage of low-carbon travel is calculated by group rather than by individual, the ANOVA analysis for this variable is not conducted and its F value (*p*) is displayed as "--".

5.5 Results of the spatial microsimulation

Optimising the population reconstruction process with the Total Absolute Error statistic, the FMF software was used to link the attributes across the different data sources and create realistic synthetic populations in 2000 for urban Beijing. The synthetic population reconstruction was undertaken at the fine sub-district geography and contains 721,894 individuals aged 15 or over.

5.5.1 Sensitivity analysis

The simulated annealing approach is stochastic therefore a sensitivity analysis was conducted to test whether the output is sensitive to the randomised number (seed value) in the software. The range of synthetic datasets produced is to determine whether the algorithm is reaching a global optimal solution despite the random seed being changed (effectively altering the simulated annealing algorithms starting position in the possible search space). The nature of the simulated annealing algorithm means that it will examine a wide area of the available search space to configure the synthetic population. The sensitivity analysis conducted here is to ensure that the parameters controlling the amount of 'work' the algorithm undertakes are sufficiently set to allow a globally optimal solution to be reached for each population. If the algorithm input parameters are too restrictive, suboptimal solutions will be produced resulting in wide discrepancies between the 146 zones over the resulting synthetic populations. The variation in results would likely manifest over a smaller number of populations, 5 may suffice, however 10 was deemed to be appropriately robust while not being overly wasteful of computing, storage or analysis resources.

This study generated 10 synthetic populations using different seed values and calculated the standard deviation of the constrained output attributes. By and large, the standard deviation for the constraining attributes (e.g. gender, age, education) is close to zero in almost all of the sub-districts. For example, Figure 5.1 illustrates the standard deviation of education for each geographic zone. It can be seen that the standard deviation is zero in most of the sub-districts, indicating that the distribution of people with different education levels is exactly the same for each area despite the variation in seed value, hence the optimisation process is working effectively and the output is not sensitive to the randomised seed value. However, four geographical zones do exhibit a high standard deviation in the primary and tertiary education categories while the secondary education category remains consistent. This indicates that the Simulated Annealing optimisation algorithm is not able to correctly configure the education constraint for these four zones in a consistent manner.

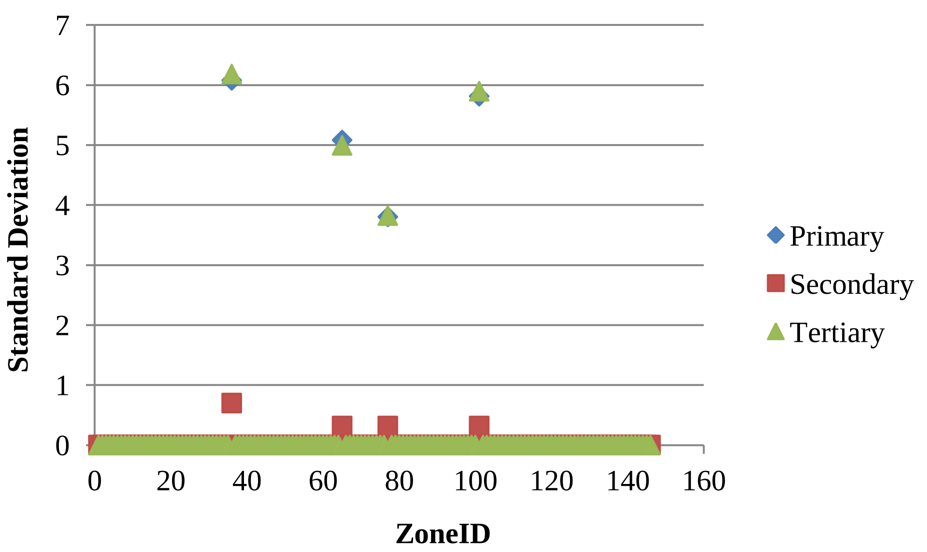

Figure 5.1: Standard deviation of education for each geographic zone

Using attributes from the travel survey data for the 10 resulting reconstructed populations the standard deviation of people's average trip frequency and daily travel distance is also computed for each sub-district, respectively. It shows that the standard deviation of trip frequency is less than 0.05 in most sub-districts (Figure 5.2) and the standard deviation for travel distance is also relatively small, less than 0.8 in most sub-districts (Figure 5.3), demonstrating that the optimisation process is robust and that the results are not sensitive to the initial seed value. The four districts with large standard deviations in the education constraint discussed above show very small variation for average trip frequency or daily travel distance. This suggests that despite the variation within the education constraint the impact on the final simulated daily travel attributes is not large.

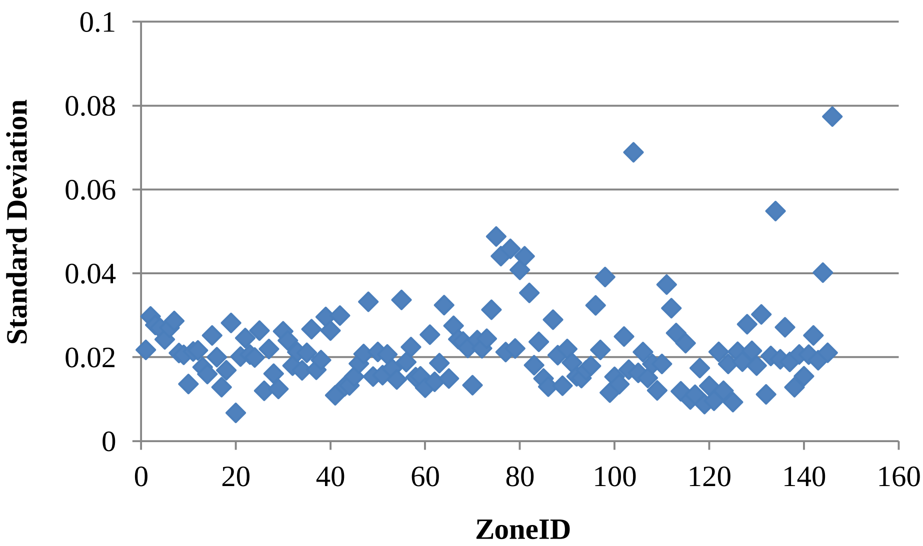

Figure 5.2: Standard deviation of trip frequency for each geographic zone

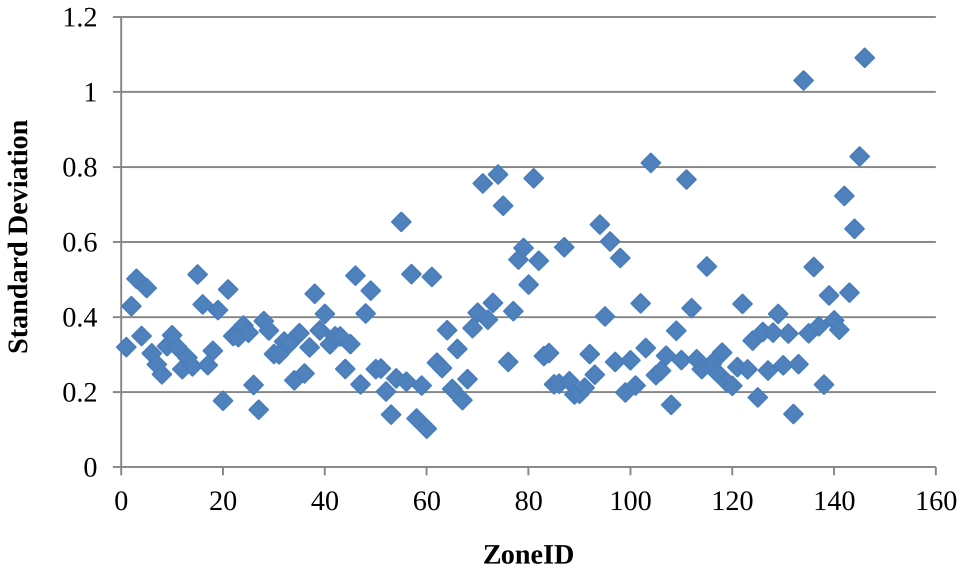

Figure 5.3: Standard deviation of travel distance for each geographic zone

5.5.2 Constraint evaluation

A reconstructed population from the ten generated was selected at random for comparison to observed aggregate data. Table 5.5 shows the goodness-of-fit evaluation statistics, which demonstrate a very close match to the observed census data within the reconstructed population. Most of the constraining tabulations and cross-tabulations at the sub-district level are reproduced with very little or no misclassification. The highest level of misclassification is seen in the education constraint where the TAE is more than 1,000 although the percentage error (PE) is less than 0.1%, which is still a very good overall fit (Harland et al., 2012).

Table 5.5: Representation of the model constraints at the sub-district level

Constraints	SRMSE	TAE	PE	TE	CPE
Gender	0.001	74	0.005	37	0.010
Age	0.002	82	0.006	41	0.011
Age by Gender	0.003	82	0.006	41	0.011
Education	0.014	1260	0.087	630	0.175
Employment	0.000	2	0.000	1	0.000
Occupation	0.000	2	0.000	1	0.000
Employment by Occupation	0.000	2	0.000	1	0.000
Housing tenure	0.000	0	0.000	0	0.000
Housing area	0.003	192	0.013	96	0.027

It is worth noting that the education constraint was the most variable constraint in the sensitivity analysis conducted above, and it is clear that there is some difficulty with representing this constraint for a small number of geographical areas. This is possibly due to the specific geo-demographics in these zones (i.e. most individuals have low educational attainment). However, it has also been shown that the variability of the education attribute across a small number of zones has little impact on the resulting travel attributes estimates; therefore the underlying cause of the variability will not be explored any further here.

5.5.3 Spatial Simulation of urban travel and CO_2 emission

The next stage involved linking the travel data to the microsimulated synthetic population and both spatially simulating the population's travel behaviour, and estimating their transport CO_2 emissions, at the sub-district geography for urban Beijing. Figures 5.4 – 5.7 show, by quartile, the average distance travelled, percentage of low-carbon travel, average and total CO_2 emission for each sub-district.

The average simulated travel distance of the synthetic population in urban Beijing is approximately 20 km per person per day in 2000, compared to 22 km reported by an independent government household travel survey (Beijing Transportation Research Centre, 2002). This latter survey excludes walking trips and will thus be an overestimate of average travel distance across all modes, the travel metric which was adopted.

The simulation thus provides a good agreement with observed travel behaviour. Note that the average distance travelled by sub-district varies substantially around this city wide average. Figure 5.4 shows that people resident in the central urban zone (Xicheng, Dongcheng, Xuanwu, Chongwen) do not travel as far on a typical workday, whilst people resident in the inner suburban zone, particularly some sub-districts of Haidian and Chaoyang, travel further, more than 20 km per person per day. This may be due to the difference in urban form features across these areas. The traditional urban space in inner city Beijing is characterised by its high population density, mixed land use, and proximity to services, while most suburban areas, built after the 1978 economic reform, adopted western planning ideas prevalent at the time, and so developed housing in single-use, lower density and car-oriented neighbourhoods. This contrast in urban form is identified in prior observations of travel behaviour and CO_2 emissions for Beijing (e.g. Qin and Han, 2013).

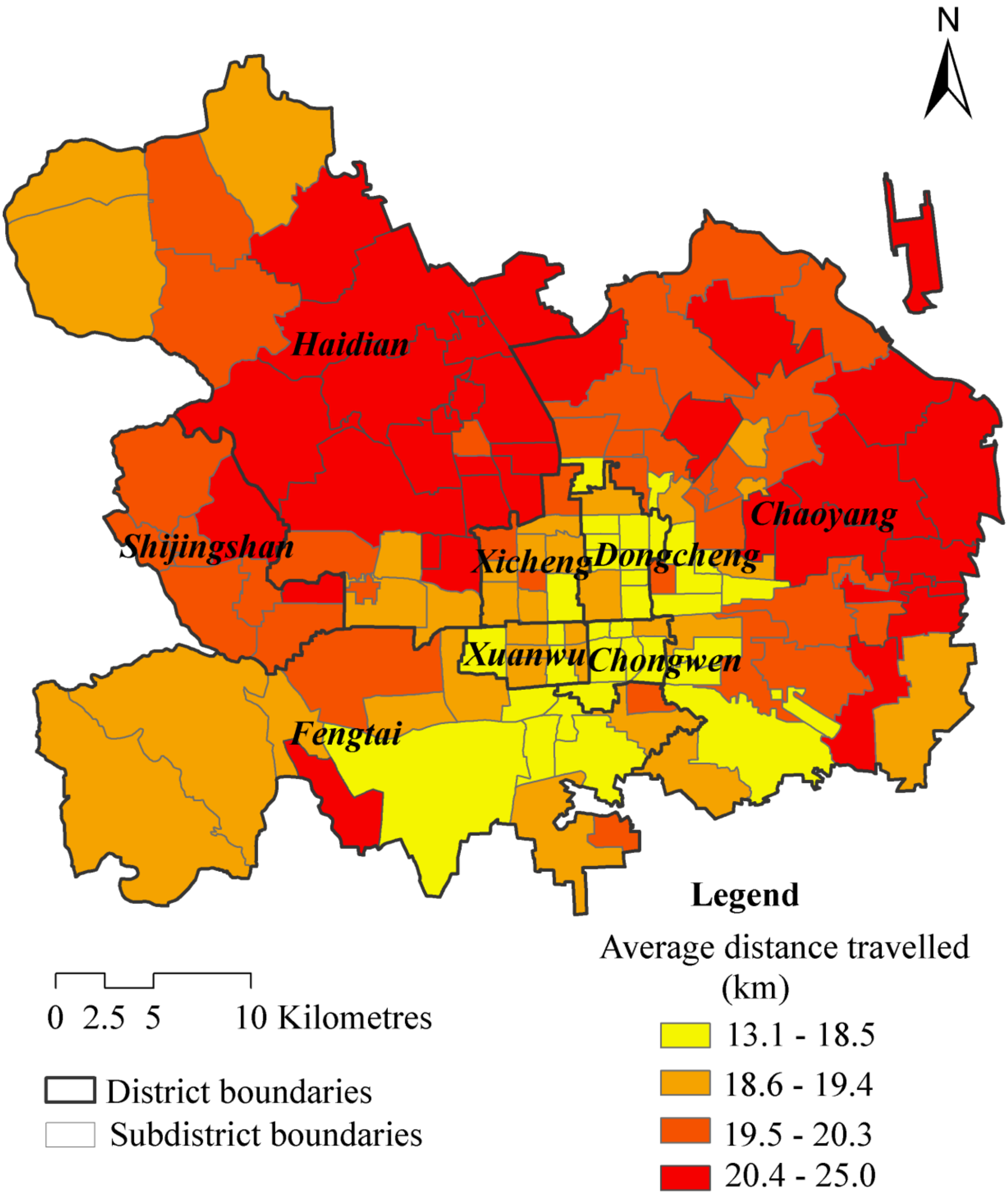

Figure 5.4: Average distance travelled by the synthetic population in each sub-district

The mode choice analysis (Figure 5.5) shows the variability in low-carbon travel mode (walk, cycle, bus, subway) by area. On average, about 90% of trips in urban Beijing are made by low-carbon transport modes; this is in good agreement with the observed 88% share reported by the Beijing Transportation Research Centre (2002) survey. This simulation is also in close accord with the 90% value reported in a household interview survey conducted in the eight urban districts of Beijing in 2001 by Zhao et al. (2011). Some geographical variability can be observed. Residents of northern inner-suburban zones have a lower share of low-carbon travel, with more than 10% of trips here made by car, whilst car travel is lower in the central urban and peripheral urban zones; here more than 93% of trips are made by low-carbon modes.

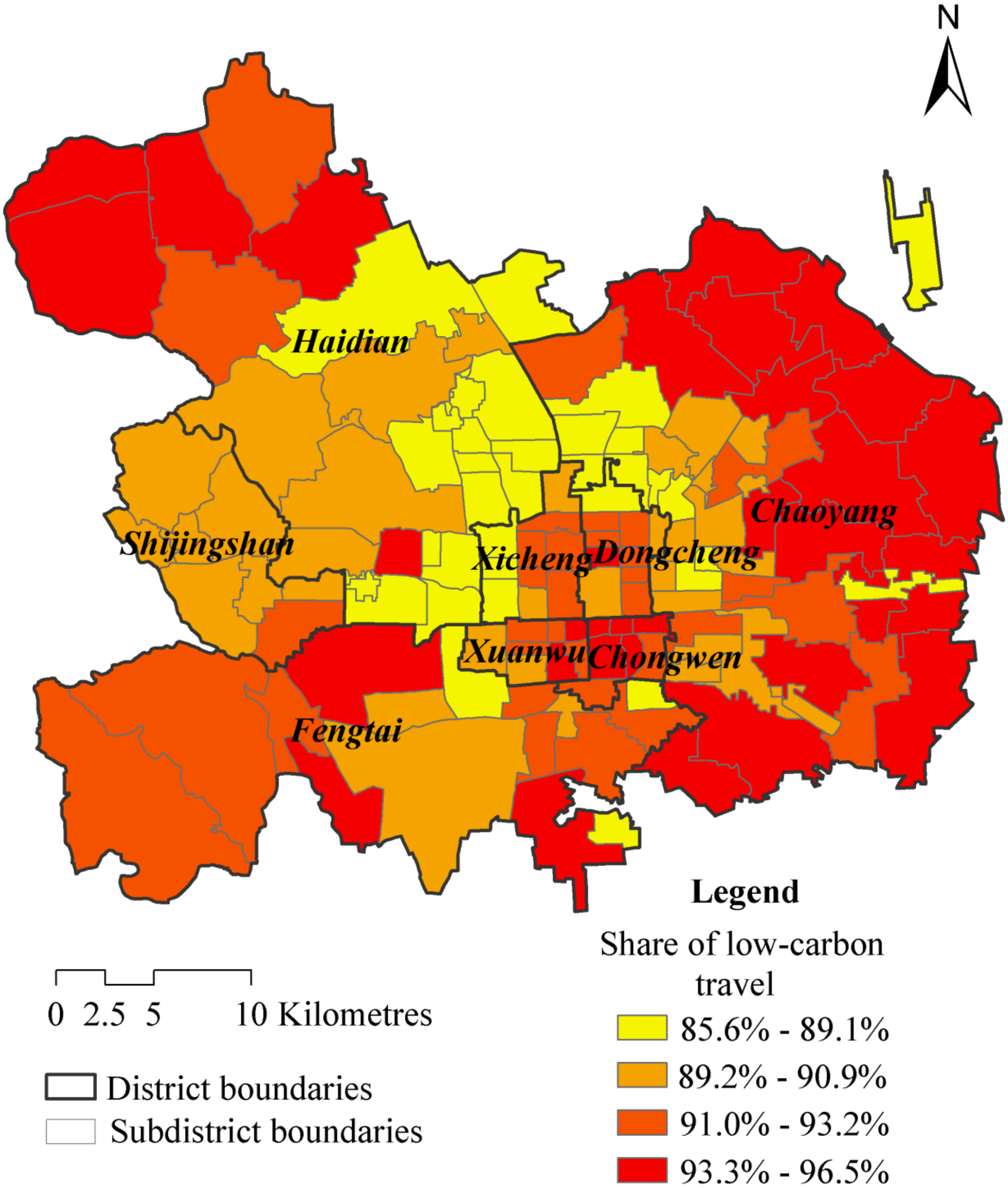

Figure 5.5: Share of low-carbon travel by the synthetic population in each sub-district

The next stage involved estimating the average CO_2 emission from the synthetically constructed population for each sub-district (Figure 5.6). On average, the transport CO_2 emission from people's daily travel in urban Beijing is 1.44 kg per person per day. People resident in most of Haidian and northwest Chaoyang sub-districts have higher CO_2 emission (>1.55 kg per person per day), as people resident here travel further and make greater use of the car. In contrast, residents of the more compact central urban area have lower CO_2 emission.

Multiplying the total population by the average CO_2 emission for each geographical zone, the total mass CO_2 emission across the urban sub-districts of Beijing can be estimated (Figure 5.7). The total emissions for many sub-districts in the inner suburban area is much higher than that in the central urban area, although the population density in the central area in relatively high. The peripheral zones in the inner suburban area, particularly in northwest Haidian and east Chaoyang, have a much lower total emission, mainly due to their low population density. However, if current trends of suburbanisation and rising car ownership continue (Zhao et al., 2011), the total CO_2 emissions in the peripheral zones is likely to increase substantially. These types of questions can be effectively examined by future microsimulation work, in particular through investigating population growth over time under a variety of different scenarios.

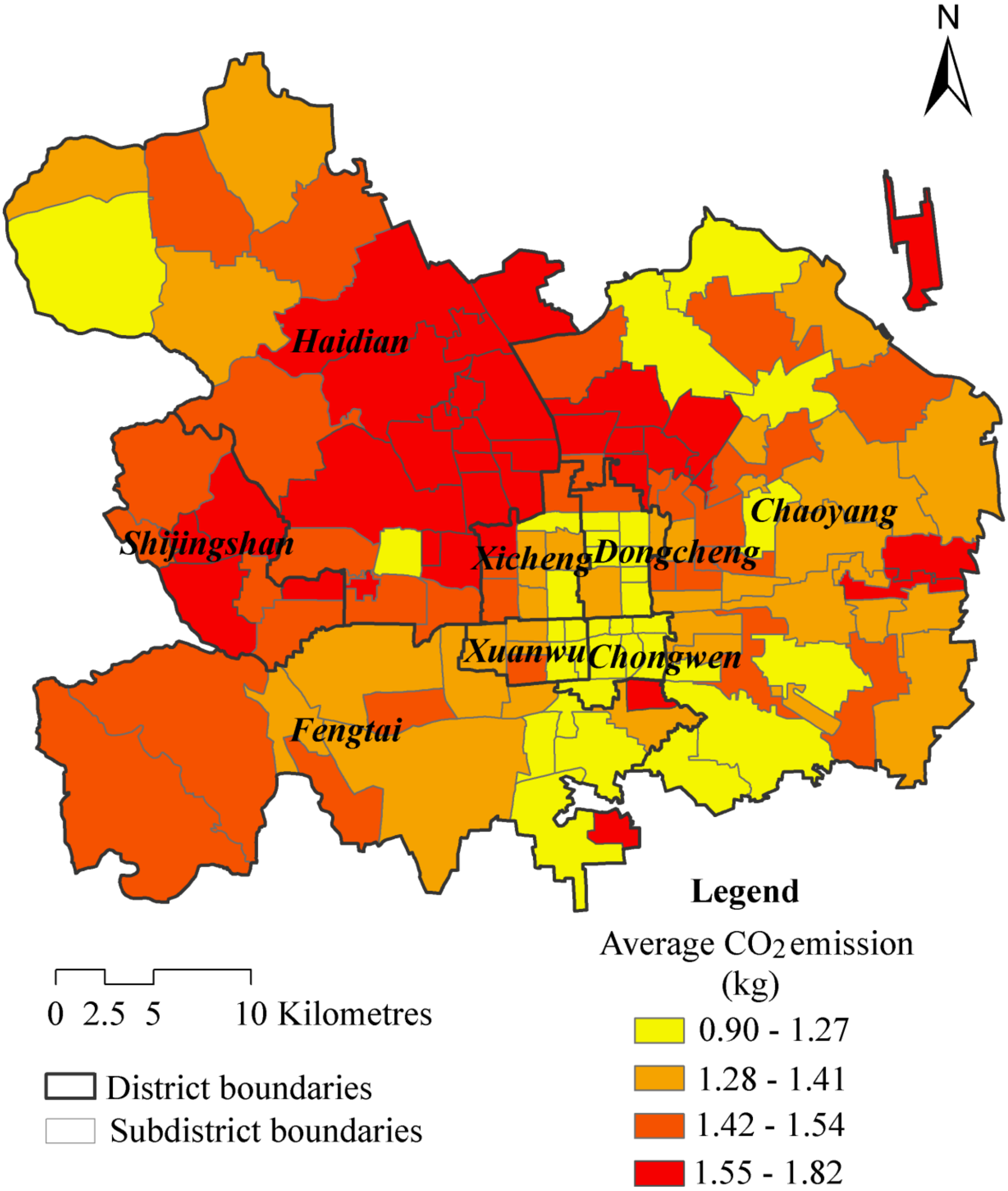

Figure 5.6: Average CO_2 emission from the synthetic population in each sub-district

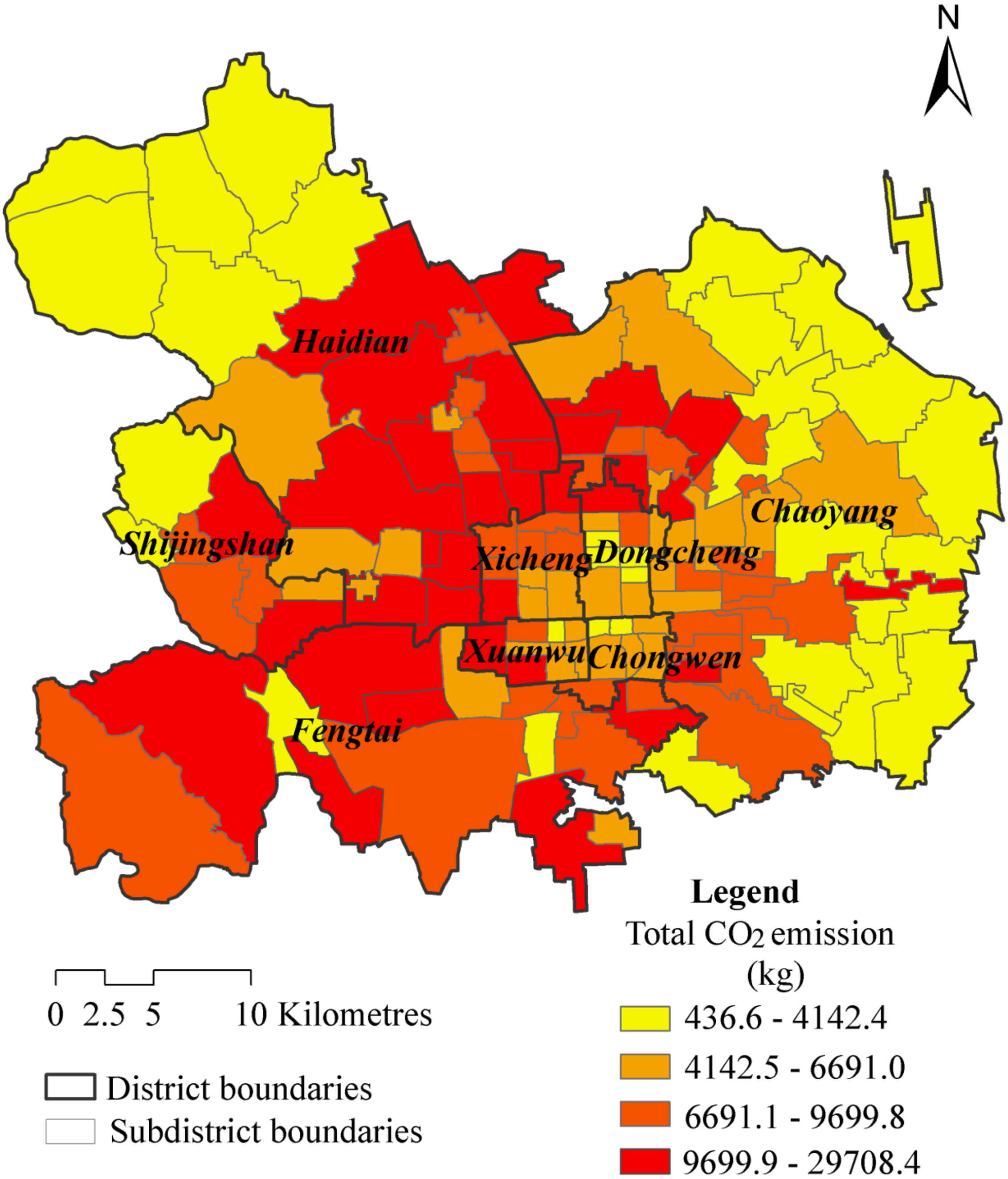

Figure 5.7: Total CO_2 emission from the synthetic population in each sub-district

5.6 Discussion and conclusion

5.6.1 Socio-economic indicators

In prior research, transport CO_2 emissions are usually related to the economic growth level of a region and linked with socio-economic indicators (e.g. GDP, per capita GDP, per capita disposable income) to assess the city- or district-level transport CO_2 efficiencies (e.g. Timilsina and Shrestha, 2009; Cai et al., 2012). The "*CO_2 efficiency*" is defined based on the eco-efficiency concept, which is "*the product or service value per environmental influence*" (Tahara et al., 2005). Some critical aspects of CO_2 efficiency include CO_2 emissions per GDP, CO_2 emissions per capita per GDP, and CO_2 emissions per capita vs. per capita disposable income. Although the relationships between transport CO_2 emission and socio-economic indicators were examined in several prior studies, their conclusions remain controversial. For example, Timilsina and Shrestha (2009) indicated GDP and per capita GDP are strongly correlated with transport CO_2 emissions in China, while other researchers suggested the relationship between transport CO_2 emissions and per capita GDP was insignificant (Cai et al., 2012).

Based on the simulation results of transport CO_2 emission from urban travel, this section further discusses the correlations of socio-economic indicators and transport CO_2 emission in urban Beijing. However, as the economic indicators, like GDP, or per capita GDP, are only published at the district level, there needs to be an aggregation of the total CO_2 emission from people's daily urban travel into the district level (Figure 5.8). The CO_2 emission in Haidian district is the highest, about 310 tonnes on a typical workday, followed by Chaoyang district with approximately 280 tonnes. In contrast, the districts in the urban central area, i.e. Dongcheng, Xicheng, Chongwen, and Xuanwu, have lower CO_2 emission from people's daily urban travel. In total, transport CO_2 emission estimates from the synthetic population (aged 15 and above, about 10% sample of the total urban population) peek at 1,038 tonnes on a typical workday in urban Beijing for the year 2000.

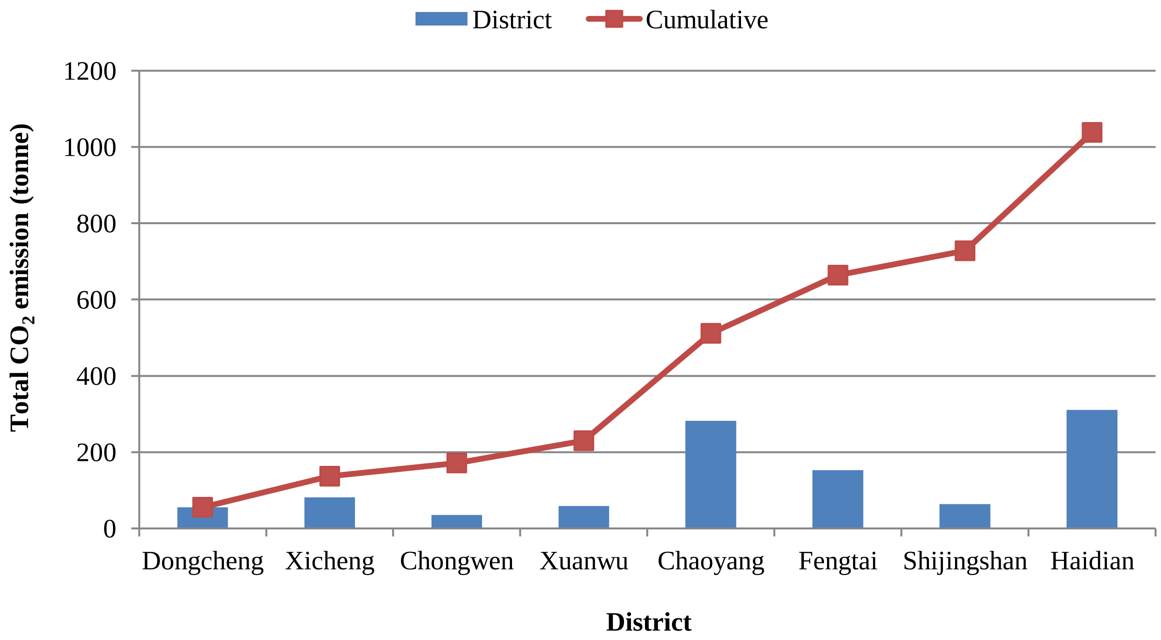

Figure 5.8: District CO_2 emission and the cumulative total in 2000

Using data from the Beijing Statistic Yearbook, a regression analysis of transport CO_2 emission and some socio-economic indicators is conducted. As illustrated in Figure 5.9 (Left), the relationship between transport CO_2 emission and GDP is statistically significant ($p = 0.010$, $R^2 = 0.698$). China's economic development mainly depends on industrial production, export, and infrastructure construction (Cai et al., 2012), and transport CO_2 emission is indicated to be influenced by the intensity of economic production activities. The relationship between transport CO_2 emission and total urban population in each district is also significant (p = 0.000, R^2 = 0.986), as shown in Figure 5.9 (Right).

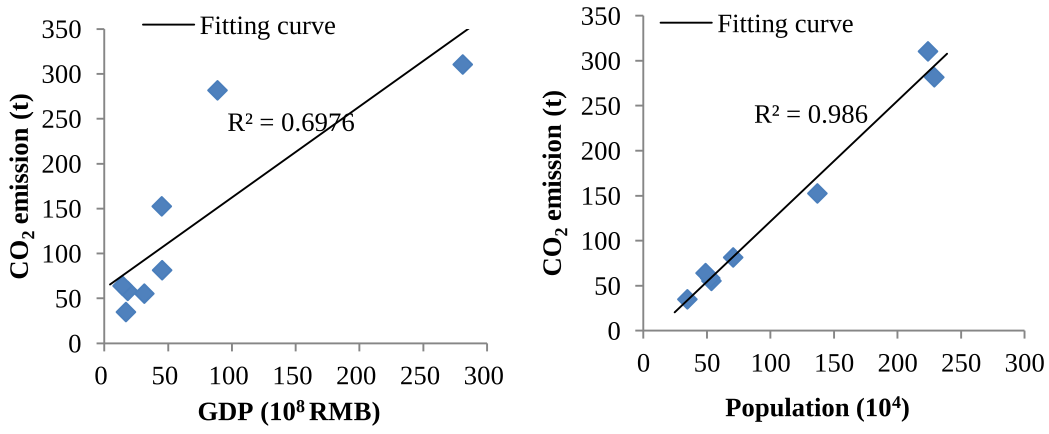

Figure 5.9: Regression between transport CO_2 emission and GDP (Left) and population (Right)

In contrast, as shown in Figure 5.10, the relationship between transport CO_2 emissions and per capita GDP is not significant (p = 0.174, R^2 = 0.283), which indicates the potential driving forces of transport CO_2 emissions are the production activities rather than consumption activities. Moreover, the transport CO_2 emissions from people's daily travel are affected by the car usage. We also analysed the regression between transport CO_2 emissions and residents' income, as the share of car owners might increase with the increase of people's disposable income. However, such relationship is not significant (p = 0.146, R^2 = 0.317), which signifies per capita disposable income of urban residents is not the main factor of transport CO_2 emissions.

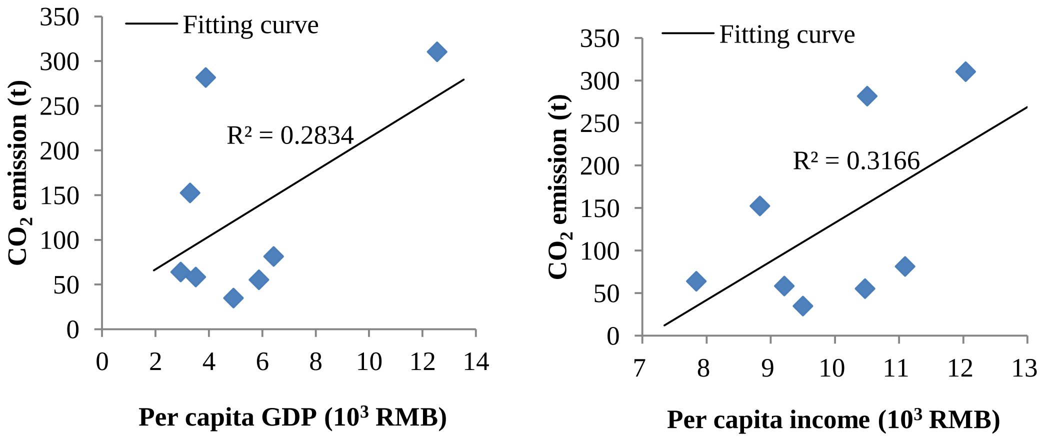

Figure 5.10: Regression between CO_2 emission and per capita GDP (Left) and per capita disposable income of urban residents (Right)

5.6.2 Conclusion

Using an activity diary survey and the fifth population census in 2000, this chapter first creates a representative and realistic synthetic population at a fine geographic scale in urban Beijing. It then spatially simulates the synthetic population's daily travel behaviour, including travel distance and mode choice, and estimates the average and total transport CO_2 emission from urban travel across different geographic zones. This work contributes to the spatial microsimulation application at the micro-spatial scale in geography and transport fields in developing countries, where such research is very scarce.

The microsimulation results show that people resident in the inner suburban zone, particularly in most Haidian and Chaoyang sub-districts, travel further, make fewer low-carbon trips, and emit more carbon per workday than average. In comparison, residents in the central urban zone, characterised by a high population density, mixed land use, and high accessibility to services and public transit, adopt lower carbon travel behaviour. Whilst these results are particularly relevant to Beijing, the wider point is that this study has demonstrated how it is possible to simulate urban travel for a developing country mega-city, in a manner that allows credible estimation of geographically resolved transport carbon emissions. Microsimulation has allowed us to create a realistic and representative synthetic population at a fine geographic scale, and to spatially simulate that population's daily travel, including distance travelled by mode, and hence estimate transport CO_2 emission by sub-district, and for the city.

This has been achieved using limited data, a travel diary survey, and a sample population census. China has no national travel survey, and Beijing municipal government travel surveys have only published results at aggregate level (confidentiality issues may constrain release of more individual level data). It has thus drawn upon travel diary data that is a rather modest data set considering the scale of Beijing. Furthermore, the population data which has been drawn upon is a 10% sample of the city population. However, the simulated annealing algorithm applied here has been used to synthesise the city's population in its entirety, and its travel behaviour in a manner that closely reflects travel behaviour reported at the aggregate level, in the municipal government's 2000 travel survey, and a further independent survey. This is the first time that microsimulation has been used to overcome the data deficiencies (a general absence of data) that often act as a barrier to spatial analysis of travel behaviour, and hence low carbon city planning, for any mega-city in the developing economies.

The analysis represents a sophisticated spatial microsimulation of people's daily travel and associated transport CO_2 emission, which can be served as a solid basis for low carbon city planning, or transport policy evaluation for mega cities in the developing economies. It also presents opportunities for dynamic microsimulation or scenario analysis in the future. On the basis of the work conducted here, the next chapter further dynamically simulates people's travel behaviour and estimate their, and the city's, future carbon emission. Scenario analysis is also conducted to explore how changes in people's daily travel behaviour (e.g. mode shift, tour frequency, or travel distance) may impact upon aggregate travel behaviour and transport carbon emissions. By considering different policies, in terms of private vehicle usage, land use mix, accessibility to public transit, and vehicle technology, it would also be possible to examine planning interventions that are relevant to the development of more sustainable and low-carbon urban development in China.

Chapter 6

Exploring Transport Carbon Futures in Beijing to 2030

6.1 Introduction

This chapter uses the bottom-up methodology presented in Chapter 5, to provide improved transport CO_2 emission estimates from people's daily urban travel in Beijing to 2030. Building on analysis of an activity diary survey and demographic data from the 2010 population census (as described in Chapter 3), first, spatial microsimulation is employed to simulate a realistic synthetic population's daily travel behaviour and to estimate their CO_2 emission at a fine geographic resolution in 2010 for Beijing. This chapter then compares and analyses the changes in travel behaviour and transport CO_2 emission over the decade 2000-2010, and examines the role of socio-demographics and change in urban form in contributing to the modelled trend.

Next, the transport CO_2 emission from passenger travel behaviour is projected to 2030 under four scenarios, to illustrate the utility of the approach. Within this work, scenario is defined as "an internally consistent view of what the future might turn out to be – not a forecast, but one possible future outcome" (Porter, 1985). This usually involves a range of "what if?" questions to define some possible future conditions. The typical scenario planning process compares one or more alternative future planning scenarios to a trend scenario, which is often referred to the "Business As

Usual" scenario (Bartholomew and Ewing, 2009). The general approach for scenarios in urban and transport modelling is to model the process over a recent past time period and then, (after calibration and validation), project that into the future (20-50 years ahead), with the scenarios reflecting the states (or combination of states) that the independent variables in the models could take.

For instance, He et al (2005) estimated the historical (1997-2002) oil consumption and carbon emission from China's road transport sector and developed three scenarios (non-control, low-fuel, and high-fuel economy improvement scenarios) to project future trends of oil demand to 2030. They found that the oil demand by China's road vehicles will reach 363 million tonnes by 2030 under the non-control scenario; however, with fuel economy improved, the total oil consumption will be reduced by 55-85 million tonnes by 2030. In this chapter, four scenarios (transport policy trend, land use and transport policy, urban compaction and vehicle technology, and combined policy) are developed to explore travel behaviour and transport CO_2 emission under current and potential strategies on transport, urban development and vehicle technology. This will help us better understand the role of various factors on daily travel behaviour and total CO_2 emission, and can inform alternative urban development strategies and policy implications for CO_2 emission mitigation targets set by the national and local governments.

Below, Section 6.2 presents the microsimulation results of transport CO_2 emission in 2010, and analyses the role of socio-demographics and changes in urban form in contributing to the modelled trend over 2000-2010. Section 6.3 presents the measures and parameters of four scenarios concerning transport policies, land use pattern and vehicle technology, to explore the impact of trends and possible management strategies on transport CO_2 emission from people's daily travel to 2030.

The modelling results of average per capita and total CO_2 emissions under the four scenarios are discussed and analysed in Section 6.4, with the sensitivity analysis of the travel parameters provided in Section 6.5. The conclusions of the scenario analysis are summarised in the final section.

6.2 Simulating transport CO_2 emission in 2010

6.2.1 Simulation by socio-demographic attributes

In Chapter 5, the spatial microsimulation was presented to simulate the synthetic population's daily travel behaviour and transport CO_2 emission in 2000. Using the 2000 base case as the starting point, a synthetic population was generated for 2010 using spatial microsimulation. The synthetic population's daily travel behaviour and CO_2 emission are examined across Beijing for 2000-2010. Table 6.1 presents the socio-economic data from the censuses (10% samples), which was used to constrain the microsimulation models. Many of the constraining categories reveal much variation over this period, particularly for people aged 50 and over, those with different education levels, and the employed or retired. It shows that the female population increases by about 3% from 2000-10, while the number of older people (>50 years) grows by c. 6%. People with only a low-level (primary) education accounted for nearly 44% of the population in 2000, but this had fallen to 34% by 2010, whilst those with a high-level (tertiary) education grew by 15%. The share of the employed population decreased by c.4% from 2000-10, and the unemployed, particularly the retired, increased correspondingly. The household-level constraints reveal that the share of housing owners increased by about 2%, with a corresponding decline amongst their counterparts, and that housing area changes little, with a modest increase in floor space per capita. These data are indicative of the dynamic changes taking place in the city over this period.

Table 6.1: Comparing the distribution of constraining variables between 2000 and 2010 census samples

Constraints		2000 Population census		2010 Population census	
Individual-level	*Categories*	*Count*	*Share (%)*	*Count*	*Share (%)*
Gender	Male	379,227	52.53	503,865	50.08
	Female	342,667	47.47	502,171	49.92
Age	15-29	241,159	33.41	327,823	32.59
	30-39	162,300	22.48	195,109	19.39
	40-49	142,009	19.67	178,594	17.75
	50-59	68,672	9.51	148,521	14.76
	>= 60	107,754	14.93	155,989	15.51
Education	Primary	314,669	43.59	343,015	34.10
	Secondary	217,302	30.10	242,569	24.11
	Tertiary	189,923	26.31	420,452	41.79
Employment	Employed	500,782	69.37	662,171	65.82
	Jobless	71,415	9.89	101,667	10.11
	Retired	138,759	19.22	222,757	22.14
	Other	10,938	1.52	19,441	1.93
Occupation	Students	78,294	10.85	93,642	9.31
	Workers TP1	181,548	25.15	267,379	26.58
	Workers TP2	240,940	33.38	301,150	29.93
Total	Individuals	721,894	100.00	1,006,036	100.00
Household-level	*Categories*	*Count*	*Share (%)*	*Count*	*Share (%)*
Housing area (m^2/capita)	<= 29	155,299	61.13	240,207	60.56
	>= 30	98,767	38.87	156,447	39.44
Housing tenure	owner	134,048	52.76	218,226	55.02
	tenant	120,018	47.24	178,428	44.98
Total	Households	254,066	100.00	396,654	100.00

With such changing socio-demographics, it might be expected that aggregate travel distance and transport CO_2 emission will change as people with different socio-demographic attributes have different trip or tour (trip chain) characteristics. For example, male, younger people (e.g. aged 20-39), the employed, and people with high-level education tend to travel further, while female, older people (e.g. aged 60 and above), the retired, and people with only a low-level education tend to travel shorter distances, and have lower CO_2 emissions (Ma et al., 2014a; also see Section 5.4.2). However, the nature of the aggregate changes are not easily seen, due to the complexity of the changing socio-demographics which can result in increases or decreases in travel, depending upon the demographic group in question; thus having more and older women, for example, would potentially act to reduce average travel distances, but the growth in young employed men would counteract this effect. Such heterogeneity (functional and spatial) is readily handled within the microsimulation.

Using the activity survey and census data, the Flexible Modelling Framework (FMF) was used to create a synthetic yet realistic population for Beijing in 2010, constrained by the socio-demographic attributes derived from the 2010 census (Table 6.1). The population synthesis was undertaken at fine geographical scale (the sub-district level) and contains 1,006,036 individuals aged 15 and over across eight districts of Beijing. Table 6.2 shows the goodness-of-fit statistics, which demonstrates a very close match to the observed 2010 census data within the reconstructed population. Most of the constraining tabulations and cross-tabulations at the sub-district level are reproduced with very little or no misclassification, except for the education constraint where the Total Absolute Error (TAE) is more than 2,000, although the Percentage Error (PE) is only 0.1%, which is still a very good overall fit.

Table 6.2: Representation of the model constraints at the sub-district level in 2010

Constraints	SRMSE	TAE	PE	TE	CPE
Gender	0.003	248	0.012	124	0.025
Age	0.005	314	0.016	157	0.031
Age by Gender	0.007	314	0.016	157	0.031
Education	0.022	2026	0.101	1013	0.201
Employment	0.000	6	0.000	3	0.001
Occupation	0.000	8	0.000	4	0.001
Employment by Occupation	0.000	8	0.000	4	0.001
Housing tenure	0.000	0	0.000	0	0.000
Housing area	0.000	0	0.000	0	0.000

Travel attributes (trip frequency, mode, etc.) from the travel survey are then linked to the corresponding demographic groups in the synthetic population, and the population’s daily travel behaviour is simulated spatially for Beijing in 2010. Figure 6.1 illustrates the average travel distance for each transportation mode[8] from the synthetic population across districts. For motorised travel, the average trip distance by subway is highest (c. 21 km per trip), followed by bus, car, taxi, and other transportation modes (e.g. motorcycle). These results are in agreement with the Beijing 2010 household travel survey (Beijing Transportation Research Centre, 2011), which found that people travel furthest by subway, followed by bus and car, with the non-motorised travel shortest (c. 3 km per trip for bicycle). It also reveals some geographical variability. The average trip distance for most transportation modes in the inner-suburban area is longer than in the central urban area, possibly due to differences in socio-demographics, or urban form characteristics, which is a point that is further analysed below.

[8] Walking trips are not shown in the results (the average distance by walking is about 1 km per trip with quite small variation across districts), as this mode is usually excluded in the official transportation survey and report.

However, although the population is synthesised at a fine spatial (sub-district) scale, the simulation results are only presented and compared at the district level. This is mainly because some sub-districts experienced administrative and geographical changes from 2000 (total 146 sub-districts) to 2010 (total 133 sub-districts), and the data of urban form and public/private transport developments to adjust the simulation results (see below) is only available at the district level.

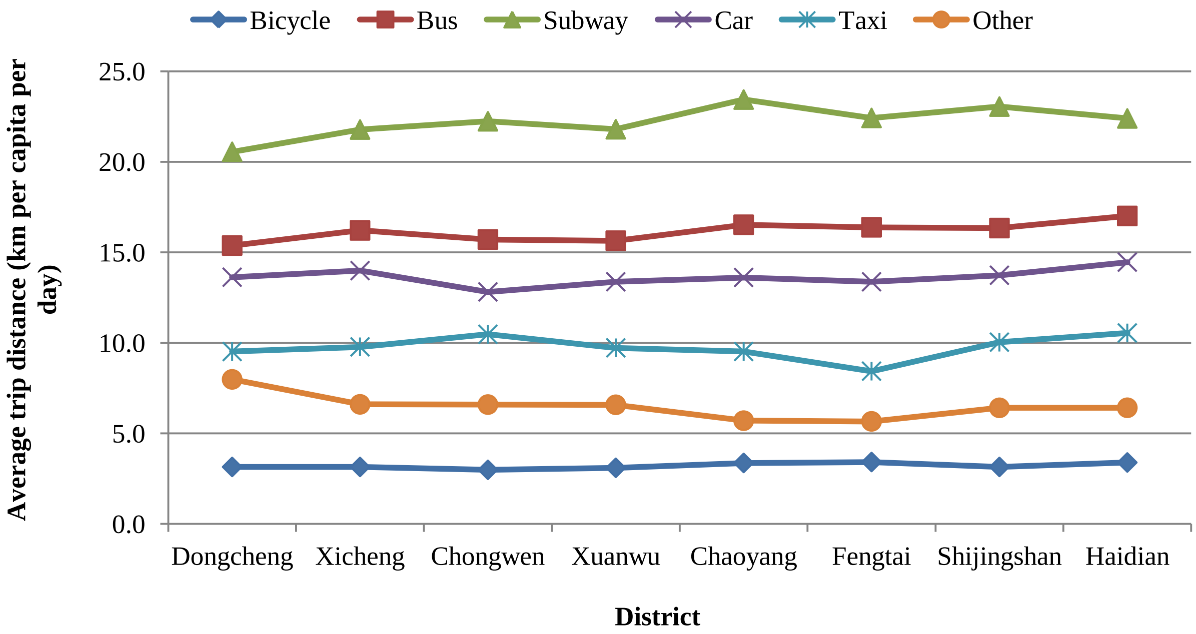

Figure 6.1: Average trip distance for each travel mode made by the synthetic population across urban districts

6.2.2 Adjustment for changes in urban form and transport developments

So far, the microsimulation is only constrained by socio-demographics. However, the simulation needs to be adjusted to account for urban form changes as well as public and private transport development. Each of these factors are known to have had a significant impact on mode choice over the period in question (Zhao and Lü, 2011; He et al., 2013). Beijing's recent growth and urbanisation has been characterised by spatial restructuring within high-tech industry zones and new housing established predominantly in the suburbs. Additionally, employment opportunities arising from the substantial redevelopment of industrial land for tertiary industries has remained concentrated in the inner city, resulting in a spatial mismatch of jobs and housing (Zhao et al., 2010; Wang et al., 2011). This has obvious implications for travel. Using population density as an indicator, it shows that the urban form of Beijing has changed from 2000 to 2010 (Figure 6.2). In 2010, the population density in the central districts (i.e. Dongcheng, Xicheng, Chongwen, Xuanwu) was 23,407 persons/km^2, a 24% reduction since 2000. In the same period density had almost doubled in the suburban area, particularly in Chaoyang (from 4,029 to 7,790 persons/km^2) and Fengtai districts (from 3,626 to 6.907 persons/km^2). This suburban growth has been accompanied by sprawl on Beijing's fringe, characterised by low density development with little mixed use, while the traditional neighbourhoods in the inner city retained their high density and mixed land use (e.g. Figures 3.7-3.8 in Chapter 3).

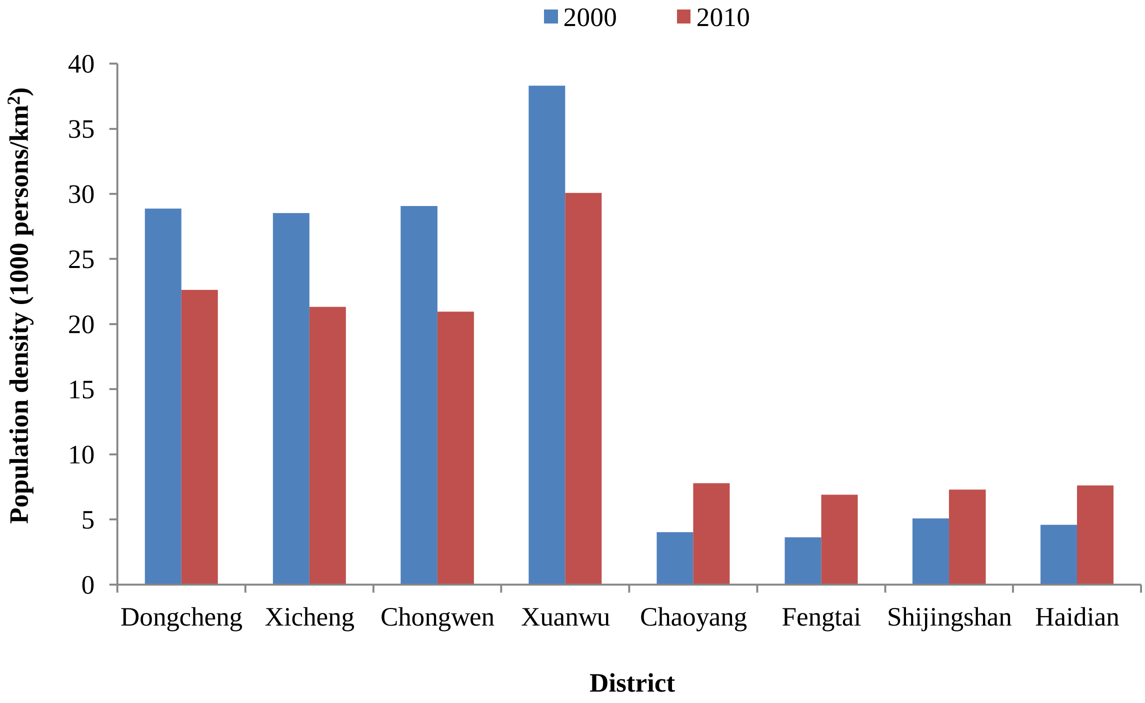

Figure 6.2: Population density in eight urban districts between 2000 and 2010

Public transport has also developed quickly (Figure 6.3); in particular the subway service, which is the focus of municipal policies for encouraging public transport in Beijing. The Beijing subway is the oldest and now busiest in China (Xu et al., 2010), with 16 lines comprising 442 km of track (second in extent only to the Shanghai Metro), compared to only 2 lines and 54 km of track in 2000 (Beijing Statistical Bureau, 2013). However, with urban expansion and rising incomes, motor vehicles ownership has also increased greatly (Figure 6.4), with a greater number of people becoming increasingly dependent on automobiles. Private car ownership doubled to three million over the period 2004-2009, and traffic congestion, air pollution, energy consumption and carbon emission, are now pressing problems in the city (Zhao et al., 2011).

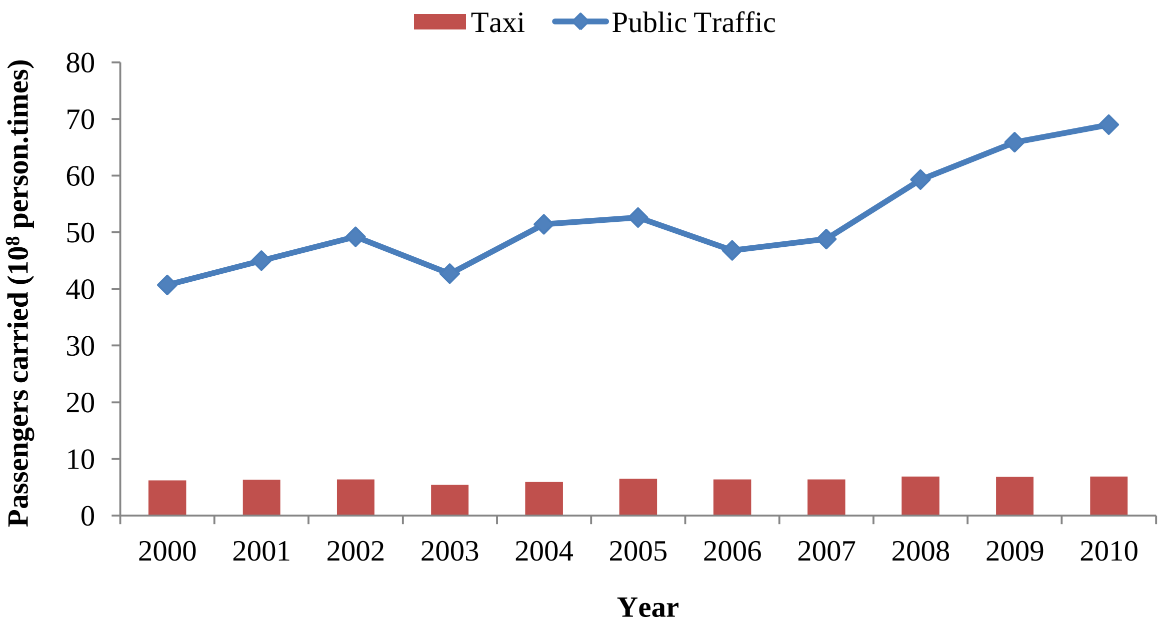

Figure 6.3: Passenger carried by different modes per year from 2000 to 2010

(Source: Beijing Statistical Yearbook 2001-2011)

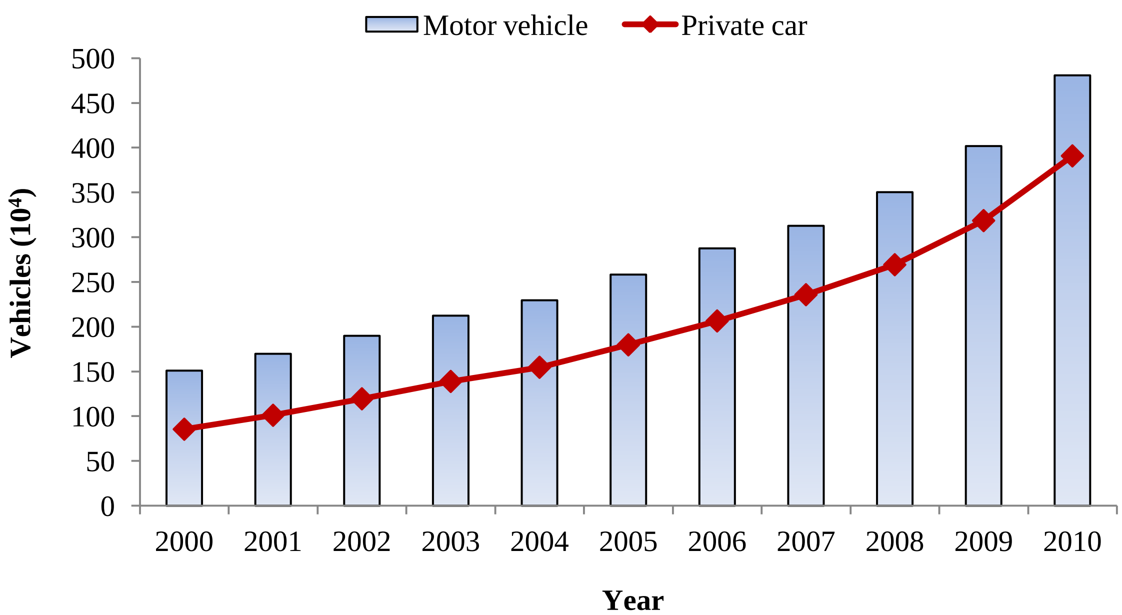

Figure 6.4: The growth of motor/private vehicles in Beijing over 2000-2010

These urban form changes and public/private transit developments are potentially important factors in explaining an elevated preference for motorised travel. To this end, measures were taken to adjust the simulated mode share by bicycle, car and subway. The most significant change to address is the sharp decline in mode share of non-motorised travel (NMT, e.g. bicycle). This decreased from approximately 70% in the early 2000s to 30-40% in the later 2000s in many Chinese cities, with an average fall of 3% per year (He et al., 2013). In Beijing, the NMT share fell by 25% from 2000-10 (He et al., 2013), and this observation is used here to adjust the simulated mode share for bicycle. As actual car ownership (ACO) for each district is available in the Beijing Statistical Yearbook and the simulated car ownership (SCO) can be derived from the microsimulation model, a simple equation is adopted to estimate the modified car share:

$$MCS_i = SCS_i \times (ACO_i / TP_i) / (SCO_i / SP_i) \times 100\% \tag{6.1}$$

where MCS_i represents the modified car share for the district i and SCS_i represents the simulated car share for the district i, TP_i and SP_i refer to the total population and sample population for the district i from the 2010 population census. The modified mode share for the subway (MSS) is calculated as 1 minus the share of other modes:

$$MSS_i = 1 - MNS_i - MCS_i - SBS_i - STS_i - SOS_i \tag{6.2}$$

where MNS_i represents the modified mode share for non-motorised travel for the district i, and SBS_i, STS_i and SOS_i refer to the simulated mode share for bus, taxi and other transportation modes (mainly motorcycle) for the district i, respectively.

Table 6.3 presents the final estimated mode share for each transportation mode in the urban districts of Beijing for 2010. On average, about 43% of trips in urban Beijing are made by public transportation modes (i.e. bus, subway), with nearly 30% made by private vehicles. This agrees well with the 40% value for public transit, and 34% for car, reported in another household travel survey conducted by the Beijing government in 2010 (Beijing Transportation Research Centre, 2011). The simulation results also show the variability in different travel modes by area. Residents of inner-suburban districts have a higher share of subway travel; with car travel below that of the central urban area. This can be explained by the fact that after 2000 the new subway lines and stations were extended to the inner-suburban areas. Residents of inner-suburban zones, who have longer travel distances, prefer subway travel as it is fast, inexpensive and uncongested. In contrast, with rising car ownership and changing urban form (for example, industrial suburbanisation, falling residential density, and a job-housing spatial mismatch), the share of car travel in the central urban area, which has not seen substantial increases in its subway network, has increased greatly.

Table 6.3: Estimated mode share in urban districts of Beijing for 2010

Mode share (%)	Bicycle	Bus	Subway	Car	Taxi	Other	Total
Dongcheng	20.6	30.1	6.0	34.1	6.0	3.3	100.0
Xicheng	18.4	30.3	4.7	37.2	6.0	3.3	100.0
Chongwen	24.5	29.9	5.3	30.9	5.8	3.6	100.0
Xuanwu	20.8	31.0	10.2	28.7	5.8	3.6	100.0
Chaoyang	17.9	31.4	14.4	26.9	5.5	4.0	100.0
Fengtai	21.9	31.8	6.8	29.7	5.6	4.2	100.0
Shijingshan	24.1	30.2	12.1	23.9	5.9	3.8	100.0
Haidian	14.0	32.3	16.7	28.5	5.3	3.2	100.0
Estimated	18.3	31.4	11.9	29.1	5.6	3.7	100.0
Surveyed	16.4	28.2	11.5	34.2	6.6	3.1	100.0

Note: The surveyed number is reported in an independent household travel survey in 2011 from Beijing Transportation Research Centre.

6.2.3 Comparing CO_2 emission over 2000-2010

Using the simulated trip distance, mode share, and emission factors (gCO_2 per person per km) derived from Grazi et al (2008), the transport CO_2 emission from the travel of the synthetic population is estimated for each district for 2010 (Figure 6.5). On average, the transport CO_2 emission from individuals' daily urban travel in Beijing is 2.21 kg per person per day. This is in good agreement with the value reported in a Beijing household carbon emission survey conducted in 2010 by Qin and Han (2013). They estimated the housing and transport carbon emissions for selected neighbourhoods in Beijing, and observed that transport CO_2 emission from people's daily travel varied widely (from 14.8 - 1,734.8 kg per person per year), with an average of 2.11 kg per person per day. Compared to the average CO_2 emission in 2000 (Figure 6.6, further details see Section 5.5.3), this shows that CO_2 emission per capita from travel has increased significantly (by about 54%) in Beijing, with that in the central urban districts (except Xuanwu) experiencing an increase since 2000 of more than 70%.

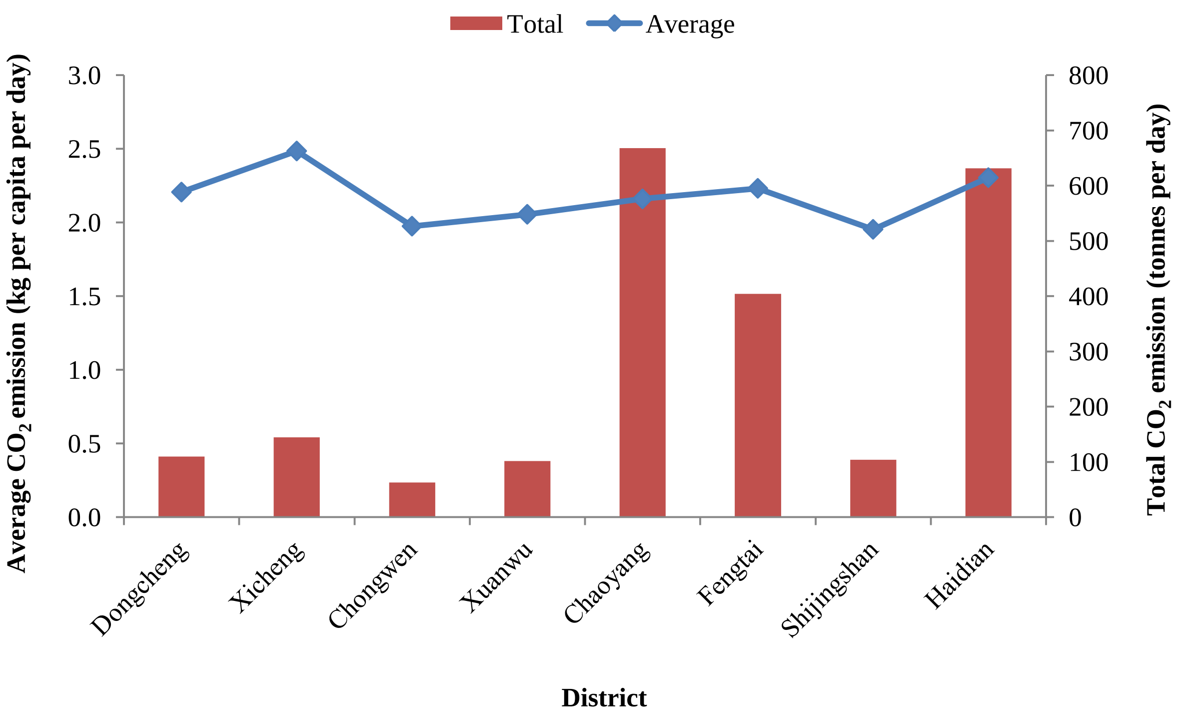

Figure 6.5: Average and total CO_2 emission from the synthetic population in 2010

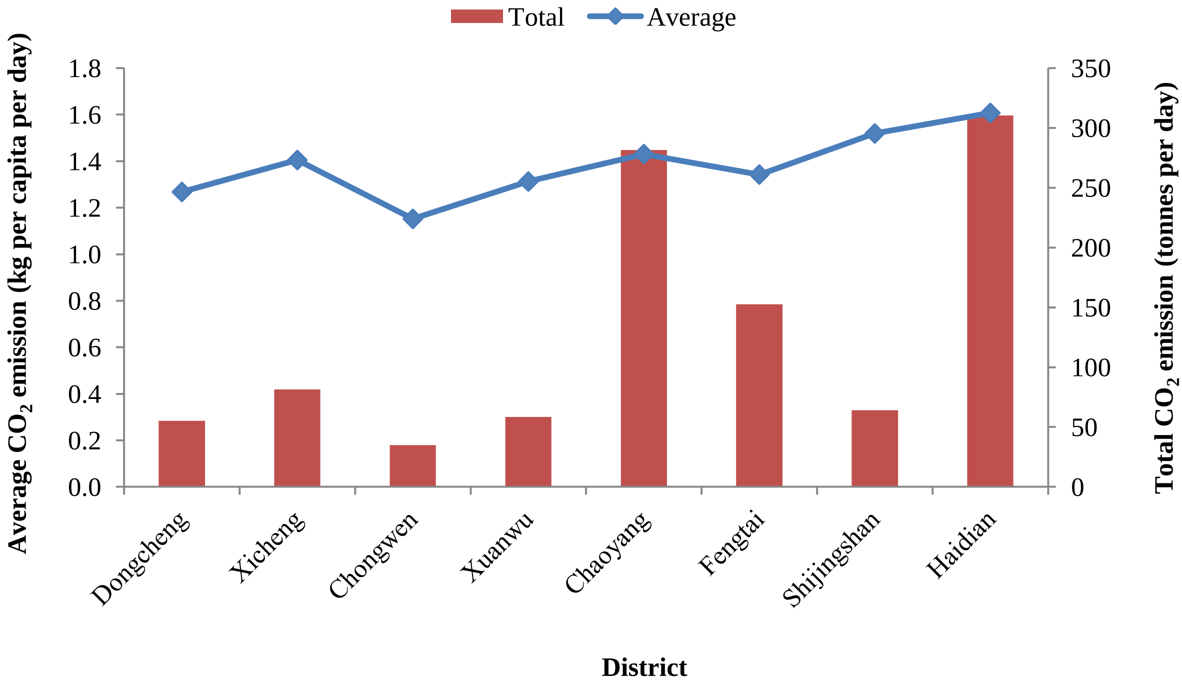

Figure 6.6: Average and total CO_2 emission from the synthetic population in 2000

Multiplying the total population by the average CO_2 emission for each geographic zone, the total mass CO_2 emission from the synthetic population (about 10% sample of the total urban population) is also estimated for each urban district of Beijing in 2010 (Figure 6.5). The total CO_2 emissions in Chaoyang and Haidian districts are very high, more than 630 tonnes on a typical workday, followed by Fengtai district with 400 tonnes or so. The emission in the central urban area is much lower than that in the inner suburban area. This is possibly due to the decreasing population density in the central area, as the average CO_2 emission in 2010 displays small variation across districts. Moreover, compared to the emission in 2000, the total transport CO_2 emission from daily travel has experienced significant increase over 2000-2010, with the growth rate approximately 114%, much higher than the population growth rate (c. 39%) in urban Beijing during this period (Figure 6.7).

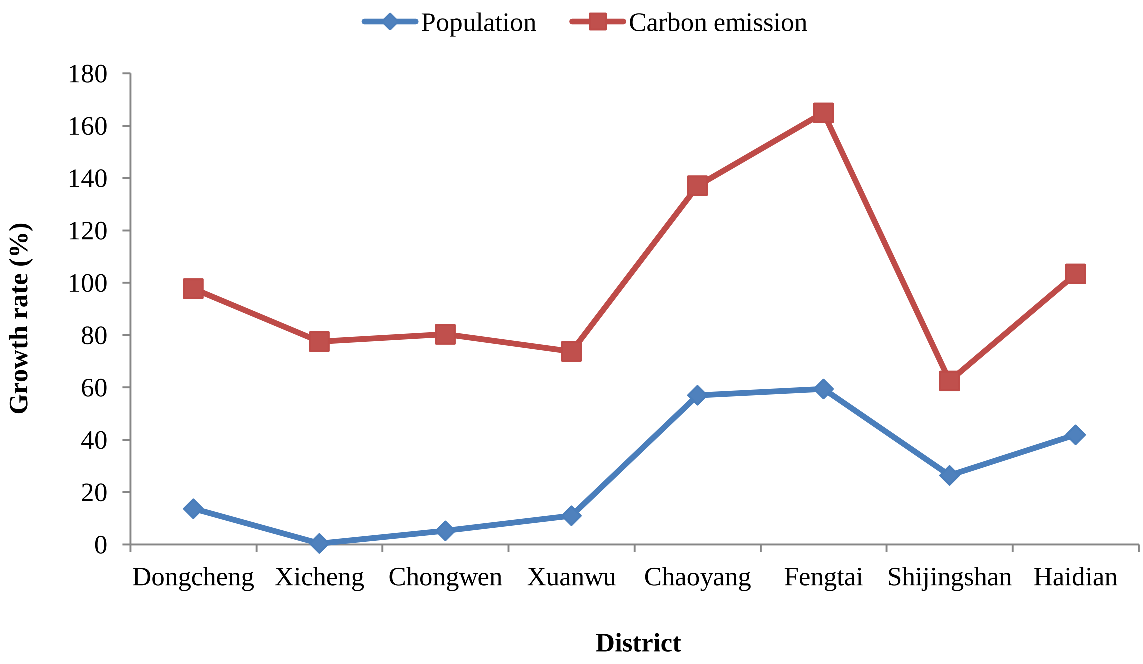

Figure 6.7: Growth rate of population and transport CO_2 emission over 2000-2010

(Source: Beijing Statistical Yearbook for population growth rate)

6.3 Scenario development

6.3.1 Overview

Section 6.2 presented baseline results for passenger transport CO_2 emission for Beijing 2000-10. These emissions are consistent with the limited verification data available from independent studies (e.g. Qin and Han, 2013). Here, the model is used to explore possible carbon futures, specifically the impact of trends and possible management strategies on transport CO_2 emission from people's daily travel to 2030. Below, four scenarios are explored: the first Transport Policy Trend (TPT) scenario examines emissions under a continuation of the current transport policy; the second Land Use and Transport Policy (LUTP) scenario examines the impact on emission of trend transport policies combined with urban development strategies, the third Urban Compaction and Vehicle Technology (UCVT) scenario examines the impact of technological change in the vehicle fleet combined with compact urban development, and the final scenario, Combined Policy (CP), examines the impact of combined transport policies, urban development strategies and vehicle technologies.

All four scenarios, (discussed in section 6.3.2 – 6.3.5 below) incorporate dynamic changes in Beijing's population; as Li et al., 2010 highlights, this is a major influence in travel demand and ultimately emissions. A range of population scenarios could be explored in this analysis, but here a common demographic change is applied to the four scenarios. Table 6.4 presents the observed population change 2000-2010 (Beijing Statistical Bureau, 2011). Average annual growth rate has been high at 3.3% and is expected to fall only slightly over the next two decades, primarily due to internal (principally rural-urban) migration in China (Yuan et al., 2008).

Two city plans have been implemented to control population growth, the "*Beijing City Master Plan (2004-2020)*" and the "*12th Five Year Plan (2010-2015)*". These plans require the local government to limit the total population in Beijing and slow its annual growth rate. All scenarios adopt the average annual growth rate of the eight districts of the central urban and inner suburban areas for the modelled population, which is projected to be 2.4% 2010-2020, and 2.2% 2020-2030 (Table 6.4). Using the estimated urban population share, the total population in Beijing is projected to be 23.96 million in 2020 and 29.79 million in 2030, which is in good agreement with the predicted 29.82 million in 2030 reported by Feng et al (2013).

Table 6.4: Population growth in Beijing over 2000-2030

Variables	2000	2005	2010	2020	2030
Population in eight urban districts (million)	8.50	9.53	11.72	14.86	18.47
Total population (million)	13.57	15.38	19.61	23.96	29.79
Urban population share [a] (%)	62.64	61.96	59.77	62.00	62.00
Population growth rate [b] (%)	2.61	2.30	3.26	2.40	2.20

[a] Urban population share = Population in eight urban districts / Total population *100%
[b] Population growth rate refers to the average annual growth rate of population in eight urban districts; 2.61 was the average annual population growth rate during 1990-2000
The population figure from 2000 to 2010 is derived from Beijing Statistical Yearbook, and the number from 2020 to 2030 is our estimates based on the projected population growth.

6.3.2 Transport Policy Trend

The Transport Policy Trend (TPT) scenario represents a continuation of current transport policies that aim to encourage public transit use and reduce travel by private vehicle. Primary measures include restrictions on private vehicle usage through regulation, rationing of car licenses, and development of a Bus Rapid Transit (BRT) system and a subway extension (Table 6.5).

Table 6.5: Transport, land use and technology measures in the four scenarios

Measures	TPT	LUTP	UCVT	CP
Improve public transport development and constrain private vehicle use	20%-off driving restrictions; maximum 150,000 car license plate release over 2014-2017; 18 BRT lines in the central city and 9 BRT lines to the suburbs by 2020; 660 km of subway by 2015	As TPT	None	As TPT
Promote urban compaction to reduce vehicle kilometres travelled (VKT) and motorised travel	None	Urban redevelopment; infill; densely developing neighbourhood centres; increasing population density; constructing basic services and facilities near residence; design pedestrian-friendly street network; etc	As LUTP	As LUTP
Develop vehicle technology to provide new clean vehicles and improve fuel efficiency	None	None	Promote emission standards, e.g. Euro 5 in 2012, Euro 6 in 2016; substitution of clean fuel vehicles, e.g. CNG buses, LPG taxis, HEV, FCV; improve fuel efficiency, e.g. 6.9 L/100km by 2015 and 4.5-5 L/100km by 2020	As UCVT

Throughout the Beijing Olympics period (July-September 2008), where concerns over poor air quality were paramount, the municipal government restricted vehicle use via a last digit license plate ban, where on alternating days only vehicles with the permitted odd or even last digit could be used (Hao et al., 2011). This 50% ban was relaxed to 20% in October 2008, using the last two licence plate digits vehicles are restricted on weekdays in the urban area, which is within the 5th ring road. To control the growth in private vehicles, limitations on issue of car license plate were introduced in December 2010. Applicants are randomly selected in a lottery and only then can they purchase a private vehicle. From 2011-13, the total lottery quota was 0.24 million; this was reduced to 0.15 million for the period 2014-2017.

Policies on improving public transit are set out in the "*12th Five Year Plan (FYP) for Public Transit Development in Beijing*". The government aims to improve the BRT network from one line (in 2007) to nine lines between the central city and suburban towns, and 18 BRT lines in the central city, by 2020 (Ma et al., 2008). Compared to regular buses, BRT buses have dedicated lanes with exclusive access, which can double operational speed from 10 to 20 km/h in the rush hour, and effectively doubles the bus system capacity. This can potentially add eight million passengers a day with no increase in the number of vehicles (Creutzig and He, 2009). The city government is also developing the subway system with plans to extend the network to 660 km by 2015.

Faster public transit can induce a significant modal shift. For example, in Seoul, a 10% increase in public transport speeds induced 5% of car drivers to switch to bus and subway (Lee et al., 2003). This is the expectation of the Beijing 12th FYP which aims to raise the share of public transit travel in urban areas to 50% by 2015, decrease the car share to 25% and achieve a bicycle share of 18%. Based on these parameters, the share of public transit under the TPT scenario is assumed to reach 52% (c. 34% bus, 18% subway) in 2020, and 57% (c. 36% bus, 21% subway) by 2030

(Table 6.6). Travel by private vehicles is assumed to decrease to 25% in 2020, and 23% in 2030, with cycling at 16%. Average trip distance by vehicle types, personal trip frequency, and the vehicle emission factor under the TPT scenario follow the 2010 simulation results and are assumed to be constant during the period 2010-2030. Walking is excluded from the travel modes in the scenario analysis, and walking trips are also excluded in the estimation of average trip frequencies. Based on the 2010 simulation results, the average trip frequency is assumed to be roughly 2 trips per person per day under four scenarios over 2010-2030.

Table 6.6: Key parameters of travel behaviour under four scenarios

Control factors	Category	TPT		LUTP		UCVT		CP	
		2020	2030	2020	2030	2020	2030	2020	2030
Mode share (%)	Bicycle	17.0	15.0	18.0	16.0	11.0	8.0	18.0	16.0
	Bus	33.5	35.6	34.5	36.6	32.4	28.0	34.5	36.6
	Subway	18.4	21.4	19.4	22.4	12.9	13.0	19.4	22.4
	Car	25.0	23.0	22.0	20.0	37.3	45.5	22.0	20.0
	Taxi	4.5	4.0	4.5	4.0	5.6	4.6	4.5	4.0
	Other	1.6	1.0	1.6	1.0	0.8	0.9	1.6	1.0
Average trip distance (km)	Bicycle	3.3	3.3	2.8	2.6	2.8	2.6	2.8	2.6
	Bus	16.5	16.5	14.0	13.2	14.0	13.2	14.0	13.2
	Subway	22.6	22.6	19.2	18.1	19.2	18.1	19.2	18.1
	Car	13.8	13.8	11.7	11.0	11.7	11.0	11.7	11.0
	Taxi	9.7	9.7	8.2	7.8	8.2	7.8	8.2	7.8
	Other	6.1	6.1	5.2	4.9	5.2	4.9	5.2	4.9
Emission factor (g/person/km)	Bicycle	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Bus	73.8	73.8	73.8	73.8	59.0	55.4	59.0	55.4
	Subway	9.1	9.1	9.1	9.1	7.3	6.8	7.3	6.8
	Car	178.6	178.6	178.6	178.6	142.9	134.0	142.9	134.0
	Taxi	178.6	178.6	178.6	178.6	142.9	134.0	142.9	134.0
	Other	113.6	113.6	113.6	113.6	90.9	85.2	90.9	85.2

6.3.3 Land Use and Transport Policy

The Land Use and Transport Policy (LUTP) scenario assumes, in addition to the transport measures described above, that travel growth will also be tackled using urban planning and design policies. Recent urban development has followed a planning model, familiar in the western world, of land use zoning, with single use, large-lot residential development and auto-oriented street design. The urban form of Beijing is now characterised by low density development with little mixed use (Zhao, 2010). Alternative planning strategies have been tried elsewhere that have proved effective in encouraging non-motorised travel and reducing vehicle kilometres travelled (VKT) (e.g. Grazi et al., 2008). These 'new urbanist', 'smart growth', and 'transit-oriented development' strategies seek to develop a more compact urban form characterised by high density and mixed land use, with ready access to work and services facilitated by prioritisation of public transit (Mitchell et al., 2011).

To date, there is no explicit policy to promote 'smart growth' ideas in Beijing, although some local-level practices have introduced an 'eco-city' concept elsewhere in China, for example, Tianjin (Chinese Society for Urban Studies, 2009). In the LUTP scenario, it assumes that the compact urban development is pursued, together with the transport policies described above that promote mass public transport and strictly control private cars. Primary compaction measures include urban redevelopment in the old urban residential area, infill, densely developing neighbourhood centres accommodating a range of household types and land uses, increasing population density by 50% in the suburban districts, constructing basic services and facilities near residences to put the activities of daily living within walking distance, and developing a pedestrian-friendly street network in the suburbs (Table 6.5).

Such measures are assumed to have significant impacts on travel and mode choice if adopted for Beijing. Reviewing 85 land use-VKT scenarios in the US, Bartholomew and Ewing (2009) found that vehicle kilometres travelled (VKT) under different planning scenarios ranged from 5% above the regional trend to 32% below it; and that the difference is larger for longer planning horizons. Comparing the travel distance in different (traditional and commodity housing) neighbourhoods from the Beijing 2007 travel survey, with adopting compact urban development (e.g. mixed land use, increasing population density), the average trip distance by vehicle types is assumed to have a 15% reduction in the LUTPS by 2020 and a further 5% reduction by 2030, respectively (Table 6.6). Regarding the mode share, 3% car travel in the TPT scenario is assumed to be shifted to bus, subway and bicycle with a 1/3 split each, as suggested in some prior studies (e.g. He et al., 2013). Vehicle emission factors are assumed to be the same as the TPT scenario over 2010-2030.

6.3.4 Urban Compaction and Vehicle Technology

In the Urban Compaction and Vehicle Technology (UCVT) scenario, densification or compaction policies are used, with the addition of aggressive promotion of clean vehicle technology. This includes strengthening emission standards of in-use and new vehicles, improvement of fuel efficiency, and substitution of alternative clean fuel types (Table 6.5). In China, both central and local governments have made substantial efforts to promote the development and use of clean vehicle fuels, such as liquefied petroleum gas (LPG), compressed natural gas (CNG), electric vehicles (EV), hybrid electric vehicles (HEV) and fuel cell vehicles (FCV). This has been through the uptake of policies and legislations, including the ‘National Clean Vehicles Action’ (1999), ‘Renewable Energy Law’ (2005), and ‘Rules on the Production Admission Administration of New Energy Automobiles’ (2007) (Hu et al., 2010).

With these government interventions, LPG and CNG vehicles increased rapidly in bus and taxi fleets. By 2005, Beijing had more than 2,000 CNG buses and 600 LPG taxis and approximately 32,000 gasoline/LPG bi-fuel taxi. These vehicles were demonstrated to have better performance on the road than the conventional vehicles (Hao et al., 2006). However, compared to global HEV sales, which grew rapidly from 40,000 in 2002 to 509,000 in 2007, growth in clean fuel vehicles in China has been slow, although there has been considerable investment in EV/HEV/FCV research and development projects (Hu et al., 2010). This scenario assumes that the government will continue to encourage new energy projects, and subsidise HEV and FCV vehicle purchases, so that the share of new clean vehicles in use increases to match EU’s current level by 2030.

Policies to improve fuel efficiency and emission standards are also included in this scenario. China issued its first two-phase vehicle fuel-economy standards for passenger vehicles in 2004, in order to improve the fuel efficiency of the fleet by 15% (Huo et al., 2012). The average fuel consumption rates were reduced from 9.11 L/100km in 2002 to 8.06 L/100km in 2006 and 7.87 L/100km in 2009 (Wagner et al., 2009; Wang et al., 2010). The third phase fuel-economy standard, similar to the US CAFE standard, has been designed and will be adopted to improve fuel efficiency to 6.9 L/100km by 2015 and 4.5-5 L/100km by 2020 (Huo et al., 2012). Moreover, the Beijing government also tightened the vehicle emission standards and implemented the Euro 4 standard for light-duty vehicles in 2008. It plans to catch up with the EU in future by introducing more stringent emission standards, i.e., Euro 5 in 2012 and Euro 6 in 2016, to control emissions (Wu et al., 2011).

Estimates of aggregate reduction in CO_2 emission factors for Chinese passenger transport from fuel efficiency improvements and clean fuels vary, including 17% (Liu et al., 2007), 22% (Ou et al., 2010) and 25% (Zhang et al., 2005). This scenario assumes mid-level values for 2020 of 20%, rising to 25% in 2030, compared to the trend value. VKT is assumed to be the same as the LUTP scenario. Regarding the mode share, as no major transport policies are implemented, the mode share by car is assumed to follow the historical trend[9] (2000-2010), accounting for approximately 37% in 2020 and 45% in 2030, whereas the share by public travel and NMT reached 56% in 2020 and 49% in 2030, respectively (Table 6.6).

6.3.5 Combined Policy

While the three scenarios above (i.e. TPT, LUTP, and UCVT) address specific measures in different aspects in isolation, the final scenario, Combined Policy (CP), assumes all these measures discussed above are considered altogether to reduce the transport CO_2 emissions from people's daily travel, including the transport policies, compact urban development and vehicle technologies (Table 6.5). A complete combination of these measures is assumed to have substantial impacts on travel distance, mode choice and emission factor at the same time (Table 6.6). Results and analysis of these four scenarios on future transport CO_2 emissions in urban Beijing are presented in the following section.

[9] Based on the historical trend, the car share increased by 11.2% from 2000 to 2010; the compaction policy will make 3% car share shifted to the public and bicycle travel. Therefore, the car share will increase 8.2% in the UCVT scenario, with 37.3% (29.1%+8.2%) in 2020 and 45. 5% (37.3%+8.2%) in 2030.

6.4 Results

6.4.1 Average CO_2 reduction potential

Based on the assumptions above in section 6.3, an average per capita CO_2 emission for passenger transport under the four scenarios to 2030 is calculated. This is calculated from the mode share by trip frequency by travel distance and mode specific CO_2 emission factor, as:

$$AverageCO_2 = \sum MS_j \times ATF \times ATD_j \times EF_j \tag{6.3}$$

where MS_j refers to the mode share by vehicle type j (j = bicycle, bus, subway, car, taxi, and other), ATF represents the average trip frequency on a typical workday (i.e. 2 trips per person per day), ATD_j is the average trip distance by vehicle type j, and EF_j the emission factor associated with the vehicle type j.

Figure 6.8 presents the results from 2000 to 2030. Compared to the sharp increase from 2000-2010, transport CO_2 emission under the TPT scenario will grow more slowly to 2.30 kg per person per day in 2020 and 2.24 kg in 2030, as a continuation of current transport policies is considered effective in both encouraging public transit use and reduced private car travel. When both transport and urban development policies are employed (LUTP), CO_2 emission falls to 1.85 kg per person per day by 2020 and 1.70 kg by 2030, this is mainly due to the lower VKT.

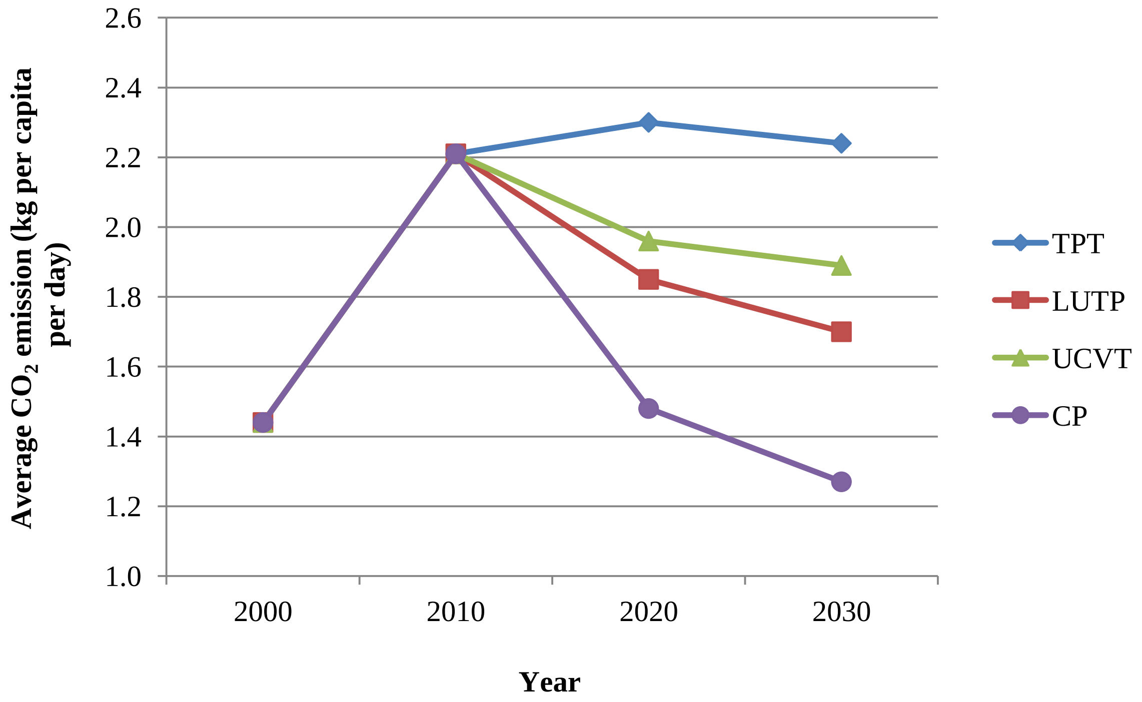

Figure 6.8: Average CO_2 emission from people's daily urban travel over 2000-2030

Under the UCVT scenario, where vehicle technology is aggressively promoted with compact urban development, the average CO_2 emission reaches 1.96 kg per person per day in 2020 and 1.89 kg in 2030, falling 14% from 2010. However, when transport policies, compact urban development and vehicle technologies are employed together (CP), CO_2 emission falls sharply to 1.48 kg per person per day by 2020 and 1.27 kg by 2030, reducing 43% relative to 2010. It suggests that, although transport policies, urban compaction and vehicle technology are feasible tools, they cannot significantly reduce transport CO_2 emissions from people's daily travel in isolation. The most effective solution to mitigate transport carbon emission in the future is the combination of those solutions concerning travel behaviour, urban planning and vehicle technologies.

6.4.2 Total CO_2 emission comparison

Total CO_2 emission from people's daily travel is calculated by the total population (see Table 6.4, the projected full population in eight urban districts in 2020 and 2030) multiplied by the average CO_2 emission, as:

$$TotalCO_2 = \sum MS_j \times (ATF \times TP_t) \times ATD_j \times EF_j \qquad (6.4)$$

where TP_t refers to the total population in year t (t = 2020 or 2030).

Figure 6.9 presents the total transport CO_2 emission in urban Beijing in 2020 and 2030. It shows that, under the trend scenario (TPT), total transport CO_2 emission reaches about 34,200 tonnes per day in 2020 and 41,400 tonnes per day in 2030, with car travel accounting for half of all transport emissions (Figure 6.10). Together with urban compaction strategies to decrease VKT, total transport CO_2 emissions under the LUTP scenario are about 20% below the trend scenario in 2020, and 24% less in 2030, with the proportion of total CO_2 from public transit rising to 46% by 2030 (Figure 6.10).

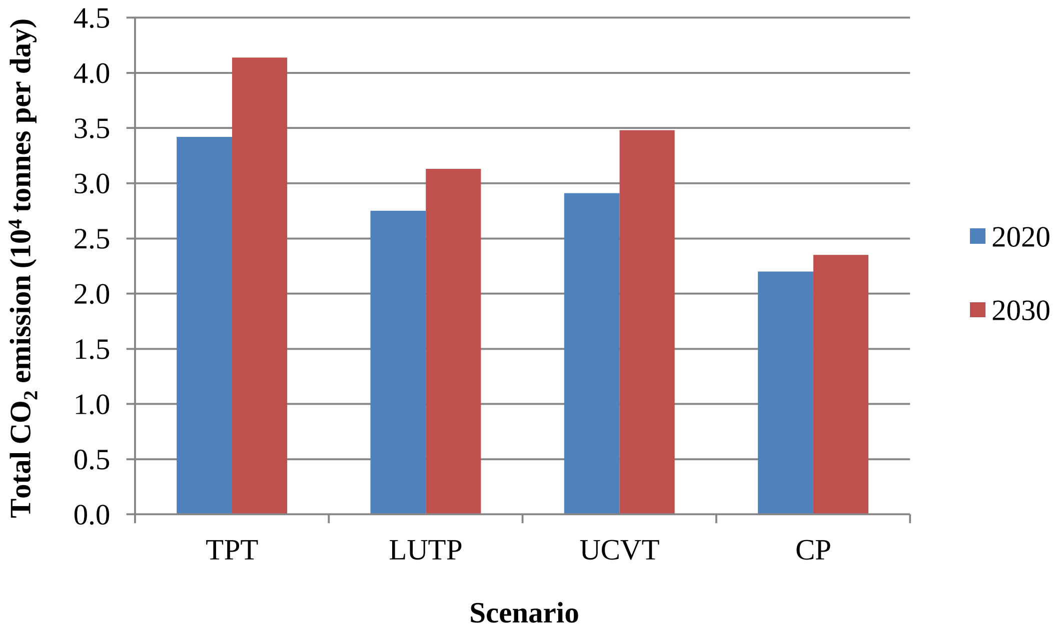

Figure 6.9: Total transport CO_2 emission from daily travel in urban Beijing

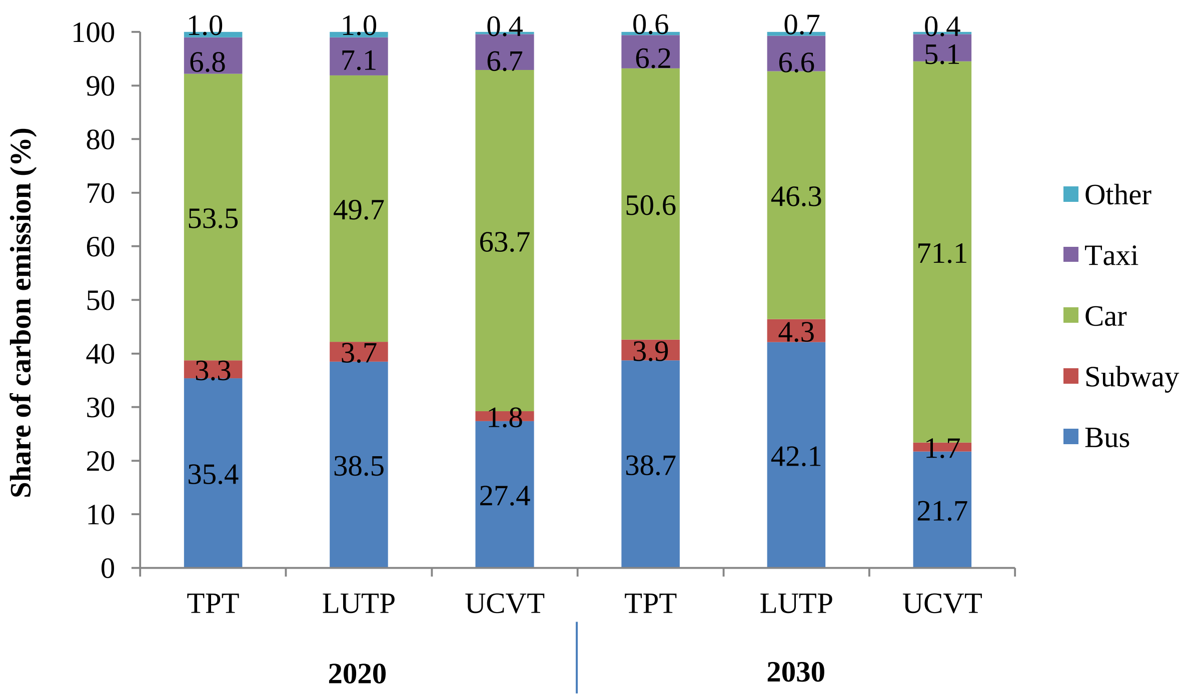

Figure 6.10: Transport CO_2 emission by vehicle types in 2020 and 2030

In contrast, with compact urban development and vehicle technology taken into account, total transport CO_2 emission under the UCVT scenario is 16% below the trend scenario in 2030, with the car accounting for more than 70% of the total CO_2 emission (Figure 6.10). This is mainly due to the larger vehicle population and increased car travel, which suggests that continuing to both encourage public transit use and constrain car travel in Beijing through transport policies, is a priority solution for reducing transport carbon emission. However, these measures will be more effective if developed in conjunction with travel sensitive land use policies and advanced vehicle technologies, as total transport CO_2 emissions under the CP scenario decrease sharply, about 36% below the trend scenario in 2020, and 43% less in 2030.

6.5 Sensitivity analysis

To address the uncertainty in travel assumptions, a sensitivity analysis was conducted to examine the model's responses to variations of input parameters. Each time, one of the travel parameters (Table 6.6) was changed by 20% (the normally used value, e.g. He et al, 2013), while the others were kept constant. The resulting transport CO_2 emissions were then compared to the estimated carbon emissions under the trend or reference scenario, and the sensitivity value of each travel parameter is examined by the following equation:

$$S_j = \Delta EC_j / EC \times 100\% \tag{6.5}$$

where S_j is the sensitivity value of a specific travel parameter (e.g. mode share, trip distance, or emission factor) for vehicle type j (j = bicycle, bus, subway, car, taxi, and other); EC refers to the estimated CO_2 emissions for trend scenario in 2030 and ΔEC_j represents the increments or decrements of CO_2 emissions with the travel parameter of vehicle type j changing by 20%.

The sensitivity analysis reveals that transport CO_2 emissions from people's daily travel in urban Beijing are largely insensitive to bicycle, subway, taxi and other vehicle types (e.g. motorcycle), as a 20% change in that travel parameter resulted in less than a 2% change in the emissions (Figure 6.11). In contrast, the variation in trip distance, mode share or emission factor by private car would be most sensitive to, or have significant impact on transport CO_2 emissions, as its sensitivity value is approximately 10%, followed by bus, about 8%.

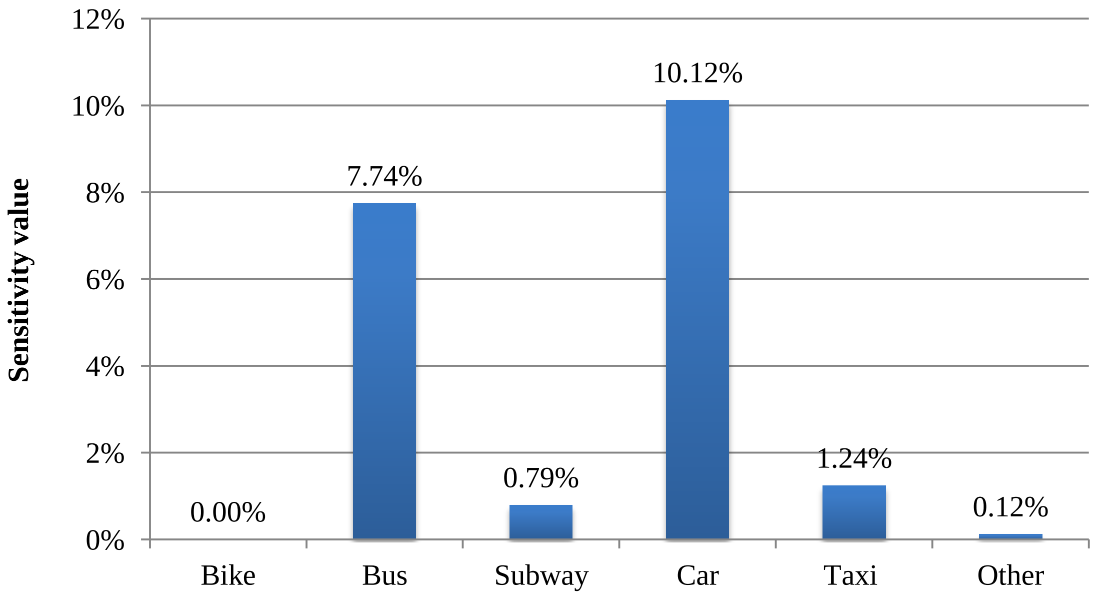

Figure 6.11: Sensitivity analysis of travel parameters

6.6 Conclusions

In contrast to prior studies which estimate transport CO_2 emissions using aggregate vehicle population statistics, this chapter presents a new 'bottom-up' methodology to simulate and project transport CO_2 emissions from people's daily urban travel using disaggregate travel attributes for a Chinese mega-city to 2030, where published travel survey, energy statistics or census data are usually very poor. Using a spatial microsimulation approach, this study firstly estimates transport CO_2 emission from people's daily travel behaviour at disaggregate level in urban Beijing in 2010. The simulation results show that the average CO_2 emission from urban travel has increased significantly from 2000-10, reaching 2.21 kg per person per day in 2010. It also suggests that the total mass transport CO_2 emission in urban Beijing has increased by 114% since 2000, with the Chaoyang and Haidian districts being particularly high emitters.

Next, on the basis of the estimated historical emissions, this chapter also develops four major scenarios concerning transport policies, urban planning and vehicle technology to examine how changes in people's daily travel behaviour (e.g. trip distance, mode share) may impact upon transport carbon emission in urban Beijing to 2030. These scenarios (i.e. transport policy trend, land use and transport policy, urban compaction and vehicle technology, and combined policy) are developed to illustrate the model capability, and they are reasonable reflections of possible strategies for Beijing. The modelling results show that compared to the trend scenario, employing both transport and urban development policies could contribute a further 24% reduction of the total carbon emission to 2030. Moreover, when transport policies, compact urban development and vehicle technologies are combined, the total transport CO_2 emission falls sharply, about 36% below the trend scenario in 2020, and 43% less in 2030. The results show that the most effective solution to mitigate transport carbon emission in the future is the combination of those solutions concerning travel behaviour, urban planning and vehicle technologies.

Chapter 7

Conclusions

7.1 Introduction

China has experienced rapid urbanisation and spatial restructuring since the 1980s. This has been accompanied by major growth in travel, which has brought with it the associated issues of energy consumption, greenhouse gas emission, traffic congestion and local air pollution (Feng et al., 2013). Few studies have focused on investigating the relationship between CO_2 emissions from an individual's daily journey and China's changing urban form at a disaggregate level. With relatively sparse data on travel behaviour in China, this thesis develops a new 'bottom-up' methodology to provide improved transport CO_2 emission estimates based on individuals' observed daily travel behaviour for Beijing. This is achieved through the development of a spatial microsimulation that takes account of people's daily travel behaviour at fine geographical scale. This is the first time that spatial microsimulation has been used to overcome the data deficiencies that often act as a barrier to spatial analysis of travel behaviour, and hence low carbon city planning, for any megacity in the developing countries. The developed 'bottom-up' methodology provides greater insight into the spatial variability of transport CO_2 emissions, and allows a range of scenarios to be tested out that examine travel behaviour at a disaggregate level.

Moreover, to illustrate the utility of the approach, this thesis also estimates the transport CO_2 emissions from passenger travel behaviour to 2030 under four scenarios. These scenarios are developed to explore travel behaviour and transport CO_2 emissions under current and feasible future strategies on transport policy, urban development and vehicle technology. It provides a more detailed and realistic evaluation on the planning interventions that are relevant to the development of more sustainable and low-carbon urban development in China. The remainder of this chapter is structured as follows. Section 7.2 discusses the three research objectives (and six tasks) established in Chapter 1 (Section1.2), reflecting on the extent to which the objectives have been met, the limitations of the analysis, and the principal conclusions that can be drawn. Section 7.3 presents recommendations for policy and practice, and for further research development.

7.2 Research summary

The central aim of this thesis was to improve our understanding of the impact of urban form, and daily travel behaviour on transport CO_2 emission in the context of rapid urbanisation and spatial restructuring in China. To achieve this aim, a 'bottom-up' methodology was developed to spatially simulate a large population's daily travel behaviour at fine geographical scale. This provided improved evidence of transport CO_2 emissions for the period 2000-2030, based on observed daily travel behaviour of individuals. Three specific objectives (including six tasks) were established in Chapter 1 and are now revisited and discussed here.

7.2.1 Objective One: Travel Modelling

Objective One – To comprehensively and microscopically analyse the relationships between urban form, household and individual socio-demographics and tour-based travel behaviour (*Travel Modelling*).

Using the tour as the basic unit of analysis, Chapter 4 investigates how the socio-demographic attributes of households, individuals, and urban form characteristics, at both residence and workplace, influence tour-based daily travel behaviour (Objective One, task 1). This approach accounts for urban form and socio-demographics in a series of discrete choice models to analyse the trip-chaining behaviour for three principle aspects: tour generation or frequency, tour scheduling process, and tour interdependence mechanism. In contrast to prior research that analysed aggregate samples (e.g. Krizek, 2003; also see the discussion in Section 2.3.2.3), this chapter examines tour behaviour at a disaggregate level, and further investigates the urban form – trip-chaining relationships for workers and non-workers, separately, taking one, two and three tours in a single day (Objective One, task 2). This allows for a consideration of both tour sequence, and tour interdependence, which has rarely been considered before.

This disaggregated analysis of urban form – trip-chaining behaviour provides a more sophisticated understanding of tour-based travel decisions and an empirical basis to inform land use and/or travel planning. It also contributes to the notion of predictive behaviour that leads itself to being modelled using individual-based modelling techniques, such as microsimulation. However, it is restricted to tour generation, schedule and interdependence analysis on a typical workday; travel behaviour on the weekend, which may be more flexible and potentially be influenced by neighbourhood-scale urban form, is not addressed here due to data limitations. Moreover, the intra-household dependency (e.g. intra-household interactions between the male and female household heads), and correlations between people's trip-chaining behaviour on Sunday and the subsequent Monday, are currently too complex and not tested in this thesis.

Modelling results in Chapter 4 show that socio-demographic attributes of households and individuals correlate significantly with people's tour-based behaviour. For instance, workers with high income or in households with children tend to take fewer tours on a typical workday; but when they do leave home, they make more intermediate stops. Older people tend to take more tours and participate in non-work activities before they travel to work; and women tend to make more stops within a tour, although there is no significant gender difference in tour frequency as observed in developed countries (e.g. McGuckin and Murakami, 1999). Non-workers with lower educational attainment tend to take fewer tours on a typical workday, and those with children in their households tend to take more tours and participate in some family obligation activities *en route*.

Urban form characteristics at home and at workplace are significantly associated with tour frequency, but differ with respect to tour complexity. For example, higher residential density is correlated with more home-based tours with fewer stops for workers, while mixed land use at workplace with higher density and accessibility leads to more stops within one work tour or a more complex tour pattern. With respect to non-workers, people living in neighbourhoods with higher density or better access to subway station tend to leave home more often and make more intermediate stops than their counterparts on a typical workday. The research in

Chapter 4 also reveals, for the first time, a tour interdependence effect for residents who undertake multiple tours on a typical workday. A paper on the basis of this chapter has been published in a peer-reviewed journal; see Ma et al (2014b).

7.2.2 Objective Two: Microsimulation Modelling

Objective Two – To spatially simulate a large population's daily travel behaviour (including travel distance and mode choice) at a fine geographical scale and estimate transport CO_2 emissions from daily urban travel at the disaggregate level over 2000-2010 (*Microsimulation Modelling*).

Using the understanding of travel behaviour developed in Chapter 4 (based on an activity diary survey), and the 2000 population census, Chapter 5 first applies a simulated annealing algorithm to create a realistic synthetic population at the sub-district level for 2000 in Beijing (Objective Two, task 1). The population synthesis is developed within a generic 'Flexible Modelling Framework' based on the simulated annealing technique, and the constraints in the microsimulation model are socio-demographic attributes, including age, gender, education, employment, and occupation, which are significant influences on travel behaviour (as shown in Chapter 4). The reconstructed population is validated by the observed aggregate data using several established goodness-of-fit evaluation statistics. Using the microsimulated synthetic population, Chapter 5 then spatially simulates the population's daily travel, including trip distance and mode choice, and estimates transport CO_2 emission from daily urban travel at the sub-district level for 2000 in urban Beijing (Objective Two, task 2).

The analysis in Chapter 5 represents a sophisticated spatial microsimulation of people's daily travel and associated transport CO_2 emission, which can be served as a solid basis for low carbon city planning, or transport policy evaluation for mega cities in developing economies. However, this has been achieved using limited data, a travel diary survey, and a sample population census. China has no national travel survey (Pucher et al., 2007), and data from Beijing's municipal government travel surveys have only been published at aggregate level (confidentiality issues may constrain release of more individual level data). We have thus drawn upon travel diary data that is a modest data set considering the scale of Beijing. Furthermore, the population data we have drawn upon is a 10% sample of the city population. Nonetheless, the simulated annealing algorithm applied here has been used to synthesise the city's population in its entirety, and its travel behaviour in a manner that closely reflects travel behaviour reported at the aggregate level (see Section 5.5).

There are some further limitations to this research. First, the constraints in the microsimulation models are all socio-demographic attributes. Other attributes, like attitudinal and lifestyle variables, and spatial locations, which might impact on people's daily travel behaviour, are not taken into account. This is mainly because these variables are not available in the activity diary survey and population census datasets. Furthermore, this work only used weekday (Monday) samples to estimate transport CO_2 emission from people's daily urban travels on a typical workday, while the weekend information is not included in the analysis. The microsimulated emissions could be adjusted to recognise differences in travel patterns for different days of the week, but the travel observations needed to produce the relevant scaling factors are not currently available, hence the emissions are for a weekday (Monday) only. Although the sample size is small, the survey microdata is representative in terms of the sampling procedure used – the survey area covering all different types of neighbourhoods in the central urban and inner suburban zones of Beijing (see Section 3.6.1). By comparing attribute combinations between the census data and the survey dataset, the survey population is also representative of the observed target population. As there are no similar studies estimating transport CO_2 emission from people's daily urban travels at a micro scale for urban Beijing, and such detailed accurate data is not available, it is difficult to validate the results of the analysis at the disaggregate level. However, verification at the aggregate level was possible by comparing the synthetic travel characteristics with some government household travel surveys (e.g. Beijing Transportation Research Centre, 2002) and other independent household interview surveys (e.g. Zhao et al., 2011). This shows that the simulated travel distance and share of low-carbon travel are in good agreement with this independent information.

To conclude, the microsimulation results in Chapter 5 show that people resident in the inner suburban zone travel further, make fewer low-carbon trips, and emit more carbon per workday than average. In contrast, residents in the central urban zone, characterised by a high population density, mixed land use, and high accessibility to services and public transit, adopt low-carbon travel behaviour. This analysis presents a new 'bottom-up' methodology through the development of a spatial microsimulation of people's daily travel, and provides improved transport CO_2 emission from urban passenger travel at a disaggregate level. A paper on the basis of the work in Chapter 5 has been published in a peer-reviewed journal; see Ma et al (2014a).

Using the 2000 base case as the starting point, Chapter 6 applies the 'bottom-up' methodology presented in Chapter 5 to simulate a realistic synthetic population's daily travel behaviour and estimate their CO_2 emission in 2010 for urban Beijing

(Objective Two, task 3). The dynamic changes in travel behaviour and transport CO_2 emission over 2000-2010 are also analysed. The simulation results show that the average CO_2 emission from urban travel has increased significantly from 2000 to 2010, reaching 2.21 kg per person per day in 2010. The total mass transport CO_2 emission in urban Beijing has increased by 114% since 2000, with the Chaoyang and Haidian districts being particularly high emitters. The role of socio-demographic attributes and change in urban form and transport development is also examined for the modelled trend during this period.

7.2.3 Objective Three: Scenario Modelling

Objective Three – To project transport CO_2 emissions from passenger travel behaviour to 2030 under urban scenarios, to mitigate carbon emissions in the future and facilitate China's sustainable urban development (*Scenario Modelling*).

Chapter 6 presents a scenario analysis of transport CO_2 emissions from passenger travel behaviour to 2030 (Objective Three, task 1). Using the baseline results for passenger transport CO_2 emission for Beijing 2000-10, Chapter 6 further explores how changes in people's daily travel behaviour (e.g. trip distance, mode share, etc) may impact upon transport carbon emission in urban Beijing to 2030. Four scenarios (transport policy trend, land use and transport policy, urban compaction and vehicle technology, and combined policy) are developed to explore travel behaviour and transport CO_2 emission under current and potential strategies on transport, urban development and vehicle technology.

In contrast to prior studies which estimate transport CO_2 emissions using aggregate vehicle population statistics (e.g. Dhakal, 2009), this research employs an alternative approach to simulate and project transport CO_2 emissions from people's daily urban travel using disaggregate travel attributes, which enables examination of the influence on emission of factors that operate at a more resolved functional level and enables exploration of development scenarios and policy or plan interventions. However, as it only projects the transport CO_2 emission from passenger travel for urban Beijing (eight urban districts), it is difficult to compare the results of our analysis with other studies mostly conducted at a wider scale (e.g. China). Furthermore, only four scenarios are developed to explore transport CO_2 emissions concerning transport policy, urban development and vehicle technology, while urban compaction and vehicle technology are not examined on their own.

Nevertheless, these scenarios are reasonable reflections of possible strategies for Beijing, and they are the options that are under discussion by urban planners and policy makers in Beijing (He et al., 2013). The modelling results show that compared to the trend scenario, employing both transport and urban development policies could contribute a further 24% reduction of the total carbon emission to 2030. Moreover, when transport policies, compact urban development and vehicle technologies are combined, the total transport CO_2 emission falls sharply, about 36% below the trend scenario in 2020, and 43% less in 2030. It suggests that the most effective solution to mitigate transport CO_2 emission in the future is the combination of those solutions concerning travel behaviour, urban planning and vehicle technologies. A paper on the basis of the work in Chapter 6 has been submitted for publication (Ma et al., 2014c).

7.2.4 Conclusion

To conclude, this thesis examines in detail the impact of urban form, and daily travel behaviour on transport CO_2 emission at a disaggregate level in urban Beijing. It combines a spatial microsimulation approach from geography and activity travel research from the transport field and applies this in a developing country for a long period, where detailed data to undertake fine scale analysis of phenomena such as travel behaviour and associated transport CO_2 emissions is very scarce. It also develops a 'bottom-up' methodology to provide improved transport CO_2 emissions at a disaggregate level and allows the effect of different policies, strategies or technologies to be more realistically evaluated. However, as there are some limits to this thesis, and practical constraints including a lack of building energy data for the study area, the effect of urban form on residential energy use and life-cycle carbon emission is not investigated. It is hoped that, with some future development, these analysis techniques and modelling methods could be significant tools to support urban spatial analysis, residential energy consumption forecasts, and environmental and health policy evaluation.

7.3 Recommendations for policy and future research

7.3.1 Policy Implications

Since the 1990s, China's urban development has largely followed the western model of mono-functional residential development with an auto-oriented transport system (Wang and Chai, 2009). The rapid urban expansion has been accompanied by urban sprawl on Beijing's fringe, characterised by low population density and little mixed use, while the inner city retains highly diverse traditional neighbourhoods with high density, mixed land use, and high accessibility to services and public transit (e.g. Zhao, 2010). Using Beijing as a case study, this thesis demonstrates that urban form has a significant influence on people's daily travel behaviour and transport CO_2 emission. High population density, mixed land use, and good access to public transit could reduce dependence on private automobile usage, make residents travel shorter distance, and emit less carbon on a typical workday. It suggests that, *ceteris paribus*, the Chinese government should encourage compact urban development to mitigate CO_2 emission and combat climate change.

Transport policy is also an effective tool in mitigating carbon emissions from daily urban travel. With transport policies pursued to encourage public transit use and reduce travel by private vehicle, total transport CO_2 emission will grow more slowly in the future, compared to the sharp increase from 2000-2010. The modelling results show that, under the Transport Policy Trend scenario, the average transport CO_2 emission from daily urban travel will grow more slowly to 2.30 kg per person per day in 2020 and 2.24 kg in 2030 (Figure 6.8). And with a continuation of current transport policies, the total transport CO_2 emission reaches about 34,200 tonnes per day in 2020 and 41,400 tonnes per day in 2030, with car travel accounting for half of all transport emissions (Figures 6.9-6.10).

Moreover, when both transport and urban development policies are employed, average CO_2 emission falls to 1.85 kg per person per day by 2020 and 1.70 kg by 2030, mainly due to the lower VKT (Figure 6.8). Total transport CO_2 emissions under the Land Use and Transport Policy scenario are about 20% below the trend scenario in 2020, and 24% less in 2030, with the proportion of total CO_2 from public transit rising to 46% by 2030 (Figures 6.10). However, reduction of urban carbon emissions will require a combination of behavioural changes, urban planning, transport development, and other technology fixes and economic instruments, such as improved fuel efficiency and electric vehicles, and fuel/vehicle taxation. When transport policies, compact urban development and vehicle technologies are employed together (i.e. Combined Policy), average CO_2 emission falls sharply to 1.48 kg per person per day by 2020 and 1.27 kg by 2030 (Figure 6.8). Total transport CO_2 emissions under the Combined Policy scenario also decrease sharply, about 36% below the trend scenario in 2020, and 43% less in 2030 (Figure 6.9). The government should continue to make efforts to promote the development of clean vehicle technology and use of clean vehicle fuels. The modelling results suggest that although transport policies, urban compaction and vehicle technology are feasible tools, they cannot significantly reduce transport CO_2 emissions from people's daily travel in isolation. The most effective solution to mitigate transport carbon emission in the future is the combination of those solutions concerning travel behaviour, urban planning and vehicle technologies.

7.3.2 Research development

The previous section has outlined some implications for policy and practice, and this section suggests some future research and development that might be advantageous to transport and environment research, and to academic knowledge in general. First, whist the results are particularly relevant to urban Beijing, the wider point demonstrated here is how it is possible to simulate urban travel for a developing country mega-city, in a manner that allows credible estimation of geographically resolved transport carbon emissions. Future research could apply the 'bottom-up' methodology presented in this thesis to other big cities to microsimulate urban travel, estimate transport carbon emissions, and further develop a dynamic microsimulation system. Second, whilst transport CO_2 is focused on here, the methodology could also be useful for estimating emissions of other pollutants relevant to local air quality (e.g. CO, NO_x, SO_2), or identifying where congestion may become more serious in the future.

Moreover, building on the spatial microsimulation of transport CO_2 emissions, future research could dynamically simulate the socio-spatial distribution of air quality and associated disease burden at fine geographical resolution, to investigate the evolution of environmental and health inequalities in developing countries, where air pollution levels such as fine particulates (PM_{10}, $PM_{2.5}$) are the highest in the world, and a very significant public health risk (e.g. Zhang et al., 2013). Future development could relate environmental justice research from geography with public health studies to estimate disease burden, particularly for socially deprived groups, evaluate environmental and public health policies, and provide policy implications for the government to redress environmental and health inequalities.

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