The Link between Urban Form and Travel: A Focus on Public Transport Demand and Methodological Issues

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The research presented here is my own, except where the work of others has been referenced.

Niovi Karathodorou
Abstract

This thesis is concerned with the link between urban form and travel behaviour. We focus on two issues that have been overlooked in the existing empirical literature: the measurement of land use mix and the relation between urban structure and city-wide public transport patronage.

In the last twenty years, there has been a substantial interest on the effects of land use mix on travel behaviour. The literature uses a variety of metrics to measure land use mix, but there is limited understanding of how the choice of metric affects estimates of the link between land use mix and travel. Researchers also measure urban form, and in particular land use mix, at various geographical scales. Past studies examining the effects of spatial scale on estimates of the urban form-travel demand relationship, offer limited evidence on land use mix measures.

The first part of this thesis examines how the metric and spatial scale used in land use mix measurement affect our understanding of the relation between land use mix and travel, employing both simulation and empirical econometric analyses. The simulation analysis uses randomly generated data to construct and test alternative land use mix measures. The empirical analysis tests alternative metrics and alternative spatial scales in the context of public transport trip frequency in London.

The last part of the thesis, presents some further econometric models of public transport demand, to investigate the effect of city structure on city-wide public transport patronage. The study extends previous work on the topic in a number of ways. These include considering more detailed measures of urban form; dealing with methodological issues related to endogeneity and experimenting with various functional forms.
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List of Acronyms

2SLS: Two-Stage Least Squares
AIC: Akaike Information Criterion
ATE: Average Treatment Effect
BIC: Bayesian Information Criterion
BLS: Bureau of Labour Statistics
CAS: Census Area Statistics
CBD: Central Business District
FHA: Federal Highway Administration
FTA: Federal Transit Administration
GIS: Geographical Information Systems
GLUD: General Land Use Database
GMM: Generalized Method of Moments
iid: independent and identically distributed
IV: Instrumental Variables
LSOA: Lower Super Output Area
LTDS: London Travel Demand Survey
MAUP: Modifiable Areal Unit Problem
MSA: Metropolitan Statistical Area
NapTAN: National Public Transport Access Node
NB: Negative Binomial
NTD: National Transit Database
OLS: Ordinary Least Squares
OS: Ordnance Survey

SEM: Structural Equation Modelling

TfL: Transport for London

USPS: United States Postal Service

UZA: Urbanized Area

VMT: Vehicle Miles Travelled

ZCTA: Zip Code Tabulation Area
Chapter 1: Introduction

To determine whether land-use policies can be used as a tool for shaping travel behaviour, an extensive literature has developed over the last three decades on the relationship between urban form and characteristics of travel demand. This thesis contributes to the literature on this theme by focusing on the link between urban form and public transport use and by addressing some of the methodological limitations of previous work. This introductory chapter presents the background, motivation and objectives of the thesis. By way of context, the first section provides a brief history of US suburban expansion and explains why the merits of suburban living are currently being questioned. Section 2.1 presents the motivation and objectives of the thesis and section 2.3 explains the research contributions. Finally, the last section provides an outline of the thesis.

1.1 Background

The early literature on the link between urban form and travel has almost exclusively come from the US. For that reason, it is worth having a quick glance at the birth and development of US suburbia and how it gave rise to said literature.

The first planned suburban communities in the US appeared in the late nineteen century. They were initially created by private developers who, owing considerable real estate at the outskirts of cities, had prompted the construction of transit lines to and from the city centre. Known as the streetcar suburbs, these communities did not extend further than a walking distance from the transit station (Cervero, 1996b). Following Henry Ford’s establishment of mass-production in car manufacturing in 1913, the US became the first country to claim mass car ownership. By 1927, 1 out of 5 Americans owned an automobile (Hall, 2002). The spread of car ownership accelerated the rate of suburbanization and extended the suburbs further away from the city centre. In the 1920s, the suburbs’ rate of growth exceeded for the first time that of the central cities (Peck, 1928). That decade saw the suburbs growing by 39% as opposed to the central cities’ mere 19%, with even more prominent differences in some
places: 67% suburban versus 23% central city growth in New York City, as well as 126% versus 12% and 107% versus 5% in Cleveland and St Louis respectively (Hall, 2002).

The development of the quintessential American suburb has its roots to the concept of Garden Cities put forward by Ebenezer Howard (1898) (Hall, 2002; Christoforides, 1994). Howard ([1948] 1947) envisioned pre-planned communities that would combine the assets of both urban and rural living, and would relieve the overcrowded slums of London. Howard’s Garden City was conceived as a socially and economically self-sufficient town with its own schools, recreational facilities and local industry to provide employment; nevertheless, it would be subordinate to an existing larger urban centre. It would have a population of approximately 30,000 residents, ample space, parks and tree-lined streets, and would be surrounded by a belt of agricultural land that prohibits its expansion. It would be built around a central park, with public buildings at the centre followed by the commercial areas, residences and finally, in the outer ring of the city, the local industry. Developments in the UK that were realised based on Howard’s ideas include Letchworth Garden City and Welwyn Garden City (Hall, 2002).

Influenced by Howards’s ideas, architects Clarence Stein and Henry Wright conceived and constructed, in 1929, the suburban community of Radburn in New Jersey, the archetypical example of the early American suburbs built for the car era. Radburn’s design incorporated a hierarchical arrangement of roads, realised by the novel idea of the superblock: a large block surrounded by main roads with cul-de-sacs that prevented through traffic leading to the residences. The purpose was to separate pedestrians and vehicles, and keep the ills of car traffic out of the community (Hall, 2002; Christoforidis, 1994; Cervero, 1996b). The superblock concept was later to be incorporated in numerous suburban communities. (Christoforidis, 1994)

Radburn lacks one of the key features of Howard’s Garden Cities, namely the presence of local industry that provides employment and ensures the community’s self-sufficiency (Christoforidis, 1994). In general, US suburban design condones the physical separation of distinct land uses; commerce, offices and industry are excluded from residential neighbourhoods. The practise was encouraged by zoning laws that forbid the mixing of incompatible land uses. Although examples of zoning can be found as early as 1880 (in Modesto, California), zoning laws became widespread following the Ambler Realty v. Village
of Euclid court case in 1926. Then, the US Supreme Court upheld the right of the village of Euclid in Ohio to enact planning laws that regulated the use of land, laws conceived to avert the industrialisation of the village (Hall, 2002). The ruling aimed to avert the health and security hazards that were deemed inherent to commercial and industrial activity (Schilling, 2005).

Suburban development was briefly halted with the onset of the Great Depression, but a rapid development of car-oriented suburbs followed after the end of the Second World War (Hall, 2002). Although the motivating ideal behind suburban communities was the promotion of healthy living environments and a higher quality of life, there were several factors that brought about their unprecedented development in the US: the neglect of urban infrastructure during the Great Depression and World War II; the imminent housing crisis at the end of the war; the low cost involved in the construction of suburban developments; mortgage loans and highway expansion (Modarres and Kirby, 2010). A characteristic example of the speed and extent of the post-war suburban boom is the development of Levittown in Long Island, New York, with more than 17,000 homogeneous single-family dwellings, constructed on identical quarter-acre lots (Christoforidis, 1994). The 1950s was the decade where the largest suburban growth in US history took place (Hall, 2002). By 1960, 31% of US residents lived in suburbs compared to 32% in central cities. In 1920, the corresponding shares were 14% and 25% respectively. By 2000, half of the American population lived in suburbs compared to 30% in central cities (Schilling et al, 2005).

Suburban living was conceived as the solution to the health and security risks associated with urban areas living due to traffic, crime, overcrowding, low housing quality, lack of green space and concerns over the waning of the sense of community (Modarres and Kirby, 2010). However, following the 1950s suburban boom, critics of the suburbs started pointing to the destruction of farmland and the natural environment caused by suburban development, the lack of community feeling amongst residents, and the inevitable car dependency of residents and the resulting environmental consequences (Christiforidis, 1994; Jacobs, 1961; Calthorpe, 1993). Surprisingly, despite the origins of the suburban movement in the desire for healthy living, suburbanisation is now often criticised for its adverse health effects due to the inactive lifestyles of the car dependent residents (e.g. Badland and Schofield, 2005).
In the 80s and the 90s, movements such as New Urbanism emerged that endorsed the development of neighbourhoods that are compact and walking-friendly, have a variety of land uses and types of housing, and offer alternative transportation choices (Katz, 1994; Christoforidis, 2004). Such neighbourhoods are commonly described as neo-traditional, a term evocative of the traditional settlement patterns that were prevalent in the pre-auto years (Christoforidis, 2004). However, support for neo-traditional developments is not universal (e.g. Gordon and Richardson, 1997) and there is still an ongoing debate on how neighbourhoods should be structured.

A large part of the criticism concerning suburban development regards the lack of transportation choices for residents (Christoforidis, 1994). Suburbs are typically located far from city centres, have good highway access, but often poor transit provision. In addition, they are often exclusively residential, so that no shops or other facilities exist at a walking distance (Hall, 2002). It is often claimed that these features make transit use and walking impractical, and force residents to rely on the car to reach their work, do their shopping or travel to other activities. The lack of dense development also increases distances, which further obstructs walking and hinders the viability of transit provision. (Cervero and Kockelman, 1997; Calthorpe, 1993) In addition, despite being originally introduced to eliminate traffic from communities and provide a safe street environment, the cul-de-sacs of the superblock design are often blamed as an impediment to walking due to the lack of connectivity between destinations (Katz, 1994; Cervero, 1996b). The growing car dependence has significant environmental and health consequences, as it fosters gasoline overconsumption and the consequent emissions, as well as inactive lifestyles.

Land use policies are often suggested as a way to tackle car dependence (e.g. Newman and Kenworthy, 1989). It is argued that by intensifying densities, bringing shops and jobs close to residences, and encouraging grid-like street patterns and pedestrian-friendly environments, walking and transit use can be promoted and car reliance limited (Newman and Kenworthy, 1989, Calthorpe, 1993; Katz, 1994). An expanding literature has addressed the issue, trying to investigate the relationship between the spatial structure of neighbourhoods or entire cities and travel, and to determine whether land use policies can be an effective tool for shaping travel behaviour (Ewing and Cervero, 2011). Although early studies were almost exclusively from the US (e.g. Cervero, 1991; Frank and Pivo, 1994), studies from Europe, Asia and Latin America have also been published, especially in more recent times (e.g. Stead, 2001; Lin and
Yu, 2011; Estupinan and Rodriguez, 2008). The literature looks at various aspects of travel (e.g. distances travelled, trip frequency, mode choice), as well as various modes (e.g. car, transit, non-motorized modes). A variety of features relating to urban or neighbourhood structure are investigated, often collectively referred to as ‘urban form’, ‘built environment’ or ‘land use’. These features typically, but not exclusively, relate to density of development, the mixing of land uses and the configuration of street networks (Cervero and Kockelman, 2007; Ewing and Cervero, 2011; Leck, 2006).

Although many studies support the presence of a link between urban form and travel, several studies draw the opposite conclusion. There is also uncertainty regarding the size of the effect. Furthermore, some researchers question the practicality of employing land use policies to influence travel behaviour (Heres-Del-Valle and Niemeier, 2010; Brownstone and Fang, 2009; Brownstone, 2008). A detailed review of the empirical literature on the urban form-travel behaviour relationship is offered in chapter 2. The relationship between urban form and travel is still an active area of research. In the next section we explain the gaps in the literature that form the motivation of this thesis and define the thesis’ objectives.

1.2 Motivation and objectives
The empirical literature on the link between urban form and travel spans three decades and as a result is broad and diverse, and has evolved to employ more sophisticated statistical techniques. The findings are often conflicting, which presents difficulties in identifying key messages for policy action. Identifying the factors giving rise to different empirical findings is hard due to differences in data used, model specifications and geographical coverage between studies. A potential factor explaining the mixed conclusions is the inconsistency in urban form measurement between studies. Although rigorous urban form metrics have been developed, there have been few attempts to systematically examine how the choice of metric influences our understanding of the urban form-travel behaviour relationship. The first motivation of this thesis is the paucity of research on the measurement of urban form. In particular, we focus on land use mix, namely the degree of integration of different land uses, as it one of the most widely studied and broadly represented aspects of urban form. We investigate how the choice of land use mix metric affects our understanding of the relation between land use mix and travel, using both an empirical and a simulation approach.
The second motivation of this thesis regards the effect of the spatial unit of measurement of land use mix on findings regarding the relation between land use mix and travel. Inconsistency in the geographical units used for urban form measurement is a further possible reason for the diverse empirical findings reported in the literature. The spatial units used for the measurement of geographical variables are widely acknowledged to affect research outcomes. The effect is commonly known as the Modifiable Areal Unit Problem (MAUP), a name that arises from the fact that spatial units are modifiable. The presence of MAUP has been extensively demonstrated in various empirical and simulation contexts. Despite its potential significance in the context of urban form, to our knowledge, only two studies have systematically examined its impact in the modelling of the urban form-travel relationship (Zhang and Kukadia, 2005; Mitra and Buliung, 2011). Their analyses include few land use mix measures.

The last motivation for the thesis regards the effect of urban structure on public transport patronage. There are various theoretical reasons supporting the presence of a link between urban form and public transport use. For instance, population density makes transit provision more viable, which in turns encourages public transport use (Calthorpe, 1993). The built environment around transit stations can affect how comfortable people feel about walking to the station, and hence influence their propensity to use the corresponding transit service (Estupinan and Rodriguez, 2008). Retail and other facilities near stations allow people to combine a transit commute with shopping or other activities, thus making transit use more appealing (Cervero and Kockelman, 2007). The effect of the built environment on transit mode choice has been extensively studied (e.g. Cervero, 1991, 1996a; Frank and Pivo, 1995; Cervero and Gorham, 1995; Zhang, 2004; Bento et al, 2005; Susilo and Maat, 2007; Pinjari, 2007). Public transport trip frequency has received less attention, despite its importance in determining the viability of a public transport system. Most studies look at either the effect of the neighbourhood environment on individual trip making (e.g. Kitamura et al, 1997; Meurs and Haaijer, 2001; Chatman, 2008) or the impact of transit stations’ surroundings on boarding and alightings (e.g. Estupinan and Rodriguez, 2008; Sohn and Shim, 2010; Kuby et al, 2004; Sung and Oh, 2011; Cervero, 2006; Parsons and Brickenhoff, 1996). Instead, we focus on the structure of the whole urban area on aggregate transit patronage, and seek to address the shortcomings of previous literature studying this link. These will be presented in more detail in the next section.
The motivations described above give rise to the three main objectives of this thesis:

1. To investigate the effect the use of alternative land use mix measures can have on our understanding of the link between land use mix and travel behaviour. The issue is studied both using simulated analysis and in an empirical model of public transport demand.

2. To examine the impact that the choice of spatial scale in the measurement of land use mix can have on findings regarding the relationship between land use mix and travel.

3. To study the link between city-wide public transport patronage and city structure.

1.3 Research contributions
Despite the significant interest in the effects of land use mix, to our knowledge, only one paper deals with land use mix per se. Song and Rodriguez (2005) provide a critical review of land use mix metrics from various disciplines including transport, and suggest measures from other fields that can be applied in the land use mix context. They also present an empirical application that estimates correlation coefficients for some of the reviewed measures for a US city.

Song and Rodriguez (2005) do not focus on land use mix measures from the travel behaviour perspective. The empirical analysis, in particular, includes few of the measures employed to explain travel behaviour. In addition, it is subject to certain limitations. First, it only compares measures which we intuitively expect to capture the same aspect of land use mix, rather than measures that seem intuitively dissimilar despite being used to represent the same concept. Second, the authors do not test the various land use mix metrics in a full travel behaviour model. Last, results are based on a limited geographical area and may not be transferable to other areas.

In this thesis we address some of the limitations of Song and Rodriguez’s (2005) work. In contrast to Song and Rodriguez (2005), we compare measures which may seem intuitively dissimilar as long as they have been included in the literature under the general concept of land use mix. We employ both simulation and empirical analyses to investigate different land use mix measures from the travel behaviour literature. The simulated analysis uses randomly
generated cities and travel behaviour data, and hence circumvents the issue of transferability of results between different geographical areas. The method allows the researcher complete control over the specification and permits the repetition of the analysis for diverse city configurations. The simulated analysis is complemented by an empirical model for public transport trip frequency in London, in which the various land use mix measures are applied. To our knowledge, this is the first application of a wide range of land use mix measures in an empirical travel behaviour model. Furthermore, the study provides the first evidence regarding the urban form-travel behaviour relationship in the London area.

In addition to the land use mix metric used, the estimated effect of land use mix on travel could be affected by the geographic unit of measurement of land use mix. The effect of spatial scale on our understanding of the link between urban form and travel behaviour has been systematically investigated only in two studies (Mitra and Buliung, 2011; Zhang and Kukadia, 2005). The analyses include few land use mix measures. To investigate the effect of spatial scale on findings regarding the relation between land use mix and travel, we measure the various land use mix measures for several spatial scales and apply them in public transport trip frequency models for London. The previous literature has, in general, found that geographical scale affects results, but that the effect is not consistent for all measures tested. For instance, Zhang and Kukadia (2005) find that spatial scale influences the magnitude, but not the significance of the effect of population density on mode choice. On the other hand, spatial scale appears to affect both the magnitude and the significance of the effect of the employed land use mix measure. The findings underline the possibility that distinct land use mix metrics are affected differently by changes in geographical scale and that different measures could be more suitable for different scales. Therefore, they emphasize the value of studying the impact of scale on outcomes regarding the link between land use mix and travel for the diverse land use mix metrics in the literature.

Finally, this thesis extends the study of Taylor et al (2009) on public transport patronage. Taylor et al (2009) present a model of city-level public transport demand, which is estimated using data from multiple transport systems and includes a large number of covariates. The study is motivated by the fact that models for public transport patronage tend to be based on a single or few transport systems and to include only a small number of the variables that could potentially influence public transport use. The authors recognize the role various aspects of urban form might play in determining transit demand. However, they only test population
density in their model, which can be a crude measure of an urban area’s structure. In addition, the study has certain limitations relating to the application of instruments to deal with endogeneity. Specifically, the authors do not clearly define the instruments used and do not test for instrument validity and relevance.

We extend Taylor et al.'s (2009) work by estimating a public transport patronage model using the same dataset, in which we apply detailed measures of urban form, that describe the distribution of both population and employment in a city. In addition, we address the limitations regarding the use of instrumental variables by constructing appropriate tests for exogeneity and relevance. Taylor et al. (2009) only treat public transport supply as endogenous. We further estimate models that consider both transit supply and urban form to be endogenous. As the literature includes various functional specifications for transit demand models, we also experiment with various functional forms. Last, we investigate the effect of urban form both on general transit and bus transit in particular.

1.4 Outline of thesis
The thesis is organized in 8 chapters, including the present one. There are two review chapters (chapters 2 and 3) and four empirical chapters (chapters 4 to 7). A brief summary of each chapter is given below.

Chapter 2 provides a review of the literature on the relationship between urban form and travel behaviour. We discuss the aspects of travel behaviour investigated, the travel data used and key methodological issues, and review the evidence available from existing studies. In addition, we examine the various ways in which urban form is represented in past studies.

Chapter 3 reviews the method of instrumental variables, a statistical technique to control for endogeneity that is used in chapters 5 and 7. The application of the method both in linear and non-linear models is presented. The problem of endogeneity is widely acknowledged as critical for empirical work in the field and the treatment of this effect, or lack thereof, is a key methodological issue that differentiates previous studies.
Chapter 4 deals with the measurement of land use mix. We examine the land use mix measures reviewed in chapter 2 more critically and run simulations to explore how different measures affect our understanding of the links between travel demand and land use mix.

Chapter 5 extends the work of chapter 4 by testing various land use mix measures in an empirical application. We use the Ordnance Survey MasterMap Address Layer 2 dataset and the General Land Use Database for England (GLUD) to construct several distinct land use mix measures and apply them in a disaggregate model for public transport trip frequency. Travel data are obtained from the London Travel Demand Survey (LTDS), a travel diary survey covering the Greater London area.

Chapter 6 is an extension of chapter 5. In chapter 6, we re-estimate the models of the previous chapter, measuring land use mix at various spatial units, to investigate the impact of spatial scale on the conclusions reached.

In Chapter 7, we use data on population and employment provided by the US Census Bureau to construct city-wide urban form measures representing population concentration and the balance between employment and population. We then estimate a city-level model of public transport patronage using transit data from the National Transit Database, which holds data provided by public transport operators in the US. Instrumental variables estimation is used to deal with the issue of endogeneity between transit supply and demand, and between urban form and transit demand. We consider various model specifications, including testing different functional forms and estimating separate models for all public transport modes and bus modes only.

Chapter 8 presents some concluding remarks, outlines the limitation of the thesis and discusses some potential directions for future research.
Chapter 2: Literature review

2.1 Introduction
The effect of urban structure on travel first gained prominence with the study of Newman and Kenworthy (1989), who meticulously collected a large set of cross-sectional data for 32 cities in Europe, Canada, Asia, Australia and the USA, and used them to study the relationship between urban structure and car dependence. The authors used gasoline consumption as a measure of car dependence. They found negative correlations between gasoline consumption and various variables describing urban structure: population density, employment density, the number and proportion of jobs in the city centre and the proportion of population in the inner city. On the other hand, they found road and parking supply to be positively correlated with fuel consumption.

Newman and Kenworthy (1989) used elasticities of gasoline consumption with respect to income and price from previous studies to adjust gasoline consumption of non-US cities to reflect what it would be if they had US income and prices. Even after the adjustments, European cities in the dataset were found to consume 71% less gasoline in the short term and 47% in the long term. Asian cities consume even less: 87% less than US cities in the short term and 79% in the long term. The authors attributed these differences to population density and, more generally, urban structure. They further argued that the relationship between fuel consumption and urban density is multiplicative and identified a threshold value for density at which, they believed, significant energy savings occurred. Their policy recommendations included increasing population density, strengthening the city centre, restricting road and parking supply and developing public transport.

Newman and Kenworthy’s (1989) work has been criticized for its lack of a complete multivariate analysis (Gomez-Ibanez, 1991; Mindali et al, 2004; Van de Coevering and Schwanen, 2006). This shortcoming makes the presence of a threshold value for density dubious (Gomez-Ibanez, 1991). Despite its faults, Newman and Kenworthy’s (1989) work is significant because it brought the potential relation between urban form and travel in the spotlight.
Since Newman and Kenworthy’s study, a stream of papers examining the link between urban form and travel have been published. Although initial papers were often focusing on simple descriptive statistics (e.g. Ewing et al, 1996, Handy, 1996a), increasingly complicated econometric models have been estimated linking urban form to various aspects of travel relating to trip generation, mode choice, travel distances and travel times. Subsequently, a number of reviews and meta-analyses have sought to summarize this extensive body of work, sometimes focussing on particular aspects of the literature (e.g. Badoe and Miller, 2000; Boarnet and Crane, 2001; Brownstone, 2008; Ewing and Cervero, 2001, 2010; Handy, 1996b; Leck, 2006, Stead and Marshall, 2001; Mokhtarian and Cao, 2008, and Cao, Mokhtarian and Handy, 2006, for a review regarding the issue of endogeneity; Handy, 2005, for a review on walking). In addition to empirical studies, a number of simulation studies have also investigated the relationship between land use and travel (e.g. Kulash et al, 1990; McNally and Ryan, 1993; Stone et al, 1992; Rabiega and Howe, 1994; Moeckel et al, 2003; Wadell, 2002).

More recently, the health sector has taken a massive interest on the effects of urban form on active transport (e.g. walking, cycling etc) as well as recreational walking, physical activity, weight and obesity (for reviews of the literature see Badland and Schofield, 2005, Bauman and Bull, 2007, Feng et al, 2010, Handy, 2005, Saelens and Handy, 2008). The hypothesis is that dispersed urban forms encourage the modern sedentary lifestyle, including sedentary travel, and hence contribute to the increasing obesity levels.

This chapter provides a review of the literature on the link between urban form and personal travel, focussing on empirical econometric studies. It is structured as follows. The next section presents model specification and estimation issues relating to the literature. Section 2.3 summarizes substantive findings. Section 2.4 discusses the various urban form measures employed in the literature before some concluding remarks are made in section 2.5.

2.2 Travel behaviour and urban form

Empirical analyses of the urban form-travel demand relationship examines a number of variables related to personal travel, typically using one of two approaches. The first regards the estimation of mean response regression models of the form $E(y|x) = f(x)$, where $y$ is a
variable related to travel demand and $x$ is a vector of factors affecting $y$, that includes urban form. Travel variables commonly modelled include trip frequency (total or by specific modes), travel distance (total or by specific modes) and shares of trips by different modes. Some authors examine less common travel variables. For instance, Krizek (2003a,b) and Noland and Thomas (2007) consider tours\(^1\) instead of trips. Handy et al (2005, 2006) and Cao et al (2007) consider changes in driving and/or walking evaluated on a 5-point scale by surveyed individuals. Travisi et al (2009) construct a mobility impact index; this is evaluated as a weighted sum of all commute trips within and out of a city, where the weights depend on travel time and the mode used.

The second approach involves estimation of discrete choice models for the probability of selecting option $j$ from a set of $J$ alternatives. The probability $P_j$ of an individual choosing $j$ is modelled as $P_j = f(x)$, where $x$ is a vector of covariates that includes urban form. Discrete choice models are based on the assumption that an individual derives a certain utility $U_j$ by selecting $j$, and chooses alternative $j$ only if $U_j > U_i$ for all $i \neq j$\(^2\). The method is mainly used to model the choice between alternative transport modes, but has also been applied in other contexts. For instance, Susilo and Maat (2007) model the probability of commuting outside the municipality of residence. Guo (2009) models the choice between two distinct paths from the subway station to the workplace.

Studies differ in the type of travel they consider. Although many studies look at total travel, travel for specific purposes is often considered. These include:

- work
  (e.g. Cervero, 1991; Cervero and Gorham, 1995; Pinjari et al, 2007; Grazi et al, 2008; Zahran et al, 2008; Maat and Timmermans, 2007)
- non-work

---

\(^1\) Tour is a sequence of trips starting and ending at the same location.

\(^2\) $U_k$ ($k = 1, 2, ..., J$) is modelled as the sum of an observed ($V_k$) and an unobserved ($\varepsilon_k$) part: $U_k = V_k + \varepsilon_k$ $V_k$ is usually taken to be a linear function of $x$, $V_k = x'\beta$ ($\beta$ is a vector of parameters to be estimated). The vector $\varepsilon = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_J)$ is assumed to have a joint probability density $g(\varepsilon)$. The probability $P_i$ can then be expressed as

$$P_i = P(U_i > U_j, \forall i \neq j) = P(V_i - V_j > \varepsilon_i - \varepsilon_j, \forall i \neq j) = \int_\varepsilon I(\varepsilon_i - \varepsilon_j < V_i - V_j, \forall i \neq j) g(\varepsilon) d\varepsilon$$

Different choices of $g(\varepsilon)$ give rise to different forms for $P_i$. 
(e.g. Crane and Crepeau, 1998; Boarnet and Sarmiento, 1998; Greenwald and Boarnet, 2001; Cervero and Duncan, 2003; Chatman, 2008)

- shopping
  (e.g. Frank and Pivo, 1995; Handy and Clifton, 2001; Meurs and Haaijer, 2001; Cao, Handy and Mokhtarian, 2006; Handy, Cao and Mokhtarian, 2006),

- social/recreation trips
  (e.g. Meurs and Haaijer, 2001)

- personal business
  (e.g. Cervero and Kockelman, 1997)

- personal commercial activities
  (e.g. Chatman, 2003)

- children’s leisure travel
  (e.g. Lin and Yu, 2011)

The effect of urban form on travel could depend on the travel purpose considered, as suggested by studies that have estimated the same model for different travel purposes (Cervero and Kockelman, 1997; Frank and Pivo, 1995; Meurs and Haaijer, 2001; Zhang, 2004; Zhang, 2005).

Both disaggregate (individual, household or trip) and aggregate travel data are used for model estimation. For instance, mode choice has been investigated both in discrete choice models based on disaggregate data (e.g. Zhang, 2004; Cervero and Duncan, 2003; Crane and Crepeau, 1998) and in continuous models that use the share of trips by each mode as dependent variables (e.g. Cervero, 1991; Cervero and Gorham, 1995; Van de Coevering and Schwanen, 2006). Public transport trip frequency has been represented by city-wide transit patronage using data from transit operators (e.g. Taylor et al, 2007), station boardings and alightings (e.g. Estupinan and Rodriguez, 2008; Sohn and Shim, 2010; Kuby et al, 2004; Sung and Oh, 2011) and individual trip frequency by transit (e.g. Chatman et al, 2008; Kitamura et al, 1997; Meurs and Haaijer, 2001). Walking trip frequency has been modelled as individual walking trip frequency (e.g. Handy and Clifton, 2001; Greenwald and Boarnet, 2001; Cao, Handy and Mokhtarian, 2006), counts of walking commuters by county (e.g. Zahran et al, 2008) and counts of pedestrians passing by a selected point in a 10min interval.
(e.g. Rodriguez et al, 2009). It should be noted that disaggregate models are more common than aggregate models.

Table 2.1 presents information on the dependent variables, and the source, level and geographical coverage of travel behaviour data for 65 reviewed studies.

Early studies on the topic – as well as the majority of studies in general – use data from the US, where land availability, zoning policies and the historical context, which was briefly described in Chapter 1 (Section 1.1), led to large scale construction of sprawling, residential-only suburbs. More recently, studies from other parts of the world, such as Spain, Germany, Holland, Belgium, Netherland, Colombia, Hong-Kong and Taiwan, have been completed.

Studying various geographical areas is important, as results from one area may not be transferable to other areas due to factors such as culture or policies. Comparing results from distinct areas is hard due to the substantial differences in model specification between studies. Observed differences could be due to model specification rather than country specific effects. However, using pooled data from different countries, Guiliano and Narayan (2003) and Buehler (2010, in press) provide evidence that urban form effects differ between countries. In particular, Guiliano and Narayan (2003) use a sample of pooled UK and US disaggregate data to estimate models for trip frequency and daily distance travelled. They conclude that although British people make less trips and travel less miles than their US counterparts, the effect of density is, in general, more pronounced in the US. Buehler (2010, in press) pools data from two comparable disaggregate surveys from the US and Germany to estimate models for travel distance by car and mode choice. Results suggest that urban form variables can have a different effect on travel behaviour in the two countries, but the difference depends on the travel and urban from variables considered.

The next section presents some key methodological issues in the literature.
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<thead>
<tr>
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<th>Year</th>
<th>Travel Behaviour Data Source</th>
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<th>Aspect of travel considered</th>
<th>Travel purpose††</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cervero (1991)</td>
<td>US</td>
<td>nationwide</td>
<td>1989</td>
<td>Report on Travel Characteristics at Large Scale Suburban Centers (by National Cooperative Highway Research Program NCHRP)</td>
<td>A</td>
<td>trips, % trips by mode, vehicle occupancy</td>
<td>work</td>
</tr>
<tr>
<td>Cervero and Gorham (1995)</td>
<td>US</td>
<td>Los Angeles, Orange County</td>
<td>1995</td>
<td>US Census</td>
<td>A</td>
<td>% trips by transit</td>
<td>work</td>
</tr>
<tr>
<td>Cervero and Radisch (1996)</td>
<td>US</td>
<td>San Francisco Bay Area</td>
<td>1990/1</td>
<td>1990/1 Bay Area Travel Survey (BATS)</td>
<td>D</td>
<td>mode choice</td>
<td>work, non-work</td>
</tr>
<tr>
<td>Cervero (1996a)</td>
<td>US</td>
<td>11 metropolitan areas</td>
<td>1990</td>
<td>1990 US Census</td>
<td>A</td>
<td>% trips by transit</td>
<td>work</td>
</tr>
<tr>
<td>Schimek (1996)</td>
<td>US</td>
<td>nationwide</td>
<td>1990</td>
<td>Nationwide Personal Transportation Survey</td>
<td>D</td>
<td>car distance, car ownership, car trips</td>
<td>all travel</td>
</tr>
<tr>
<td>Cervero and Kockelman (1997)</td>
<td>US</td>
<td>San Francisco Bay Area</td>
<td>1990/1</td>
<td>1990/1 Bay Area Travel Survey (BATS)</td>
<td>D</td>
<td>car distance, mode choice</td>
<td>all travel, work, non-work, personal business</td>
</tr>
<tr>
<td>Kitamura et al (1997)</td>
<td>US</td>
<td>San Francisco Bay Area</td>
<td>1993</td>
<td>self-administered survey</td>
<td>D</td>
<td>trips, trips by mode, % trips by mode</td>
<td>all travel</td>
</tr>
<tr>
<td>Sanches and Arruda (2002)</td>
<td>Brazil</td>
<td>Sao Carlos</td>
<td>unclear</td>
<td>self-administered travel diaries to students and staff of the Federal University of Sao Carlos</td>
<td>D</td>
<td>mode choice</td>
<td>all travel</td>
</tr>
</tbody>
</table>
Table 2.1 (continued) Dependent variables and source, level and geographical coverage of travel behaviour data employed in studies

<table>
<thead>
<tr>
<th>Authors</th>
<th>Country</th>
<th>Area/City</th>
<th>Year</th>
<th>Travel Behaviour Data Source</th>
<th>A/D⁴</th>
<th>Aspect of travel considered</th>
<th>Travel purpose⁵⁶</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cervero and Duncan (2003)</td>
<td>US</td>
<td>San Francisco Bay Area</td>
<td>2000</td>
<td>2000 Bay Area Travel Survey (BATS)</td>
<td>D</td>
<td>mode choice</td>
<td>non-work, excl. heavy shopping</td>
</tr>
<tr>
<td>Rodriguez and Joo (2004)</td>
<td>US</td>
<td>Chapel Hill &amp; Carrboro, North Carolina</td>
<td>1997</td>
<td>data for student and staff commuters to the University of North Carolina in Chapel Hill from mailback survey originally conducted to measure effectiveness of proposed policy changes to the University's Transportation System</td>
<td>D</td>
<td>mode choice</td>
<td>travel to university for work/study</td>
</tr>
<tr>
<td>Khattak and Rodriguez (2005)</td>
<td>US</td>
<td>North Carolina</td>
<td>unclear</td>
<td>self-administered survey</td>
<td>D</td>
<td>trips, distance, time</td>
<td>all travel, non-work</td>
</tr>
<tr>
<td>Zhang (2005)</td>
<td>US</td>
<td>Boston</td>
<td>1991</td>
<td>Boston Activity-Travel Survey (travel diary)</td>
<td>D</td>
<td>trips, time</td>
<td>work, education, shopping, social, personal business, picking/dropping someone, other</td>
</tr>
</tbody>
</table>
### Table 2.1 (continued) Dependent variables and source, level and geographical coverage of travel behaviour data employed in studies

<table>
<thead>
<tr>
<th>Authors</th>
<th>Country</th>
<th>Area/City</th>
<th>Year</th>
<th>Travel Behaviour Data Source</th>
<th>A/D</th>
<th>Aspect of travel considered</th>
<th>Travel purpose††</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scheiner and Holz-Rau (2007)</td>
<td>Germany</td>
<td>Colloge</td>
<td>2002/3</td>
<td>StadtLeben project (2002/3)</td>
<td>D</td>
<td>% trips by mode, distance</td>
<td>all travel</td>
</tr>
<tr>
<td>Cao et al (2007)</td>
<td>US</td>
<td>Northern California</td>
<td>2003</td>
<td>same as Handy, Cao and Mokhtarian (2005)</td>
<td>D</td>
<td>changes in driving, changes in walking (on a 5-point scale)</td>
<td>all travel</td>
</tr>
<tr>
<td>Wells and Young (2008)</td>
<td>US</td>
<td>Georgia, Alabama, Florida</td>
<td>2003-2006</td>
<td>pedometer readings, participants from women who have partnered with the self-help housing organization Habitat for Humanity</td>
<td>D</td>
<td># of steps</td>
<td>all travel</td>
</tr>
<tr>
<td>Guo (2009)</td>
<td>US</td>
<td>Boston</td>
<td>1994</td>
<td>sunway onboard surveys conducted by the Central Transportation Planning Staff (CTPS)</td>
<td>D</td>
<td>choice model for different paths***</td>
<td>work</td>
</tr>
<tr>
<td>Travisi et al (2009)</td>
<td>Italy</td>
<td>nationwide</td>
<td>1991</td>
<td>Italian National Census</td>
<td>A</td>
<td>mobility impact index*</td>
<td>work</td>
</tr>
<tr>
<td>Garcia-Palomares (2009)</td>
<td>Spain</td>
<td>Madrid</td>
<td>2001</td>
<td>2001 Census</td>
<td>A</td>
<td>time, % trips by mode, % trips by destination</td>
<td>work</td>
</tr>
</tbody>
</table>
Table 2.1 (continued) Dependent variables and source, level and geographical coverage of travel behaviour data employed in studies

<table>
<thead>
<tr>
<th>Authors</th>
<th>Country</th>
<th>Area/City</th>
<th>Year</th>
<th>Travel Behaviour Data Source</th>
<th>A/D†</th>
<th>Aspect of travel considered</th>
<th>Travel purpose††</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rodriguez et al (2009)</td>
<td>Colombia</td>
<td>Bogota</td>
<td>2005</td>
<td>pedestrian counts by auditors</td>
<td>A</td>
<td>walking trips (pedestrian counts)</td>
<td>all travel</td>
</tr>
<tr>
<td>Sohn and Shim (2010)</td>
<td>South Korea</td>
<td>Seoul</td>
<td>unclear</td>
<td>Seoul Metro Corporation &amp; Seoul Metropolitan Rapid Transit System</td>
<td>A</td>
<td>boardings per station</td>
<td>all travel</td>
</tr>
<tr>
<td>Van Acker and Witlox (2010)</td>
<td>Belgium</td>
<td>Ghent urban region</td>
<td>2000-2001</td>
<td>Ghent Travel Behaviour Survey</td>
<td>D</td>
<td>car onwership &amp; car use (binary variable)</td>
<td>all purposes, trips up to 60km</td>
</tr>
<tr>
<td>Bhat and Eluru (2009)</td>
<td>US</td>
<td>San Francisco Bay Area</td>
<td>2000</td>
<td>2000 Bay Area Travel Survey (BATS)</td>
<td>D</td>
<td>car distance</td>
<td>all travel</td>
</tr>
<tr>
<td>Heres-Del-Valle and Niemeier (2010)</td>
<td>US</td>
<td>California</td>
<td>2000/1</td>
<td>travel diary survey by CALTRANS (California Department for Transportation) (travel diaries supplemented by GPS loggers for some respondents)</td>
<td>D</td>
<td>car use &amp; car distance</td>
<td>all travel</td>
</tr>
<tr>
<td>Lin and Yu (2011)</td>
<td>Taiwan</td>
<td>Taipei</td>
<td>2007</td>
<td>Questionnaire survey delivered to students of randomly selected classes from the 4th, 5th and 6th grade of selected schools in Taipei, students and apprented were expected to complete the survey together/ I can simply say questionnaires delivered to students via/at schools</td>
<td>D</td>
<td>trips, mode choice</td>
<td>children's leisure travel</td>
</tr>
<tr>
<td>Sung and Oh (2011)</td>
<td>South Korea</td>
<td>Seoul</td>
<td>unclear</td>
<td>Seoul Metropolitan Government</td>
<td>A</td>
<td>station boarding</td>
<td>all travel</td>
</tr>
<tr>
<td>Noland and Thomas (2007)</td>
<td>US</td>
<td>nationwide</td>
<td>2001</td>
<td>2001 National Household Transportation Survey</td>
<td>D</td>
<td>tours, trips per tour</td>
<td>all travel</td>
</tr>
<tr>
<td>Van Acker and Witlox (in press)</td>
<td>Belgium</td>
<td>Ghent urban region</td>
<td>2000-2001</td>
<td>Ghent Travel Behaviour Survey</td>
<td>D</td>
<td>distance, car ownership, stops per tour, car use (binary variable), time</td>
<td>work</td>
</tr>
</tbody>
</table>

*weighted sum of all commute trips within and out of a city; the weights depend on travel time and the mode used
**choice model for the probability that an individual commutes outside the home municipality
***model for the choice between two different paths to access work from the subway station, one involving only walking and one involving a subway route transfer and walking
† A=Aggregate, D=Disaggregate
††Not all models estimated for all travel purposes given

legend
trips = number of trips
car = car, personal vehicle or single occupancy vehicle, often including motorcycles
transit = all public transport modes or specific modes of public transport by mode = separate models estimates for at least two distinct modes
% trips by 'x' = the share of trips that was completed by mode 'x'
walking trips = number of walking trips (e.g. individual walking trip frequency, pedestrian counts etc)
transit trips = car trips and cycling trips defined similarly
distance = distance travelled
car distance = distance travelled by car
transit distance and walking distance similarly defined
mode choice = discrete mode choice model (binary or multinomial)
& denotes first-part of joint model structure
2.2.2 Key issues in the literature

2.2.2.1 Endogeneity between urban form and travel behaviour

A major estimation issue in the literature on the urban form-travel link is endogeneity between urban form and travel behaviour. In the classical linear model

\[ y = X\beta + \varepsilon \]

where \( y \) is the dependent variable, \( X \) a set of covariates, \( \beta \) a vector of parameters to be estimated and \( \varepsilon \) an unobserved error term, endogeneity occurs when

\[ E(\varepsilon/X) \neq 0. \]

The definition can be likewise extended to non-linear models. Endogeneity can have various causes, such as the omission of variables that are correlated with the error term or the presence of a two-way relationship between the dependent variable and one or more covariates (simultaneity). In the urban form-travel context, endogeneity can occur if individuals are predisposed towards specific travel behaviours and consequently, are self-selecting themselves into neighbourhoods whose land-use configurations can support their travel preferences. Consequently, the link between urban form and travel might not be a simple one-way relationship. Certain authors interpret endogeneity between urban form variables as a case of omitted variables, where the omitted variables relate to attitudes or lifestyle choices that affect both travel and residential location choices.

Endogeneity is a serious issue because it renders parameter estimates inconsistent. If it is left untreated, parameter estimates simply show an association between urban form and travel rather than a causal effect. Early studies (e.g. Frank and Pivo, 1995; Schimek, 1996; Handy and Clifton, 2001) fail to acknowledge the issue and consequently can only establish a correlation between urban form and travel, which has limited policy implications. However, several studies implement various approaches to deal with endogeneity. These include the use of variables describing lifestyle attitudes or neighbourhood preferences, the use of longitudinal data, the estimation of joint models such as structural equations models (SEM) and the application of instrumental variable techniques. The methods employed to control for endogeneity are discussed in detail in the next section along with the conclusions reached. Mokhtarian and Cao (2008) and Cao, Mokhtarian and Handy (2006) also offer a detailed review.
2.2.2.2 How should we measure urban form?

Although endogeneity is the most widely acknowledged and researched issue in the literature, there are other methodological issues that have been addressed to a much lesser extent. A look at the literature quickly reveals the surprisingly vast array of urban form measures. It is not only that different features relating to city or neighbourhood structure have been investigated (e.g. density of development, mixing of land uses, street network patterns), each of these aspects has been measured by a number of distinct metrics. Past studies often led to contradictory findings regarding the urban form-travel behaviour link; the inconsistency in urban form measurement between studies could be a possible factor explaining the conflicting conclusions. However, there have been few attempts to investigate the effect the choice of measure can have.

In chapter 4 and 5, we investigate the effect the metric employed in measuring a specific aspect of urban form, land use mix, can have on our perception of the relationship between land use mix and travel demand. Given the potential importance of urban form measurement and the emphasis placed in this thesis on the measurement of land use mix, in section 2.4, we present a detailed overview of the urban form measures employed in past studies.

2.2.2.3 At what scale should we measure urban form?

The spatial scales used in the literature vary widely between studies\(^3\). Aggregate studies measure urban form (and travel behaviour) for various geographical units ranging from entire urban areas (e.g. Van de Coevering and Schwanen, 2006; Taylor, 2007) to smaller administrative or statistical units (e.g. Cervero, 1996b; Cervero and Gorham, 1995; Zahran et al, 2008; Travisi et al, 2009; Garcia-Palomares, 2009), suburban employment sites (e.g. Cervero, 1991), transit stops (e.g Estupinan and Rodriguez, 2008) or road segments (e.g. Rodriguez et al, 2009).

Although certain disaggregate studies consider urban form at the city level (e.g. Bento et al, 2005), the majority of studies measure urban form variables at smaller scale, the ‘neighbourhood’. Neighbourhood boundaries are often taken to coincide with existing administrative or statistical boundaries (eg. Chatman, 2003; Rodriguez and Joo, 2004; Brownstone and Fang; 2009). On the other hand, certain researchers define their own

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\(^3\) A few exceptions of urban form measures that are not scale dependent exist.
geographical buffers to measure the neighbourhood environment (e.g. Chatman, 2008; Cervero, 1996a; Cervero and Duncan, 2003; Handy et al, 2005, 2006). The size of such spatial units varies greatly between studies. For instance, Cervero (1996a) uses circular units with a 300 feet radius (91 meters), while Handy et al (2005) considers circular buffers with radii up to 1600m. Table 2.2 illustrates the variety of spatial units used to measure urban form in past studies.

The potential influence of spatial scale on research findings has been emphasized in various empirical and simulation contexts (e.g. Gehlke and Biehl, 1934; Openshaw and Taylor, 1979; Flowerdue et al, 2008; Briant et al, 2010; Amrhein, 1995; Spielman and Yoo, 2009). On the other hand, few studies on the urban form-travel behaviour link have addressed the issue (Zhang and Kukadia, 2005; Mitra and Buliung, 2011; and to a lesser extent Boarnet and Sarmiento, 1998; Greenwald and Boarnet, 2001). In chapter 6, we investigate the effect of spatial scale on the measurement of the land use mix-public transport demand relationship. The chapter also provides an overview of the literature on the issue of spatial scale in the context of the urban form-travel behaviour link.
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<th>Study</th>
<th>Spatial Scale</th>
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<td>Cervero (1996a)</td>
<td>300 feet buffer</td>
</tr>
<tr>
<td>Cervero and Kockelman (1997)</td>
<td>census tract or two adjoining census tracts together (US)</td>
</tr>
<tr>
<td>Kitamura, Mokhtarian and Laidet (1997)</td>
<td>neighbourhoods of approximately 1 square mile in size</td>
</tr>
<tr>
<td>Crane and Crepeau (1998)</td>
<td>0.5 mile circle, census tract (US)</td>
</tr>
<tr>
<td>Boarnet and Sarmiento (1998)</td>
<td>census tract (US), census block group (US), 0.25 miles circle, zip code (US)</td>
</tr>
<tr>
<td>Greenwald and Boarnet (2001)</td>
<td>census block group (US), 0.25 mile circle, 1 mile circle, zip code (US)</td>
</tr>
<tr>
<td>Stead (2001)</td>
<td>ward (UK), local authority (UK)</td>
</tr>
<tr>
<td>Bagley and Mokhtarian (2002)</td>
<td>neighbourhoods of approximately 1 square mile in size</td>
</tr>
<tr>
<td>Sanches and Arruda (2002)</td>
<td>census tract (Brazil)</td>
</tr>
<tr>
<td>Chatman (2002)</td>
<td>census tract (US)</td>
</tr>
<tr>
<td>Giuliano and Narayan (2003)</td>
<td>postal service unit (UK), census tract (US)</td>
</tr>
<tr>
<td>Cervero and Duncan (2003)</td>
<td>1 mile circle, 5 mile circle</td>
</tr>
<tr>
<td>Krizek (2003)</td>
<td>census block (US), 150 metre grid cell</td>
</tr>
<tr>
<td>Zhang (2004)</td>
<td>transportation analysis zone (US, Hong-Kong), 800 metre grid cell</td>
</tr>
<tr>
<td>Rodriguez and Joo (2004)</td>
<td>block group (US)</td>
</tr>
<tr>
<td>Handy, Cao and Mokhtarian (2005)</td>
<td>400 metre, 800 metre and 1600 metre circle</td>
</tr>
<tr>
<td>Handy, Cao and Mokhtarian (2006)</td>
<td>400 metre, 800 metre and 1600 metre circle</td>
</tr>
<tr>
<td>Susilo and Maat (2007)</td>
<td>municipality (Holland)</td>
</tr>
<tr>
<td>Scheiner and Holz-Rau (2007)</td>
<td>neighbourhoods of unspecified size</td>
</tr>
<tr>
<td>Cao, Mokhtarian and Handy (2007)</td>
<td>400 metre, 800 metre and 1600 metre circle</td>
</tr>
<tr>
<td>Vance and Hedel (2007)</td>
<td>zip code (Germany)</td>
</tr>
<tr>
<td>Vance and Hedel (2008)</td>
<td>zip code (Germany)</td>
</tr>
<tr>
<td>Pinjary et al (2007)</td>
<td>transport analysis zone (US)</td>
</tr>
<tr>
<td>Chen et al (2007)</td>
<td>census tract (US)</td>
</tr>
<tr>
<td>Frank et al (2007)</td>
<td>1 km buffer along the street network</td>
</tr>
<tr>
<td>Noland and Thomas (2007)</td>
<td>census tract (US)</td>
</tr>
<tr>
<td>Estupinan and Rodriguez (2008)</td>
<td>250 metre circle</td>
</tr>
<tr>
<td>Wells and Young (2008)</td>
<td>0.25 mile buffer along the street network, census tract (US), transportation analysis zone (US)</td>
</tr>
<tr>
<td>Brownstone and Fang (2009)</td>
<td>census block (US)</td>
</tr>
<tr>
<td>Maat and Timmermans (2009)</td>
<td>250 metre grid cell (moving average over many cells used)</td>
</tr>
<tr>
<td>Rodriguez et al (2009)</td>
<td>250 metre circle</td>
</tr>
<tr>
<td>Van Acker and Witlox (2010)</td>
<td>census tract (Belgium)</td>
</tr>
<tr>
<td>Grazi et al (2008)</td>
<td>municipality (Holland)</td>
</tr>
<tr>
<td>Heres-Del-Valle and Niemeier (2010)</td>
<td>census tract (US), Zip Code Tabulation Area (US)</td>
</tr>
<tr>
<td>Buehler (2010)</td>
<td>municipality (Germany), census tract (US)</td>
</tr>
<tr>
<td>Buehler (in press)</td>
<td>municipality (Germany), census tract (US)</td>
</tr>
<tr>
<td>Lin and Yu (2011)</td>
<td>Li (basic administrative unit in Taiwan)</td>
</tr>
</tbody>
</table>

Note: In studies employing multiple scales, different scales are used for distinct urban form variables or models.
2.3 **Substantive results on the relationship between urban form and travel**

The literature contains many conflicting findings regarding the urban form-travel behaviour relationship and therefore, it is hard to draw general conclusions. The task of comparing study results is complicated by the wide range of travel and urban form variables considered in past studies. In addition, most studies fail to report elasticities and hence, the size of the estimated effects cannot be compared. Nevertheless, some authors have attempted to perform meta-analyses of the existing results that provide valuable insights.

Leck (2006) completed a meta-analysis of 17 studies, which supplied 32 data points. He circumvented the problem of the lack of elasticities by concentrating on the significance rather than the magnitude of results and analysing p-values. He found that population/residential density at the trip origin has a significant negative effect on vehicle miles travelled (VMT), vehicle hours travelled, vehicle trip frequency and the probability of commuting by car. On the other hand, it has a significant positive effect on the probabilities of commuting by public transport or walking. The effect of employment density at the destination has effects of the same sign as population density for all the dependent variables considered, but in contrast to population density it was found insignificant for vehicle hours travelled and the number of non-work vehicle trips. Land use mix was found to have a significant negative influence on VMT and the probability of commuting by car, and a significant positive impact on the probabilities of commuting by public transport or walking. The effect of street network configurations on the probabilities of commuting by car and by transit were also studied, but they were found to be insignificant.

The problem of the lack of elasticities was addressed by the effort of Ewing and Cervero (2010), who completed the arduous task of calculating elasticities for the numerous studies that fail to report them\(^4\). The calculated elasticities were used for a meta-analysis in which weighted\(^5\) average elasticities for vehicle miles travelled (VMT), walking and transit use with respect to various urban form variables were calculated. The review includes both published and unpublished studies, but focuses on disaggregate studies, because the authors are interested in estimating elasticities that predict individual behaviour. Unavoidably, only studies for which the necessary data to calculate elasticities were available are included.

\(^4\) The estimated elasticities are approximate because they are calculated at the point of means of the data, an approach not suitable for non-linear models

\(^5\) Weighting was by sample size.
When such data were not readily available in a paper, Ewing and Cervero (2010) contacted authors for further information, an approach that was however not always fruitful. Ewing and Cervero (2010) further excluded studies that were limited in scope (for instance, studies that considered travel to school only) and studies that used urban form measures that were subjective, derived using factor analysis or transformed into categorical variables.

The estimated weighted elasticities are generally low; they vary in absolute value from 0 to 0.39. Some are particularly low. For instance, the weighted elasticities of VMT, walking and transit use with respect to residential/population density, the most prominent urban form measure, are -0.04, 0.07 and 0.07 respectively. The corresponding elasticities with respect to employment density are even lower: 0, 0.04 and 0.01 respectively. The urban form variable that has the highest effect on VMT is distance to downtown (-0.22). On the other hand the highest impact on walking is caused by intersection/street density followed by distance to the store (0.39 and 0.25 respectively). Regarding transit use, the built environment measure with the highest influence is the percentage of 4-way intersections (0.29), which has the same effect as distance to the nearest transit stop.

The meta-analyses of Ewing and Cervero (2010) and Leck (2006) do not take into account the quality of studies. A key factor determining the quality of studies is whether and how they control for endogeneity between urban form and travel behaviour. Below, we critically review studies that have attempted to control for endogeneity and discuss their results. Unfortunately, in most cases it is not possible to draw conclusions on the size of the estimated effects as elasticities are rarely presented.

As noted in section 2.4, several researchers explain endogeneity between urban form and travel as a result of the omission of attitudinal variables that affect both travel and residential location choices. Subsequently, they deal with endogeneity by including variables relating to lifestyle attitudes and/or preferences regarding neighbourhood characteristics in their models (e.g. Cao, Handy and Mokhtarian, 2006; Handy, Cao and Mokhtarian, 2005; Handy, Cao and Mokhtarian, 2006; Cao, Mokhtarian and Handy, 2007; Kitamura et al, 1997; Bagley and Mokhtarian, 2002; Scheiner and Holz-Rau, 2007; Chatman, 2008). They generally find that the built environment still has an effect on travel after controlling for attitudes, although attitudes do play a role in determining travel behaviour. Kitamura et al (1997) who look at the
proportion of variance the different covariates in their models explain, conclude that attitudinal factors have a much stronger influence than urban form.

As pointed out by certain authors (e.g. Brownstone, 2008; Chatman, 2008), a major limitation of this approach is that attitudes are unlikely to be constant; instead they are likely to be jointly determined with residential location and travel habits. Indeed, several studies suggest that there is a two-way relationship between attitudes and travel behaviour (Reibstein et al, 1980; Van Vugt et al, 1996; Tertoolen et al; 1998). While an individual’s attitudes might shape his travel behaviour, an individual is also likely to change his reported attitudes to justify his behaviour. In addition, neighbourhood characteristics unrelated to the initial reasons for choosing a neighbourhood, or even neighbours’ attitudes and behaviour, can alter an individual’s attitudes and preferences following a move. Consequently, studies might be overestimating the impact of attitudinal factors on travel.

The problem is partly addressed by Bangley and Mokhtarian (2002) who estimate a structural equations model (SEM) which, in addition to travel and urban form variables, also treats some attitudinal variables as endogenous. In structural equations modelling, interdependencies between endogenous variables are explicitly modelled. Bangley and Mokhtarian’s (2002) model has the advantage that it jointly models travel, urban form and attitudinal variables. Nevertheless, not all attitudinal factors included in the model are treated as endogenous, possibly due to identification issues. A further limitation of the study is that the authors remove 100 outlying observations from the initial 615 in the sample, a rather sizeable proportion, so that the sample conforms to normality assumptions.

Bagley and Mokhtarian (2002) find that urban form has little effect on travel. In particular, they find that urban form has no effect on vehicle miles travelled and miles travelled by non-motorized modes\(^6\). On the other hand, the more suburban a neighbourhood is in character, the longer residents’ commute distances are and the longer residents travel by transit. They explain the counterintuitive positive effect of suburban characteristics on transit distances travelled by the fact that suburban residents travel long distances on the Bay Area Rail Transit system. Results suggest that suburban residents do travel more in total, albeit not

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\(^6\) No effect is reported in the relevant table. As the authors note, this could be either because there was no effect or because the effect was very small.
specifically by car. Interestingly, the authors find that residential location does not influence attitudes.

Chatman’s (2008) survey questions respondents regarding the neighbourhood characteristics they sought specifically on their last move, an approach that reduces the possible problem of attitudes and preferences becoming congruent after a move. He finds that the built environment still has an effect on travel after accounting for the characteristics sought at the last move. In particular, population density has a negative impact on the number of trips made by car and the presence of heavy rail transit increases the number of trips made by public transport. Surprisingly, the author also finds that the presence of light rail transit has a positive impact on car trips.

Cao et al (2010) provide an interesting approach using attitudinal factors. The authors apply propensity score matching to evaluate the differences in vehicle miles driven between residents of different types of neighbourhoods. In the context of Cao et al’ s study (2010), the propensity score is defined as the probability that an individual resides in a particular type of neighbourhood given her socio-demographic characteristics and neighbourhood preferences, and is estimated as a binary logit model. Individuals residing in different neighbourhoods are paired based on their propensity scores and certain criteria. For instance, the difference between propensity scores in a pair is not allowed to exceed 0.01. Individuals without a suitable matching are discarded from the sample. The average treatment effect (ATE) is estimated as the difference in mean vehicle miles driven between individuals in the same pair.

Cao et al (2010) find that residential location plays a role in determining distances driven and that this role is more important than travel preferences. Nevertheless, residential preferences still play a role in some cases. Cao et al’s (2010) method had the advantage that no assumptions need to be made regarding functional form. The study is notable because it is the first application of the propensity score/ATE method in the urban form-travel behaviour context; indeed the method has been rarely used in the transportation field. However, it still has the aforementioned limitation that attitudes are unlikely to be stable, but are liable to be jointly determined with travel and residential location.
Another interesting approach using neighbourhood preferences is provided by Schwanen and Mokhtarian (2005a,b). The authors construct dissonance indicators that measure the level of mismatch between a person’s neighbourhood preferences and their actual neighbourhood. Subsequently, they investigate how the behaviour of suburban-minded people living in urban areas compares with true urbanites as well as how the behaviour of urban-minded people living in the suburbs compares with true suburbanites. They conclude that in general people living in the suburbs become car-oriented even if they prefer not to use the car, suggesting that in suburban locations the built environment is more important than preferences. In an urban environment on the other hand, preferences can be more important than the environment; auto–oriented people appear to often use the car despite the anti-auto environment.

Several researchers employ longitudinal data to control for endogeneity. In particular, they examine the changes in travel behaviour that occur after a house move. A prominent longitudinal study is Krizek (2003b). The author uses the Puget Sound Transportation Panel to examine the behaviour of individual moving neighbourhoods in the Puget Sound Region of the US. The study’s result suggest that features related to traditional or neo-traditional neighbourhoods have a negative impact on vehicle miles and person miles travelled, but a positive effect on the number of tours. On the other hand, the effect on the number of trips per tour depends on whether urban form at the home residence or the workplace is considered.

Krizek’s (2003b) analysis has an important limitation: It assumes that the decision to move is random; individuals do not change residence to realise their travel preferences. The assumption is likely to be unrealistic. Individuals could, for instance, decide to relocate to be closer to work or other facilities. If individuals do move for transport related reasons, the change in urban form resulting from the move is not exogenous and hence, endogeneity is still an issue.

Cao et al (2007) avoid the issue by simultaneously modelling changes in travel behaviour and changes in urban form using a structural equation modelling approach (SEM). The endogenous variables used are changes in driving, changes in walking, changes in car

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7 A further limitation of the study is that the Puget Sound Transportation Panel oversamples public transport users, which makes the sample endogenous when car use is considered.
ownership and changes in ‘accessibility’, ‘spaciousness’ and ‘attractiveness’, three urban form measures derived through factor analysis on various perceived neighbourhood characteristics. The study also includes attitudinal factors as covariates, but they are treated as exogenous. The authors find that increased accessibility reduces driving and increased attractiveness promotes walking.

The model has the further advantage that, in addition to urban form and travel, car ownership is also treated as endogenous. The perceived accessibility measure of urban form incorporates perceptions regarding transit accessibility, so indirectly transit access is also treated as endogenous. However, the study also has certain limitations. First, changes in driving are measured by memory on a 5-point scale that ranges from ‘a lot less now’ to ‘a lot more now’. The measure is rather uninformative, and prone to measurement error. In addition, the use of perceived rather than objective measures of urban form makes translating any conclusions into policy difficult.

Another interesting longitudinal study is Wells and Yang (2008). The authors take advantage of a natural experiment in which low-income women were housed through a charity in different neighbourhoods. The study looks at changes in walking following the move. The authors find that increases in the number of service jobs per resident and in the number of cul-de-sacs lead to a reduction in walking. The study has a distinctive characteristic: the women in the sample, having been housed through a charity, did not choose the type of neighbourhood they moved into. Hence, any changes in urban form following the move can be treated as exogenous. However the study also has two important limitations. Due to their low-income, participants might not be using a car simply because they could not afford it rather than by preference. Furthermore, the sample size is very low (32). It should also be noted that the study used total walking rather than walking for transport as a dependent variable, measured as steps per week through the use of pedometers. Consequently, the results are not directly relevant to the transport field.

Meurs and Haaijer (2001), interestingly, estimate separate models for individuals that moved house and individuals that did not change address. They find that even for non-movers, spatial changes such as the introduction of traffic calming measures or an increase in planting have an effect on trip patterns. In particular, the introduction of traffic calming measures decreases the number of trips made by public transport; an increase in transit stops has the
opposite effect. Increases in planting in the neighbourhood have a positive impact on trip making in general and walking in particular, while increases in the time to reach the main road increases the number of trips made by car and reduces the number of cycling trips. A minor limitation of Meurs and Haaijer’s (2001) study is that they do not present the personal and household characteristics for which they control in their models.

Handy et al (2005, 2006) also use longitudinal data to investigate changes in walking and driving. They use the same data and variables as Cao et al (2007), but treat car ownership and changes in urban form as exogenous. Consequently, they suffer from the same limitation as Krizek (2003b), namely they make the somewhat strong assumption that a house move is not motivated by unfulfilled travel preferences. They find that increases in accessibility increase walking and decrease driving.

Many studies jointly model travel and residential location to control for endogeneity. Two examples, Cao et al (2007) and Bagley and Mokhtarian (2008), which use SEM, have already been discussed. Scheiner and Holz-Rau (2007) also use SEM and find that land use mix, measured as the sum of retail, service and leisure opportunities per square kilometre, increases the share of non-motorized travel. Furthermore, they find that population density and land use mix\(^8\) have a negative effect on vehicle kilometres travelled.

Pinjari et al (2007) estimate joint discrete probabilities for residential location and commute mode choice. The effect of unobserved characteristics such as lifestyle attitudes that can influence both travel and residential location is captured using a common component in the error terms of the two equations. Pinjari et al (2007) find that land use factors such as population density, employment density and street block density have an effect on mode choice.

Another approach to deal with endogeneity is to use instrumental variables (IV). Instrumental variables or simply instruments are variables that are correlated with the endogenous regressors of the model, but are uncorrelated with the error term. The method is employed in this thesis and is discussed in more detail in chapter 3. A limitation of the approach is that finding good instruments in practical applications is difficult. Poor instruments can have

\(^8\) Population and land use mix are combined in one factor using factor analysis.
significance consequences for the model, an issue that is often disregarded by researchers. Instruments need to be correlated with the endogenous variables (instrument relevance), but uncorrelated with the error term of the equation of interest (instrument validity/exogeneity). Moreover, the correlation between the endogenous variables and the instruments should not be weak. Failure of either assumption can lead to significant biases in the IV estimator and a considerable loss in efficiency. Researchers should have a good theoretical basis to justify their choice of instruments. Moreover, a number of tests have been developed to test both instrument exogeneity and instrument relevance. Although these tests have limitations, an application of IV estimation should not neglect performing them. Many studies fail to adequately support their choice of instruments both by theoretical arguments and by performing appropriate tests.

Table 2.3 summarizes the studies that have used instrumental variables; information on the dependent variables, urban form measures and instruments used are provided. The instruments used for urban form are often non-travel related neighbourhood amenities; these are assumed to affect the choice of residential location but not travel behaviour. Taylor et al (2009) and Estupinan and Rodriguez (2008) also use instrumental variables, however it is not clear which instruments they are using and hence are excluded from the discussion.
Table 2.3 Summary of studies employing instrumental variables

<table>
<thead>
<tr>
<th>Study</th>
<th>Dependent variable</th>
<th>Endogenous urban form variables</th>
<th>Instruments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boarnet and Sarmiento (1998)</td>
<td>car trip frequency (non-work travel)</td>
<td>population density, retail job density, service job density, % 4-way intersections*</td>
<td>% black population, % hispanic populations, % houses built before 1940, % houses built before 1960</td>
</tr>
<tr>
<td>Greenwald and Boarnet (2001)</td>
<td>walking trip frequency (non-work travel)</td>
<td>population density, retail job density, % area covered in grid format, pedestrian environment factor **</td>
<td>neighbourhood per capita income, % population with at least college education, % African American population, % Hispanic population, % rural dwellings, % urban dwellings</td>
</tr>
<tr>
<td>Khattak and Rodriguez (2005)</td>
<td>trip frequency</td>
<td>residential location (dummy for location in a neo-traditional neighbourhood)</td>
<td>respondents’ residential attitudes</td>
</tr>
<tr>
<td>Vance and Hedel (2007)</td>
<td>car use (binary: 1,0) &amp; distance travelled (non-work travel)</td>
<td>walking time to the nearest public transport stop, commercial outlet density, commercial outlet diversity (Shannon index), road density***</td>
<td>% buildings built before 1945, % buildings built between 1945 to 1985, % population over 65 years, % foreign residents</td>
</tr>
<tr>
<td>Vance and Hedel (2008)</td>
<td>car ownership and distance driven (non-work travel)</td>
<td>as Vance and Hedel (2007)***</td>
<td>as Vance and Hedel (2007)</td>
</tr>
<tr>
<td>Grazi et al (2008)</td>
<td>travel distance, travel distance by mode, mode-choice (work travel)</td>
<td>urban density</td>
<td>presence of children of the same gender in the hhld, # of children in hhld, # of adults in hhld, characteristics of partner's employment</td>
</tr>
<tr>
<td>Brownstone and Fang (2010)</td>
<td>car ownership, truck ownership, car travel distance, truck travel distance</td>
<td>residential density at the neighbourhood (census block group) level</td>
<td>average city (MSA) residential density</td>
</tr>
<tr>
<td>Heres-Del-Valle and Niemeier (2010)</td>
<td>car use and travel distance</td>
<td>residential density, business to housing ratio</td>
<td>% housing units built before 1939, % non-white population, % family households</td>
</tr>
</tbody>
</table>

* The urban form variables are not all included in a single model.

** Sum of subjective 1-4 scores for the following criteria: ease of street crossing, side walk continuity, street connectivity (grid v cul-de-sac) and topography

*** Four separate models estimated, each including one urban form variable.

hhld=household

MSA=Metropolitan Statistical Area
From the studies employing instrumental variables, Vance and Hedel (2007, 2008) and Heres-Del-Valle and Niemeier (2010) are the most diligent in testing the legitimacy of their instruments. Vance and Hedel (2007, 2008) perform tests for instrument validity and relevance, including tests of whether instruments are weak. Although the instruments fail for certain of the estimated models, they pass all tests for many models so that conclusions can be drawn. Commercial outlet density and road density appear to have a negative impact on car ownership, the choice to use the car and the distances driven by car for non-work related purposes. On the other hand, distance to transit appears to have a positive effect. The authors also examine the effect of the diversity of commercial outlets, but the instruments fail the test for validity and hence no conclusions can be reached.

Heres-Del-Valle and Niemeier (2010) test for both instrument validity and relevance. In their models they control for heteroskedasticity and ensure that they use a test suitable for heteroskedastic models to test for instrument relevance. Results suggest that residential density has a negative effect both on the decision to use the car and the distance travelled by car. On the other hand, the business to housing ratio does not appear to have an impact. Elasticities of car distance travelled with respect to residential density are estimated to be in the range -0.14 to -0.19. The authors contrast the estimated effects of density and fuel price, and find that similar proportional increases in fuel price and residential density can achieve the same proportional reduction in vehicle miles. They point out that policies relating to fuel prices are simpler to implement than policies relating to land use, while being equally effective, but also remark that the two policies need not be mutually exclusive.

Grazi et al (2008) find evidence that urban density has a positive effect on commute distance and commute distance travelled by car, and negative impact on commute distance travelled by public transport. On the other hand, they find no influence on commute distance travelled by non-motorised modes. The authors also suggest that urban density raises the probability of commuting by car and increases the probability of commuting by public transport with respect to non-motorised modes. The authors test the validity of their instruments. Regarding relevance, they point out that the instruments have significant coefficients in the first stage regression.
However, instruments might still be weak, so the study’s results should be treated with caution.

Brownstone and Fang (2009) do not test the legitimacy of their instruments. However, they use Bayesian methods for which the existing tests are not applicable. The authors conclude that the effect of residential density on car ownership and distance travelled is very small; the effect on truck ownership and distance travelled is however more substantial. Given the low vehicle efficiency of trucks, the authors remark that this could mean a corresponding sizeable reduction in emissions. However, the authors also conclude that the required changes in density are large and are only likely to occur in isolated developments, so that density is not a viable policy tool.

Greenwald and Boarnet (2001) find that population density, employment density and a pedestrian friendly environment have a positive effect on non-work trip frequency. Boarnet and Sarmiento (1998) consider a number of urban form variables, but only find density of service employment to affect car trip frequency. Surprisingly, the effect is positive. However, both studies only test for instrument validity, therefore their results should be treated with caution.

Khattak and Rodriguez (2005) do not provide any tests; in fact we have good reasons to believe that their instruments are not exogenous. The authors use non-transportation related attitudes as instruments to explain the choice to live in a non-residential neighbourhood, including beliefs regarding the importance of environmental protection. Environmental concerns are likely to have a direct effect on travel and therefore, the instruments might not to be exogenous. In addition, Khattak and Rodriguez’s (2005) model includes very limited socio-demographic control variables.

Last but not least, a clever choice of travel or urban form measures can eliminate or at least reduce endogeneity. Guo (2009) models the choice between two different paths to access work from the subway. One path involves an additional transfer to a different line and then a walk to work; the alternative path involves simply a walk to work. The author believes that the choice of dependent variable circumvents the endogeneity problem because the path choice from the subway to work is not
expected to be correlated with house or work location. The study concludes that built environment factors such as the presence of pedestrian friendly uses and intersection density affect path choice.

Bento et al (2005) use individual level travel data, but city-wide urban form measures. The authors argue that measuring urban form at the city level eliminates the problem of residential self-selection as individuals are likely to choose between neighbourhoods but not between cities based on their travel preferences. The authors conclude that a compact urban form with a good balance between population and employment promotes transit use and the use non-motorised modes, discourages car ownership and reduces the miles driven in personal vehicles. They note that the effect of individual urban form variables is modest, but that the combined effect of urban form, transit supply and road provision is substantial.

Do study results suggest that there is self-selection into neighbourhoods based on travel preferences? The various studies controlling for endogeneity disagree. For instance, Pinjari et al (2007), Heres-Del Valle and Niemeier (2010) and Brownstone and Fang (2009) conclude that endogeneity between urban form and travel is indeed present. On the other hand, Grazi et al’s (2008) results suggest there is endogeneity in the case of mode choice, but not in the case of travel distances. Chatman’s (2008) study suggests no self-selection occurs. The author investigates whether the preference for specific neighbourhood characteristics impacts the effect of urban form on travel. He finds that in most cases the effect does not depend on whether movers had sought specific neighbourhood attributes.

The review reveals the variability in findings in the literature. A potential factor explaining this variability is the diversity of measures employed to represent urban form. The following section provides an overview of these measures. In chapters 4 and 5 of the thesis, we study the effect the measure employed to represent a specific aspect of urban form, land use mix, can have on our understanding of land use mix-travel demand link.
2.4 Measures of urban form

Urban form is represented in the literature in diverse ways. However, the majority of urban form descriptors can be classified into three categories, widely known as the 3 D’s after Cervero and Kockelman (1997): density, diversity and design. Density regards the intensity of land use and is commonly represented by population or residential density. Diversity or land use mix refers to the degree of integration of different land uses, such as residential and retail, in a land parcel. Design includes variables describing the configuration of the street network as well as micro-elements of the built environment, such as the presence of sidewalks, bike lanes, trees or street lights. The border between the three categories is not always clear. Employment density, for instance, has been considered both as a density variable (e.g. Cervero and Kockelman, 1997; Ewing and Cervero, 2010) and as a measure of diversity (e.g. Scheiner and Holz-Rau, 2007). Studies consider one or more of the above aspects of the built environment. Often they use more than one variable representing a single of these aspects or they construct composite indicators that combine them. Furthermore, a number of studies use subjective measures of urban form or simply 0-1 dummy variables indicating different neighbourhood types. In addition to urban form measures, variables describing aspects of the transport infrastructure such as road, transit and parking provision are frequently considered. Although such factors are not strictly descriptors of urban or neighbourhood structure, they are closely related to urban form and are often classified as urban form measures by researchers.  

Below, we use the classification explained in the previous paragraph to review the numerous variables that have been employed to describe the built environment. We discuss in turn measures representing density, diversity and design, composite measures, neighbourhood type dummies, perceived neighbourhood characteristics and transport infrastructure.

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9 Ewing and Cervero (2010) identify distance to transit as the fourth D. The authors further identify a fifth D, destination accessibility. Destination accessibility includes measures based on gravity models of trip attraction and measures of distance to a central location (CBD, downtown etc). We interpret the first as land use mix measures and the latter as control variable.
2.4.1 Density

The most widely used urban form variable is population density, either population per total land area or population per residential land area. Alternatively, residential density, that is the number of dwellings per area is used (Brownstone and Fang, 2009; Chatman, 2003; Cervero, 1996b; Cervero and Gorham, 1995; Frank et al, 2007; Heres-Del-Valle and Niemeier, 2010; Krizek, 2003a,b, Wells and Young, 2008). Similarly, Chatman (2008) considers the number of residents per road mile. Garcia-Palomares (2009) uses distinct variables for the density of single-family housing and the density of multi-family housing. Guiliano and Narayan (2003) and Noland and Thomas (2007) include density as a categorical variable. Kitamura et al (1997) use a 0-1 dummy variable indicating high density. Cervero (1996a) employ 0-1 dummy variables indicating the presence of single-family detached housing, low-rise multi-family buildings or single family attached units, mid-rise multi-family buildings and high-rise multi-family buildings. Cervero (1991), who considers work trips at office sites rather than residential locations, uses the number of storeys of office buildings as an explanatory variable; this can be seen as a density indicator in the particular context. Susilo and Maat (2007) consider the number of individuals that can be reached by car or rail within 30 min, a variable that can be thought of as a density variable based on time rather than distance. Van Acker and Witlox (2010) use the percentage of built up area, which is also an indicator of density.

Another popular measure is employment density, either for total employment or specific categories of employment, usually retail or services. Employment density can be thought of both as an indicator of concentration of activity (density aspect of urban form) or as an indicator of land-use mixing, basically employment availability in an individual’s neighbourhood (diversity aspect of urban form). Examples of studies including employment density are Boarnet and Sarmiento (1998), Cervero and Duncan (2003), Chatman (2003), Chen (2007), Frank and Pivo (1995), Garcia-Palomares (2009), Greenwald and Boarnet (2001), Lin and Yu (2011), Pinjari et al (2007), Wells and Young (2008), Van de Coevering and Schwanen (2006), Zhang

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(2004). Frank et al (2007) consider the ratio of retail floor space to retail ground area, a variable indicating the intensity of retail development similarly to employment density.

Certain studies that measure urban form at the city level also consider population distribution rather than simply density. Bento et al (2005), for instance, use a measure of population centrality that indicates the extent to which urban residents tend to cluster around a central core. They compute the variable by considering the population living at fixed proportional distances from the city centre. The population centrality measure is obtained by taking the average of the cumulative proportion of population and the cumulative proportion of population weighted by distance over all of the specified distances. Van de Coevering and Schwanen (2006) also consider population distribution by including the proportion of the population living in the inner city area and the proportion of the population living in the central business district (CBD). They also consider the distribution of employment in the same way.

2.4.2 Diversity (land use mix)

Land use mix is the aspect of urban form that has been represented in the most diverse ways. Here, we give an overview of the measures used in past studies. As land us mix measures is a focal points of the thesis, we examine the measures more critically in chapter 3.

The simplest land use mix measures are dummy variables, namely binary variables that take the value 1 if a specific type of facility, such as retail or offices, is present and 0 otherwise (e.g. Cervero 1991, 1996; Kitamura et al, 1997, Sohn and Shim, 2010). Cervero (1996a) also uses a dummy variable for the presence of retail between 300 feet and 1 mile from the home location. His aim is to test the hypothesis that although stores within short walkable distances can encourage walking, stores close to the home location but at longer walking distances can have the opposite effect. They can in fact encourage driving by making it convenient for individuals to stop and shop while driving back from work.

Another widely used measure is minimum distance from an individual’s residence or work location to a specific type of facility, often, but not solely, a shop (e.g. Kitamura
et al, 1997; Handy and Clifton 2001; Cao, Handy and Mokhtarian, 2006; Cao, Mokhtarian and Handy 2007, Handy, Cao and Mokhtarian, 2005, 2006). Notably, Handy, Cao and Mokhtarian (2005, 2006) and Cao, Handy and Mokhtarian (2007) considered minimum distance to a large variety of destinations rather than simply the grocery store. These included the bank, church, library, post office, pharmacy, bakery, pizzeria, ice-cream parlour, take-away shop, health club, bookstore, bar, theatre and video rental shop. Stead (2001) measured proximity to local facilities in terms of walking time rather than distance. He used a set of categorical dummies based on walking time to reach the nearest chemist, post office or grocery store, and another set for the walking time needed to reach the nearest high street shops.

Several researchers use counts of specific non-residential activities or facilities in an individual’s neighbourhood, often divided by area when the neighbourhoods considered differ in size. Employment density falls in this category. Sometimes, specific types of employment are considered separately. For instance, Greenwald and Boarnet (2001), Chatman (2008) and Krizek (2003b) use retail employment, and Wells and Young (2008) employ service job density. Handy, Cao and Mokhtarian (2005, 2006) and Cao, Handy and Mokhtarian (2007) included the number of different types of establishments within various distance bands. They considered separately each of the fifteen types of establishment given in the previous paragraph. Susilo and Maat (2007) summed employment opportunities based on travel time rather than distance. They used the number of jobs that can be reached by car within thirty minutes, the number of jobs that can be reached by rail within the same time and the number of jobs that can be reached by car or rail within the same time.

Measures based on gravity models of trip attraction combine counts of activities and distance to an activity. They take the form \( \text{accessibility}_i = \sum_j X_j f(d_{ij}) \), where \( \text{accessibility}_i \) is the accessibility of residential location \( i \), \( X_j \) represents activity counts at location \( j \), \( d_{ij} \) is the distance, travel time or travel cost from \( i \) to \( j \), and \( f(d_{ij}) \) is an impedance function that decreases with \( d_{ij} \). Examples of impedance functions are \( e^{-\beta d_{ij}} \) and \( d_{ij}^{-\beta} \), where \( \beta \) is the distance decaying factor, a positive constant that defines how quickly the impedance function drops with distance. Accessibility measures have been used by Cervero and Kockelman (1997), Krizek
Some researchers used weighted sums rather than counts within specified areas. The measures described above simply consider a single land use category. Many researchers, on the other hand, employ indices that take into account more than one land use. Often, residential and non-residential uses are considered, commonly represented by population and employment. Bento et al (2005), for instance, used the Gini coefficient to measure the balance between employment and population. The Gini coefficient is calculated by plotting the cumulative distribution of population in the various neighbourhoods of a region against the cumulative distribution of employment (in increasing order of employment) to form a curve, named the Lorentz curve. The Gini coefficient is the ratio of the area between a 45° line representing perfect equality and the Lorentz curve over the area under the line of perfect equality. Its value ranges from 0, -completely equal distribution-, to 1, -all employment concentrated in one area.

The Gini coefficient is suitable for measuring the balance between population and employment at the city scale or across neighbourhoods rather than at individual neighbourhoods. Most authors, however, have measured the balance between jobs and housing at the neighbourhood scale. Susilo and Maat (2007), Wells and Young (2008) and Travisi et al (2009) use employment per capita as an indicator of jobs-to-housing balance. Garcia-Palomares (2009) uses employment per worker/employed residents. Heres-De-Valle and Niemeier (2010) similarly uses the ratio of businesses to housing. Stead (2010) also considers the ratio of jobs to workers, but includes it as a categorical rather than as a continuous variable in his study. Cervero and Duncan (2003) used the proportion of housing units out of the sum of employment and housing units, \( \frac{\text{housing units}}{\text{housing units} + \text{employment}} \). Likewise, other authors used the proportion of land or facilities dedicated to a specific land use (e.g. Crane and Crepeau, 1998; Bhat and Guo, 2007; Pinjari, 2007; Sanches and Arruda, 2002).

Cervero and Duncan (2003) defined the index \( 1 - \left| \frac{\text{population} - \text{employment}}{\text{population} + \text{employment}} \right| \) to measure the balance between population and employment. They estimated it both for
total employment and separately for retail and service employment. The index a special case for two land uses, residential and non-residential, of the index \( I \)
\[
I = \frac{\sum_{i=1}^{n} p_i \ln p_i - 1}{2(n-1)}
\]
where \( n \) is the total number of uses under consideration and \( p_i \) is the proportion of land use \( i \), measured either as a proportion of counts or land area. Bhat and Guo (2007) and Pinjari (2007) used the index with \( n=3 \), Sohn and Shim (2010) with \( n=4 \), Van Acker and Witlox (2010) with \( n=5 \) and Van Acker and Witlox (in press) with \( n=8 \). Cervero and Duncan (2003) used the term balance index for their measure and we will use the same term from now on to refer to the more general case.

The balance index has the advantage of being able to combine more than two uses in a single index. However, the most widely used measure that has this property is the Shannon index. Shannon (1948) defined, in the context of information theory, the quantity \( -K \sum_{i=1}^{n} p_i \ln p_i \), where \( K \) is a constant and \( p_1, p_2, \ldots, p_n \) are the probabilities of occurrence of \( n \) possible events, to measure the uncertainty of an outcome. As Vance and Hedel (2007) point out, the index has also been widely used to measure biodiversity. In the context of land use mix, Frank and Pivo (1995) defined the Shannon index as \( - \sum_{i=1}^{n} p_i \ln p_i \), where \( p_i \) is proportion of land area allocated to land use \( i \) and \( n \) is the total number of land uses present in the geographical area under consideration. Several modifications of Frank and Pivo’s definition have been used to measure land use mix in the transport (and health) literature. These will be presented in chapter 3. Furthermore, different authors have defined the Shannon index over different land-use categories. Vance and Hedel (2007, 2008) defined the sum over three classes of outlets, - retail, service and entertainment-, to represent the diversity of non-residential uses. Frank and Pivo (1995) defined it over the following seven categories: single family homes, multi-family homes, retail and services, entertainment, institutional and industrial/manufacturing. The same categories were used by Cervero and Kockelman (1997). Zhang (2004) defined the index for residential, commercial and industrial uses. Cervero and Duncan (2003) used five classes: single-family housing, multi-family housing, retail and service employment, office employment, and manufacturing, trade and other employment. Sanches and Arruda (2002) and Lin and Yu (2011) also apply a Shannon index, but it is not clear which land use categories they consider. Frank et al (2007) use the Shannon index for residential, commercial and office uses.
Another measure that incorporates multiple uses is the dissimilarity index implemented by Cervero and Kockelman (1997). Computation of the index requires partitioning of the neighbourhood in grid cells. For each cell the number of adjoining cells with different land uses is counted and the average value across all grid cells in a neighbourhood is taken. The measure differs from the Shannon and balance indices in that it is an indicator of mixing at a finer scale.

Last, Handy, Cao and Mokhtarian (2005, 2006) and Cao, Handy and Mokhtarian (2007) simply counted how many different types of establishments existed within various distance bands out of a maximum of fifteen specified categories. Along the same lines, Estupinan and Rodriguez (2008) considered the number of different land uses present around bus stops out of a total of seven possibilities.

2.4.3 Design

Design variables typically try to quantify how pedestrian friendly a neighbourhood environment is. The most commonly used variables relate to the pattern of the street network. Grid-like street patterns are assumed to facilitate walking and cycling in contrast to curvilinear ones. To account for this effect Crane and Crepeau (1998) included 0-1 dummy variables for street patterns classifying them as grid-like, curvilinear or mixed, where as Greenwald and Boarnet (2001) used the percentage of a neighbourhood’s area that is covered by grid format.

Grid like road configurations are characterised by high intersection densities and the presence of intersections with several legs. Equivalently, curvilinear street patterns are typified by cul-de-sacs and dead ends. Consequently, many authors use the number, density or proportion of dead ends/cul-de-sacs, intersections in general or specific types of intersection (e.g. Y-intersections, T-intersections, 4-way intersections etc) to represent the design of the street network (e.g. Boarnet and Sarmient, 1998; Zhang, 2004; Cervero and Kockelman, 1997; Cervero and Duncan, 2003, Estupinan and Rodriguez, 2008; Wells and Young, 2008; Frank et al, 2007; Chatman, 2008; Rodriguez et al, 2009; Lin and Yu, 2011; Guo, 2009).
Grid-like street networks are also typified by quadrilateral and small sized blocks. Consequently, Cervero and Kockelman (1997) consider the proportion of neighbourhood blocks that are quadrilateral and average block length. Similarly, Cervero and Duncan (2003) and Krizek (2003b) consider average block size and Pinjari et al (2007) the number of blocks per square mile.

In addition to street patterns, certain studies consider other design aspects or micro-elements of the built environment that indicate pedestrian friendliness. The most commonly used variables relate to the presence, width or quality of sidewalks (e.g. Guo, 2009; Chatman, 2008; Estupinan and Rodriguez; 2008; Kitamura et al, 1997; Cervero and Kockelman, 1997; Rodriguez et al, 2009). Variables relating to the presence and size of cycling paths and other cycling amenities are also popular (e.g. Cervero and Kockelman; 1997, Meurs and Haaijer, 2001; Kitamura et al, 1997; Estupinan and Rodriguez; 2008; Pinjari et al, 2007; Rodriguez et al, 2009). Cervero and Kockelman (1997), Estupinan and Rodriguez (2008) and Rodriguez and Joo (2009) also include a number of variables relating to the presence of amenities such as planting, lighting, crossing aids, wayfinding signs, benches and garbage bins, and the existence of obstructions to walking such as vehicles blocking the walkway. Likewise, Meurs and Haaijer (2001) include 0-1 dummy variables indicating whether a residence is in a pedestrian priority zone or 30km/hour area and a dummy for the presence of parks, green strips or playgrounds in an area.

Subjective evaluations of pedestrian and cycle friendliness are also used. Meurs and Haaijer (2001) include binary dummy variables indicating whether a neighbourhood is suitable for pedestrians and cyclists. Estupinan and Rodriguez (2008) include subjective evaluations of safety, cleanliness and pedestrian and cycle friendliness. Finally, Greenwald and Boarnet (2001) and Sanches and Arruda (2002) define a ‘pedestrian environment factor’ as the sum of subjective evaluations on a 1-4 scale of the following criteria: ease of street crossing, side walk continuity, street connectivity (grid v cul-de-sac) and topography.

2.4.4 Composite factors
Many studies use factor analysis to construct composite measures that incorporate more than one aspect of urban form. Krizek (2003b) applies factor analysis to
combine residential density, retail employment and average block size. Scheiner and Holz-Rau (2007) employ factor analysis on population density and the sum of retail, service and employment opportunities per km² to construct a single density and land use indicator.

Bagley and Mokhtarian (2002) estimate two factors that measure how suburban and how traditional the character of a neighbourhood is\textsuperscript{11}. They do so by using factor analysis on eighteen neighbourhood characteristics relating to population density, proximity to shops and public transport, street patterns, presence of sidewalks, perceived pleasantness of walking and cycling in the neighbourhood, parking availability and speed limits. The authors justify the use of factors rather than simple neighbourhood dummies by arguing that neighbourhoods cannot be simply classified as either traditional or suburban as they could have characteristics of both types; indeed, some neighbourhoods may be more traditional than others and not all suburban neighbourhoods are equally suburban in character.

Cervero and Kockelman (1997) use factor analysis to construct an ‘intensity’ factor and a ‘walking quality’ factor. The intensity factor incorporates retail store density, activity centre density, retail intensity, walking accessibility, park intensity and population density. The walking quality factor is estimated based on various design aspects of the built environment that were described in section 2.2.3.

Last, Cervero and Duncan (2003) apply factor analysis to create two variables, one that combines block size and the proportion of different type of intersections to represent pedestrian friendliness and one that combines different land use mix measures (Shannon index, balance index, proportion of housing out of total employment and housing).

Proponents of composite factors point out that potential multi-collinearity problems between the various urban form variables are avoided. However, a weakness of the approach is that the distinct effects of different urban form characteristics cannot be isolated and hence any conclusions are difficult to translate into policy.

\textsuperscript{11} For an explanation of the terms traditional and suburban neighbourhood see the next subsection.
2.4.5 *Neighbourhood type dummies*

A number of authors use binary dummy variables for neighbourhood type rather than or in addition to measures representing specific aspects of urban form. Neighbourhoods are usually split into traditional/neo-traditional and suburban, or transit and auto oriented. Suburban or auto-oriented neighbourhoods are typically characterised by features such as low density, separation of land uses, good highway access and residences built along cul-de-sacs as in the ‘superblock’ design described in chapter 1. Transit-oriented neighbourhoods are built around a transit station and typically have a pedestrian friendly environment that facilitates access to the station. Traditional or neo-traditional neighbourhoods incorporate features that were prevalent in town centres before the expansion of automobile ownership, such as high density, mixed uses and grid-like street configurations, as well as good transit access. Studies using neighbourhood type dummies include Cervero and Gorham (1995)\(^{12}\), Cervero (1996b), Cervero and Radisch (1996), Khattak and Rodriguez (2005), Wells and Young (2008) and Schwanen and Mokhtarian (2005a,b). In addition, Meurs and Haaijer (2001) include binary dummy variables for urban, suburban and rural environments.

Neighbourhood type dummies have the same pros and cons as measures constructed by factor analysis. In addition, they can only be applied in neighbourhoods that are clearly suburban or traditional in character. The distinction might not be clear, especially in countries where suburbanisation has been less pronounced than the US such as in Europe.

2.4.6 *Perceived neighbourhood characteristics*

As already mentioned in section 2.2.3, several studies include subjective rather than objective measures of urban form. For instance, Meurs and Haaijer (2001), Greenwald and Boarnet (2001), Bagley and Mokhtarian (2002) and Estupinan and Rodriguez (2008) use measures subjectively evaluated by the researchers or auditors. In addition, a number of researchers ask residents to evaluate themselves different aspects of their neighbourhoods.

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\(^{12}\) Cervero and Gorham (1995) also included residential density in addition to a neighbourhood type dummy.
For example, Kitamura et al (1997) include binary dummies representing respondents’ replies to ‘yes’ or ‘no’ questions in relation to their willingness to relocate, neighbourhood walkability and cycle-friendliness, parking supply, transit provision and traffic congestion. Similarly, Lin and Yu (2011) include 0-1 dummy variables indicating participants satisfaction with walkway width, walkway quality and leisure facility supply. Handy and Clifton (2001) question residents regarding their local store and use factor analysis to combine the answers into three distinct factors. The questions regard the store’s proximity and quality, parking provision, the comfort and safety of walking in the area and the presence of busy streets along the route from home to the store. Likewise, Handy, Cao and Mokhtarian (2005) ask residents to evaluate on a Likert-type scale a number of neighbourhood attributes relating to the presence of communal amenities, access to commercial areas, freeway access, transit supply, presence of sidewalks and bike routes, traffic, street lighting, safety, socio-economic diversity, neighbourhood vitality and neighbourhood appearance. Replies are used to estimate by factor analysis six measures describing the neighbourhood environment. Cao, Handy and Mokhtarian (2006), Handy, Cao and Mokhtarian (2006) and Cao, Mokhtarian and Handy (2007) use perceived neighbourhood variables similar to those used by Handy and Clifton (2001) and Handy, Cao and Mokhtarian (2005).

The intuition behind perceived neighbourhood characteristics is that it is the residents’ own perceptions of their neighbourhood rather than objective attributes that influence their behaviour. However, the use of subjective built environment measures have the drawback that they cannot be directly linked to policy. Even if research suggests that a perceived neighbourhood feature can affect travel behaviour, planners need to further determine the objective factors that shape such perceptions to formulate effective policies.

2.4.7 City shape

Bento et al (2005), who employ city-wide measures, include a variable measuring city shape. To our knowledge, it is the only study to consider city shape. The hypothesis is that trip distances are longer in long, narrow cities. To construct a measure of city shape, the authors circumscribed each city into an ellipse with the same area and
computed the ratio of the minor to the major axis. The ratio approaches 1 as a city becomes more circular.

2.4.8 Transport infrastructure

Most researchers recognise the effect of transport infrastructure, such as transit provision, road supply and parking availability, on travel behaviour and include relevant variables in their models. Improved road access facilitates and thus encourages driving. On the other hand, improved public transport provision fosters public transport use and could consequently reduce car travel. The availability or lack of parking can facilitate or impede car use respectively and thus affect travel choices. Although transport infrastructure variables are not strictly built environment descriptors, they are closely related to the built environment, and are indeed treated as built environment variables by some reviewers (e.g. Ewing and Cervero, 2010).

Transit supply is a potentially important determinant of travel behaviour, especially car and public transport use. The majority of studies investigating car or public transport travel include some measure of transit supply. Surprising, a small number of studies do not (e.g. Crane and Crepeau, 1998; Boarnet and Sarmiento, 2001; Greenwald and Boarnet, 1998). However, this may be due to lack of data or an assumption that transit provision is implicitly incorporated in urban form variables as areas that are denser, diverse or central tend to have better public transport access.

The simplest representation of public transport supply are binary dummy variables indicating the presence or adequacy of public transport services in an area (Kitamura et al, 1997; Meurs and Haaijer ,2001; Bento et al 2005; Cervero, 1996a; Schimek, 1996; Chatman, 2008; Brownstone and Fang, 2009; Garcia-Palomares, 2009). A popular measure is distance from home or work to the nearest public transport stop (bus stop, rail station, underground station or any public transport stop), either as a continuous or as a categorical variable (e.g.. Susilo and Maat, 2007; Kitamura et al, 1997; Zhang, 2004; Chen et al, 2007; Maat and Timmermans, 2009; Van Acker and Witlox, 2010; Buehler, 2010, in press). Some authors define public transport proximity based on walking time rather than distance (e.g. Vance and Hedel, 2007, 2008; Stead, 2001).

Other measures include the number of different transport modes serving an area (Scheiner and Holz-Rau; 2007) and the proportion of population serviced by an interurban bus (Garcia Plaomares; 2009). Estupinan and Rodriguez (2008), who investigate the effect of the built environment around Bogota’s Bus Rapid Transit (BRT) stations on boardings, use the number of bus alternatives other than the BRT, a dummy for the presence of a feeder bus, the number of routes served by a station, the number of vehicles per day in a station and the type of station defined by size. Lin and Yu (2011) ask residents to rate their satisfaction with their local transit service in a 1-10 scale. As noted in section 2.2.6 subjective evaluations of public transport services are included in the estimation of measures through factor analysis in studies such as Cao, Handy and Mokhtarian (2006), Handy, Cao and Mokhtarian (2005, 2006) and Cao, Mokhtarian and Handy (2007).

Road supply is taken into account less often than transit supply. Meurs and Haaijer (2001) include a dummy indicating that the main road is reachable within less than a minute. Susilo and Maat (2007) use distance to the nearest motorway. Bento et al (2005) and Vance and Hedel (2007, 2008) use road density. Van de Coevering and Schwanen (2006) consider road length per thousand inhabitants, while Taylor et al (2009) use total freeway lane miles and total road lane miles. On the other hand, certain studies include variables that combine or contrast public transport and road provision. For instance, Cervero (1996a) uses a binary dummy for the existence of four-lane highways, railroads or airports within 300 feet of a person residence and for adequacy of public transport. Van de Coevering and Schwanen (2006) consider the ratio of public transport service kilometres to road kilometres and the ratio of average transit speed to average car speed.

Access to parking is also employed less frequently than transit supply as a covariate despite its potential significance, most likely due to the difficulty of obtaining relevant
data. Nevertheless, parking supply is implicitly included in built environment measures such as urban density, as parking is naturally scarcer in denser developments due to the general lack of space. Parking supply measures include binary dummy variables indicating ease of parking at the home location (Meurs and Haaijer, 2001; Kitamura et al, 1997), the presence of a garage at the residence (Meurs and Haaijer, 2001) or the presence of parking restraints (Stead, 2001); the number of parking spaces per employee at the workplace of Central Business District (Zhang, 2004; Van de Coevering and Schwanen, 2006; Cervero, 1991) and the proportions of commercial and service parcels with off-street parking, off-street parking between the store and curb and on-street front or side parking (Cervero and Kockelman, 1997).

2.4 Urban form measurement in the thesis
The previous section outlined the various aspects of urban form that have been investigated in relation to travel behaviour. It is clear that the term ‘urban form’, or alternatively ‘built environment’ or ‘land use’, can refer to various distinct characteristics. Nevertheless, the most frequently examined features of urban form relate to the density of development, the mixing of land uses and the pattern of the street networks. This is unsurprisingly so, given that sparse development, land use zoning and Radburn’s superblock design with its street hierarchy and curvilinear network were key characteristics of the post-war suburban developments in the US (see chapter 1).

In the first part of the thesis, we focus on land use mixing at the local level, and investigate the effect of land use mix measurement on our understanding of the land use mix-transit demand relationship. We are interested specifically in mixed uses due to the particularly diverse ways in which the concept is operationalized in models. The empirical models estimated in chapters 5 and 6 also include a measure for population density. Excluding population density could bias results due to the potential correlation with land use mix.

In the last empirical chapter of the thesis (chapter 7), we deal with urban form at the city level. The choice is motivated by the fact that few studies have looked at the effect of the whole urban structure on transit demand. We also focus on the density of
development and the mixing of land uses, but at a regional scale. Instead of studying population density per se, we construct measures that reflect the distribution of population across the city. Regarding land use mix, we focus on two uses: residential and non-residential, measured by population and employment respectively. Although the choice is certainly restricted by data availability, residential and non-residential uses are undoubtedly the fundamental land use categories.

2.5 Concluding remarks

Reaching a definite conclusion from the existing literature is hard. Studies often conclude that urban form has an effect on travel, but some do not and many argue the effect is weak. Endogeneity between urban form and travel is a significant estimation issue. Many studies attempt to control for it using various approaches, each having different merits and shortcomings. Even studies that control for endogeneity do not reach consistent conclusions, both regarding the effect of urban form and whether endogeneity is present. Nevertheless, it is notable that many high quality studies find that there is an effect, especially on vehicle miles travelled (for instance, Heres-Del Valle and Niemeier, 2010; Vance and Hedel, 2007, 2008; Bento et al, 2005; Pinjary et al, 2007). Assessing the magnitude of the urban form effect is difficult, as most studies fail to estimate dimensionless measures such as elasticities. Studies that calculate elasticities such as Heres-Del Valle and Niemeier (2010) generally find them to be small. The same conclusion can be reached by Ewing and Cervero’s (2010) meta-analysis. In general, we can conclude that existing evidence suggests that urban form has a causal effect on travel, but the effect is likely to be modest.

Even if there is a causal link between urban form and travel, the policy implications are not straightforward. Certain authors argue that the effect of urban form is not large enough to make land use policies a useful tool for restricting car use. In existing settlements, achieving the dramatic changes in factors such as population density that are required to incite meaningful changes in travel habits is costly and impractical, if not unfeasible (Brownstone and Fang, 2009; Brownstone, 2008). Pricing policies are often endorsed as a more valuable tool for shaping travel behaviour as they can be equally effective to land use policies, while being less expensive and easier to implement (Brownstone, 2008; Heres-Del Valle and Niemeier, 2010). In addition,
land use policies are often viewed as an unfair suppression of individual preferences for suburban living, while pricing policies are regarded as a legitimate charging of the externalities of car use (Brownstone, 2009). However, as pointed out by Heres-Del-Valle and Niemeier (2010) the effects of the two policies can be complimentary; for instance, residents of traditional or neo-traditional neighbourhoods could have a higher response to pricing as they are not captive to the car. The idea is strengthened by Schwanen and Mokhtarian (2005), who find that suburban residents become car-oriented even if they prefer not to use the car, where as urban residents are more likely to realise their travel preferences.

Estimating the magnitude of the urban form effect is important to understand the potential of land use policies. However, the effect of urban density is difficult to measure accurately and it could be larger than suggested by the current literature for a number of reasons. First, measuring accurately urban form itself is hard. As section 2.4 illustrates, urban form is a broad concept that has been interpreted and represented in numerous diverse ways. Moreover, it is being measured at variable geographical scales (see section 2.2). Urban form measures are likely to be subject to measurement error, which can bias results. Furthermore, although the individual characteristics of the built environment considered in the literature might not have a large impact, the combined effect of diverse features could be significant. For instance, Bento et al (2005) find that although the separate effect of each urban form variable included in their models is small, the joint effect of different aspects of urban form, and transit and road supply is substantial. In addition, as Brownstone (2008) points out, studies often use data from a single country and hence, there might not be enough variation in urban form to capture the true effect. Last but not least, studies typically measure the direct effect of urban form on travel. However, urban form can also have an indirect effect. For instance, it can affect the viability of transit provision, which in turn affects travel, or the response to other factors such as fuel prices.
Chapter 3: A brief discussion of instrumental variables

3.1 Introduction
In chapter 2 (section 2.2.2), we briefly discussed the concept of endogeneity and the method of instrumental variables that can be used to eliminate it. In this chapter we present the method of instrumental variables in more detail as it is used in chapters 5 and 7 of the thesis. Instrumental variables (IV), or simply instruments, are variables that are correlated with a regressor of a model, but are uncorrelated with the error term. If a suitable instrument exists, then changes in the instrument are associated with changes in the endogenous variable but not with changes in the dependent variable of the model apart from those due to the changes in the endogenous variable. The idea is to use this property of instruments to isolate the exogenous effect of the endogenous variable on the outcome of interest. The chapter is divided in two sections. The first section explains the IV method in the context of linear models. Then, the method is discussed in relation to non-linear models. The discussion is shaped to cover the models estimated in chapters 5 and 7. An overview of the literature on instruments can be found in Cameron and Trivedi (2005, pp. 99-112, 192-199) or Greene (2008, pp. 314-353).

3.2 Instrumental variables in linear models
The classical linear model takes the form

$$y = X\beta + \epsilon$$

(3.1)

where \(y\) is a \(N\times1\) vector of observations, \(X\) a \(N\times K\) matrix of covariates whose \(ij^{th}\) element is the \(j^{th}\) covariate for the \(i^{th}\) observation, \(\beta\) a \(K\times1\) vector of parameters to be estimated and \(\epsilon\) a \(N\times1\) vector of unobserved error terms. Endogeneity occurs when \(E(\epsilon/X) \neq 0\). In the presence of endogeneity, the Ordinary Least Squares (OLS) estimator for \(\beta\), \(\hat{\beta}_{OLS} = (X'X)^{-1}X'y\), is inconsistent. The estimator \(\hat{\beta}_{OLS}\) can be written as:
\[ \hat{\beta}_{OLS} = (X'X)^{-1}X'y = (X'X)^{-1}X'(X\beta + \epsilon) = (X'X)^{-1}X'X\beta + (X'X)^{-1}X'\epsilon \]
\[ = \beta + (N^{-1}X'X)^{-1}N^{-1}X'\epsilon \]

Then, \( \text{plim} \hat{\beta}_{OLS} = \beta + \text{(plim} N^{-1}X'X)^{-1}(\text{plim} N^{-1}X'\epsilon) \) (using Slutsky’s theorem)

Consistency requires \( \text{plim} N^{-1}X'u = 0 \), which is not true if \( E(\epsilon|X) \neq 0 \).

Assuming a \( L \times 1 \) vector \( z \) of instruments exists with \( L \geq K \), then \( \beta \) can be consistently estimated by

\[ \hat{\beta}_{IV} = (X'Z(Z'Z)^{-1}Z'X)^{-1}X'Z(Z'Z)^{-1}Z'y \]

where \( Z \) is the \( N \times L \) matrix whose \( i^{th} \) row is the vector \( z \) for observation \( i \). The estimator \( \hat{\beta}_{IV} \) can be equivalently obtained using two OLS regressions, by first regressing \( X \) on \( Z \) (first stage regression) and then regressing \( y \) on the predicted values \( \tilde{X} \) rather than \( X \) (second stage regression). For this reason, it is often referred to as the two-stage least squares estimator (2SLS). It should be noted that the vector \( z \) contains all exogenous elements of \( x \), as exogenous regressors are instruments for themselves. Elements of \( z \) included in \( x \) are called included instruments and likewise, elements of \( z \) not included in \( x \) are called excluded instruments.

A frequently encountered problem in practical applications of IV is that finding good instruments is difficult. To give consistent estimators, instruments must be uncorrelated with the error term (instrument validity), but correlated with the endogenous variable (instrument relevance). In addition, the correlation between instruments and the endogenous variables must not be very low for the estimator to have good finite sample properties. Instruments that fail this last assumption are referred to as weak. If there are not enough relevant instruments to estimate a model, the model is underidentified; otherwise it is identified. In particular, if there are more relevant instruments than endogenous variables, the model is overidentified.

IV estimators provide consistent estimates, but they do so at the expense of efficiency. Moreover, although they are consistent, they are biased (the bias is towards the OLS estimates). It is well known that IV estimators have poor finite sample properties and even in large samples, they can have a large bias and large standard errors if
instruments are weak. For instance, Nelson and Startz (1990) use simulation analysis to show that the small sample properties of an IV estimator can be very different from the expected asymptotic ones in the presence of weak instruments. They demonstrate that the use of weak instruments can introduce considerable bias in both the IV estimator and the standard errors. Bound et al (1995) revisit the work of Angrist and Krueger (1991) who investigated the effect of education attainment on wage using an instrument that had a very low correlation with educational attainment, quarter of birth. Bound et al (1995) show how the F-statistic for the joint significance of excluded instruments in the first stage regression can be an indication of the size of the bias in the IV estimator. They reproduce Angrist and Krueger’s (1991) results calculating F-statistics for the excluded instruments in the first stage regression to show that some of the models have a large bias despite the large sample used by Angrist and Krueger.

A number of tests have been developed to check the legitimacy of instruments. Testing the validity of instruments is only possible in overidentified models. In the case of i.i.d. errors, Sargan’s test (Sargan, 1958) can be used to test the null hypothesis that the instruments are exogenous. The test statistic is \( R^2 \), where \( R^2 \) is obtained from the regression of the IV residuals on the full set of instruments (both included and excluded), and is distributed, under the null, as \( \chi^2(L - K) \). Unfortunately, the test’s power is somewhat limited as the null hypothesis of instrument exogeneity could be rejected either if the instruments are not valid or if the model is misspecified. In chapter 5, we estimate models with heteroskedastic error terms for which the Sargan test is not valid. In heteroskedastic models, the same test can be performed using the Hansen J statistic\(^{13} \). It is defined as \( \hat{\epsilon}'Z\hat{S}^{-1}Z'\hat{\epsilon} \), where \( \hat{\epsilon} = y - X\hat{\beta} \), \( \hat{\beta} \) is the optimal Generalized Method of Moments estimator (GMM) that minimizes \( \epsilon'Z\hat{S}^{-1}Z'\epsilon \) and \( \hat{S} \) is a consistent estimated of \( \lim_{n \to \infty} N^{-1} \sum_{n} u_{n}^{2}z_{n}z'_{n} \) (Cameron and Trivedi, 2005, p. 277). The Generalized Method of Moments is discussed in the next section. The Hansen J statistic is also \( \chi^2(L - K) \) distributed and as in the case of the Sargan’s test, rejection of the null hypothesis implies either invalid instruments or model misspecification (Cameron and Trivedi, 2005, p. 277).

\(^{13}\) In fact, the Sargan statistic is a special case of the Hansen J statistic for i.i.d. errors.
Using the correlation between an instrument and an endogenous variable as an indication of instrument relevance is only suitable in the case of one regressor, -the endogenous regressor-, and one instrument. In the case of multiple regressors and multiple instruments, an F-test for the joint significance of the excluded instruments in the first stage regression can be performed to test for model identification. However, the approach is still not valid when there are more than one endogenous variables. To illustrate this, let $x_1$ and $x_2$ be two endogenous variables and $z_1$ and $z_2$ be two instruments. If $z_1$ is highly correlated with both $x_1$ and $x_2$ while $z_2$ is uncorrelated with either endogenous variable, then the F-statistic for the excluded instruments of the first stage regressions will be significant for both variables when the instruments will clearly not be enough.

In models involving multiple endogenous variables Anderson’s (1951) canonical correlations test can be used. The canonical correlations between the regressors $X$ and the instruments $Z$ are correlations between linear combinations of the columns of $X$ and linear correlations of columns of $Z$. The null hypothesis of Anderson’s test is that the minimum canonical correlation between the instruments and the endogenous variables is zero; rejection of the null implies the model is identified. The test statistic is $Nr^2$, where $r$ is the minimum canonical correlation between the instruments and the endogenous variables, and is $\chi^2(L - K + 1)$ distributed. Alternatively, the Cragg-Donald (1993) statistic can be used to test the null hypothesis that the model is underidentified. It can be computed as $\frac{Nr^2}{1-r^2}$ and, under the null, is also $\chi^2(L - K + 1)$ distributed. Anderson’s and Cragg and Donald’s tests assume i.i.d. errors. In the heteroskedastic models estimated in chapter 7, we use instead a generalisation of Anderson’s canonical correlation test offered by Kleibergen and Paap (2006).

As explained earlier in the section, even if a model is identified, the application of IV is still problematic if the instruments are weak. Bound et al (1995) stress the importance of using the F-statistic for the excluded instruments to check whether instruments are weak, as it is approximately inversely proportional to the bias of the IV estimator. Staiger and Stock (1997) show using simulations that the F-statistic should have a value greater than 10 to ensure the bias of the IV estimator is at maximum 10% of the bias of the OLS estimator. As when simply identification is
considered, using an F-statistic to test for weak identification is not legitimate in the case of multiple endogenous variables.

Stock and Yogo (2005) provide a test for weak identification suitable for multiple endogenous variables that has an important advantage: it is based on a precise characterisation of weak instruments, a term that is often used somewhat vaguely. The authors use two approaches to define weak instruments. First, they consider an instrument to be weak if the bias of the IV estimator exceeds a specified level $b\%$ of the OLS bias. Then, they consider an instrument to be weak if the conventional $\alpha$-level Wald test based on IV statistics has an actual size that exceeds a certain threshold $r > \alpha$. They use a modification of the Cragg-Donald (1993) statistic used to test for identification, $\frac{N-L}{N L_1} CD$, where $CD$ is the Cragg-Donald (1993) statistic used for the identification test and $L_1$ the number of excluded instruments. The authors provide critical values for different values of $b$ and $r$ that must be exceeded by the test statistic for the instruments not to be weak. The critical values also depend on the number of endogenous variables in the model.

The tests for weak identification discussed hitherto are valid only in the case of i.i.d. errors. In models with heteroskedastic errors, Baum et al (2003) suggest applying the same modification on the Kleibergen-Paap statistic as Stock and Yogo (2005) on the Cragg-Donald statistic and using Stock and Yogo’s (2005) critical values.

In addition to testing their instruments, researchers should be able to provide theoretical justifications for the legitimacy of their instruments. Furthermore, checking that results are reasonable is advisable. In particular, as weak instruments can lead to a significant loss in efficiency, inspecting the standard errors of an IV model can provide signs of weak identification. However although suspiciously large standard errors can be an indication of weak instruments, Bound et al (1995) demonstrate that reasonable standard errors are not a guarantee of well-specified instruments. Bound et al (1997) re-estimate some of Angrist and Krueger’s (1991) models using a randomly generated variable as an instrument. The resulting models have reasonable coefficients and standard errors although the instrument is not relevant by construction.
Last but not least, it is possibly to perform tests on the significance of the endogenous variables that are robust to the presence of weak instruments. The Anderson-Rubin test for weak instrument-robust inference tests the null hypothesis that the coefficients of the endogenous regressions in the structural equation (i.e. the equation of interest) are jointly equal to zero. However, the test is based on the reduced form equation for the dependent variable, namely on a regression of the dependent variable on the full set of included and excluded instruments. It involves testing whether the coefficients of the excluded instruments in the reduced form equation are jointly equal to zero. Failure to reject this latter hypothesis implies that the null hypothesis cannot also be rejected. If the instruments are weak, the coefficients of the excluded instruments in the reduced form equation will be close to zero and hence the hypothesis that the coefficients of the excluded instruments in the reduced form equation are equal to zero is less likely to be rejected. In other words, failure to reject the null indicates either that the endogenous variables have no effect or that the instruments are weak. On the other hand, rejection of the null signifies that at least one endogenous variable has an effect on the dependent variable. For a discussion of the Anderson-Rubin test for weak instrument-robust inference see Baum et al (2007, p. 25).

### 3.3 Instrumental variables in non-linear models

A procedure equivalent to 2SLS cannot be used for non-linear models as it does not generally produce consistent estimates (see Cameron and Trivedi, 2005, p. 198-199). However, when models are linear in parameters a slight modification of the two-stage procedure can be used. Let $g(y) = a + \sum_j \beta_j f_j(x_j) + \epsilon$, where the sum runs over all covariates of the model. Regressing $f_j(x_j)$ rather than $x_j$ on the instruments $z$ and then regressing on $g(y)$ on $f_j(x_j)$ produces consistent results. This is clear if we define $\tilde{y} = g(y)$ and $\tilde{x}_i = f_i(x_i)$. Then the model can be rewritten in the form $\tilde{y} = a + \sum_i \beta_i \tilde{x}_i + \epsilon$, which is equivalent to equation (3.1). In chapter 7 we estimate models with a logarithmic and a Box-Cox specification and apply this method.

For models that are non-linear in parameters, instrumental variables can be applied using a generalized method of moments (GMM) framework. GMM is a generalization
of the method of moments suitable when the number of moment restrictions exceeds
the number of parameters to be estimated. In fact, GMM is a very general method of
estimation that incorporates a large number of estimators as special cases, including
common estimators such as OLS.

Assume there are $r$ moment restrictions of the form

$$E(h(v, \beta)) = 0$$

(3.2)

where $h$ is a function, $v$ a vector of observed quantities such as the dependent
variable, the explanatory variables and possibly a set of instruments, and $\beta$ is a $1 \times q$
vector or parameters to be estimated. A method of moments estimator equates to zero
the sample analogue of equation (3.2) and solves for $\beta$. This is only possible when
$q = r$. If $r > q$, the generalized method of moments attempts instead to minimizes
(i.e. to set as close to zero as possible) the quantity

$$Q = \frac{1}{N} \sum_{i=1}^{N} h(v_i, \beta) \cdot W \cdot \frac{1}{N} \sum_{i=1}^{N} h(v_i, \beta)$$

where $N$ is the number of observations and $W$ is a symmetric positive definite
weighting matrix that does not depend on $\beta$. The estimator reduces to the method of
moments estimator in the case $q = r$. Any choice of $W$ will give consistent results
(provided that it is a symmetric positive definite matrix as stated above). However,
the estimator with the smallest asymptotic variance, typically called optimal GMM
estimator, is derived for $\beta = S^{-1}$, where

$$S = \text{plim} \frac{1}{N} \sum_{i=1}^{N} h(v_i, \beta_0) \cdot h(v_i, \beta_0)'$$

and $\beta_0$ is the true value of $\beta$. In practise $S$ is unknown and an estimate has to be used.

A common approach is to use a suboptimal $W$ to obtain an initial estimate $\hat{\beta}$
(typically $W = I$ is used) and then use the estimate

$$\hat{S} = \frac{1}{N} \sum_{i=1}^{N} h(v_i, \hat{\beta}) \cdot h(v_i, \hat{\beta})$$

to obtain the optimal GMM estimator for $\beta$. Alternatively, the procedure can be
iterated. The revised estimate for $\beta$ can be used to get a new estimate $\hat{S}$ and so on. For
a discussion of GMM see Cameron and Trivedi (2005, p. 166-183).
In chapter 5, we use the GMM estimator proposed by Mullahy (1997) for models with an exponential mean, that assumes a multiplicative error structure. Let \( E(y/x) = \exp(x \beta) n \), where \( n \) an unobserved error term. If a set of instruments \( z \) exists with \( \text{dim}(z) > \text{dim}(x) \), then Mullahy shows that \( E(y \cdot \exp(-x \beta) - 1/z) = 0 \).

The law of iterated expectation gives the moment conditions \( E\left((y \cdot \exp(-x \beta) - 1)z\right) = 0 \). The condition can be operationalized as a GMM estimator that minimizes

\[
Q = \left\{ N^{-1} \sum_{i=1}^{N} z_i | y_i \cdot \exp(-x_i \beta) - 1 | \right\} W \left\{ N^{-1} \sum_{i=1}^{N} z_i | y_i \cdot \exp(-x_i \beta) - 1 | \right\}
\]

where \( N \) denotes the number of observations in the sample, \( i \) denotes the \( i^{th} \) observation and \( W \) is a positive definite weighting matrix. In application, \( W \) is estimated by \( \hat{W} = \hat{S}^{-1} \), where

\[
\hat{S} = N^{-1} \sum_{i=1}^{N} | y_i \cdot \exp(-x_i \beta) - 1 |^2 z_i z_i'
\]

and \( \hat{\beta} \) is a preliminary consistent estimate of \( \beta \). In chapter 5, we use Mullahy’s (1997) method to estimate a Poisson model with instrumental variables.

The problems associated with poor instruments that were discussed in section 3.2 extend to the non-linear case as well. However, to our knowledge, there are no relevant well-established tests for non-linear models. Qualitative assessments can be used instead to judge the legitimacy of instruments. Unreasonable results can be a sign of poor instruments. In particular, inflated standard errors can be a symptom of weak identification. In addition, Stock and Yogo (2002) suggest that model estimates that are sensitive to changes in the sample can be an indication of weak instruments. In chapter 5 we re-estimate our IV Poisson models for a random subset of the original sample as a check.

IV estimation in a linear model can also be performed in a GMM framework, similarly to the non-linear approach described above. Optimal GMM has the advantage of being more efficient that the two-stage least squares in the presence of heteroskedasticity, but has poor small sample asymptotic properties (see Baum et al, 2003, p.11; Cameron and Trivedi, 2005, p.187-188). Given our modest sample size

\[
E\left((y \cdot \exp(-x \beta) - 1)z\right) = E\left(E\left((y \cdot \exp(-x \beta) - 1)z/z\right)\right) = E\left(z \cdot E\left((y \cdot \exp(-x \beta) - 1)/z\right)\right) = E(z \cdot 0) = 0
\]
and the fact that not all our models are heteroskedastic we chose not to use the GMM approach. As remarked by Cameron and Trivedi (2005, p.188), most cross-sectional studies also employ the two-stage approach.
Chapter 4: An examination of the measurement of land use mix using simulation analysis

4.1 Introduction
Chapter 2 (section 2.4) highlighted how the representation of urban form in travel behaviour studies is not consistent. Not only are different aspects of urban form considered, these are often represented quantitatively in very diverse ways. This is particularly true when land use mix is considered. The discrepancies in measures used to represent land use mix, and more general urban form, complicates comparisons between studies. Despite the significant interest in the effects of land use diversity, few researchers have attempted to review, evaluate or compare the available measures. A noteworthy exception, Song and Rodriguez (2005) review land use mix measures from the transport, health, landscape ecology and housing markets literatures and present metrics from other fields that can be adapted and used to measure land use mix. They classify measures in three categories, accessibility, magnitude and pattern-, according to the aspects of mixed uses that they capture. The authors also present a brief empirical analysis; they estimate correlations between measures in each category for the City of Hillsboro in the Portland metropolitan area of the US, and find them to be high.

Studies in the travel behaviour literature typically consider one or two different measures and fail to discuss their advantages and drawbacks. The few authors that consider several measures usually combine them into a single variable using methods such as factor analysis (e.g. Cervero and Duncan, 2003; Cervero and Kockelman, 1997). Handy, Cao and Mokhtarian (2005, 2006) also use several land use mix variables, but they focus on testing the significance of different land uses as well as various geographical scales rather than alternative measures.

This chapter seeks to contribute to the debate on the measurement of land use mix. Similarly to Song and Rodriguez (2005), we estimate and compare various land use mix measures but our work differs from theirs in two ways. Firstly, Song and
Rodriguez’s (2005) empirical results are based on a specific city and may thus depend on the characteristics of the city under consideration. We adopt a more general approach; we use simulations to generate several hypothetical cities with various characteristics. The method has the advantage of giving the researcher complete control over the specification and of allowing replication of the analysis for various city configurations. Secondly, we test a different set of measures. Song and Rodriguez’s (2005) empirical application mainly includes diversity measures from other fields that have not yet been applied in the land use mix context, whereas we investigate the measures already employed in the travel behaviour – land use mix literature. Furthermore, Song and Rodriguez’s (2005) empirical application seeks to show mainly that measures which we intuitively expect to capture the same aspect of land use mix, are indeed correlated. In contrast, we compare measures which may seem intuitively dissimilar as long as they have been included in the literature under the general concept of land use mix. Our simulations illustrate that the use of alternative measures can often lead to diverse results and they demonstrate that the relationship between distinct measures can vary significantly in different datasets. It is important to note that the study looks at ways of measuring mixed uses rather than at which land uses are relevant in various contexts.

The chapter is structured as follows. Section 4.2 provides a brief critical examination of the properties of land use mix measures employed in the travel behaviour literature. Section 4.3 explains our methodology. Section 4.4 presents the results. In section 4.5, two specific measures are further discussed before some concluding remarks are made in section 4.6.

4.2 A critical examination of land use mix measures
In section 2.2.4 (chapter 2) we reviewed the land use mix measures used in the travel behaviour literature. Commonly employed land use mix can be summarised in the following categories:

- 0-1 dummy variables indicating the presence a specific type of facility
- minimum distance from home/work to a specific type of facility
- counts or densities of specific non-residential activities or facilities in a neighbourhood
- accessibility measures based on gravity models of trip attraction
- Gini coefficient
- Proportions/shares of a specific land use (measured as counts of facilities or land area)
- Ratios of two land uses (employment per capita, business to housing ratio etc)
- various versions of the balance index
- various versions of the Shannon index

Binary dummy variables are the most basic representation of land use mixing as they only detect the presence of alternative uses. Unlike other measures, they do not take into account proximity to facilities or the number, size and quality of facilities. They are also subject to the Modifiable Areal Unit Problem (MAUP). The greatest advantage of minimum distance based measures is that they are not subject to MAUP which affects most measures of land use mix. On the other hand, they only take into account the nearest facility and convey no information on the presence of additional facilities in the vicinity. Living near the sole local shop is different to living close to a shopping high street. Minimum distance also conveys no information on the size and quality of the nearest facility. If a local establishment does not cover residents’ needs, they will be willing to travel further to a superior facility.

Counts or densities considers all facilities/activity in a neighbourhood, but are subject to MAUP and still fail to take into account the size and quality of facilities. MAUP can be overcome by using accessibility measure based on gravity models of trip attraction. As well as not being subject to MAUP, they have the further advantage that the size of facilities can be incorporated by using, for example, total floor space instead of simple counts. Furthermore, such measures often implicitly capture the quality of facilities. The total floor space of a facility, for instance, can often be

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15 The terms accessibility measure, Gini coefficient, balance index, Shannon index and dissimilarity index have already been defined in section 2.2.2.

16 The Modifiable Area Unit (MAUP) acknowledges that analytical results based on spatial data can vary depending on the spatial scale used.
indicative of its quality as larger establishments are more likely to cover a specific need. The approach has, however, the disadvantage that assumptions are required regarding the form of the impedance function and the value of the distance decaying factor. Moreover, it is fairly data demanding.

The measures described above consider a single land use category. Other measures can incorporate multiple land uses. Measures in the travel behaviour literature that take into account more than one uses include the Gini coefficient, shares of land uses, ratios of land uses, the balance index and the Shannon index. All these measures are scale invariant: multiplying all land uses by a scalar factor does not change the indices’ value. In other words, they capture how different uses compare with each other rather how intense they are. They would, for instance, identify a neighbourhood with 300 residents and 200 jobs as being equally mixed as a neighbourhood with 600 residents and 400 jobs. This is not true for counts and accessibility measures and not necessarily true for minimum distance; these measures describe intensity of use or accessibility to uses rather than balance between uses. All multiple uses measures that have been discussed above also have the disadvantage of being subject to MAUP. Land use mix metrics that are subject to MAUP are less suitable to use when the neighbourhoods under consideration differ in land area as smaller units are more likely to be homogeneous; this can often be the case when administrative boundaries are used. In such cases, corrections can be made to account for the various unit sizes.

Among the multiple-use measures, the Shannon and the balance index have the advantage of incorporating more than two land uses in a single metric. On the other hand, they do not distinguish the contribution of individual land uses as any permutation of the land uses yields the same value. The Gini coefficient is also non-sensitive to interchanging population and employment in contrast with employment per capita and simple shares of land uses. A further drawback of the Gini coefficient is that it is not highly discriminating: many distinct Lorenz curves, and hence many distinct distributions of residential and non-residential uses, correspond to the same Gini coefficient. On the other hand, it has the advantage that it doesn’t assume that an optimum occurs when population equals employment in a neighbourhood; it rather assumes that the best possible option is when the balance between population and employment is the same across neighbourhoods. In contrast, the Shannon and balance
indices suppose an equal distribution of land uses to be the optimum scenario. In fact there is no reason why an equal amount of every land use is the best solution; neighbourhood values similar to the urban area averages could actually be more desirable. Cervero and Duncan (2003) addressed this problem by using employment and employable population.

It is worth noting that the Shannon index has been defined in the literature in slightly diverse ways. Frank and Pivo (1995) and Vance and Hedel (2007, 2008) have defined it as $-\sum_{i=1}^{n} p_i \ln p_i$, where $p_i$ is proportion of land use $i$, measures in terms of land area or counts of establishments, and $n$ is the total number of land uses. Using these definitions, the index ranges from 0, -only a single land use is present-, to $\ln n$, - $p_i = 1/n$ for all $i$. Zhang (2004) used Frank and Pivo’s (1995) formula but also “normalises” it by dividing by the logarithm of the total number of land use categories considered in the study. This way the index varies from zero to 1, rather than from 0 to $\ln n$. Cervero and Kockelman (1997) used Zhang’s definition and then computed a mean Shannon index to account for dissimilarities in the size of the tracts used for estimation. Larger areas are more likely to include more land uses; a very small tract is unlikely to contain many uses. Consequently, the authors took mean values of entropy for the tracts belonging to some larger geographical area to account for different tract sizes. Frank et al (2005, 2006) divided the Shannon index by the logarithm of the number of uses present in the neighbourhood rather than the number of uses considered in the study. For a discussion on the Shannon index as defined by Frank et al (2005, 2006) see Brown et al (2009). As Brown et al (2009) point out, with this definition, high scores of the index do not necessarily imply the presence of numerous land uses. For example, any number of uses larger than one would yield the maximum value of 1 as long as they were equally distributed. This problem can, however, be circumvented by using one of the definitions described above.

Brown et al (2009) looked into different ways of measuring land use mix, but in connection with Body Mass Index (BMI) and obesity as opposed to travel behaviour. The authors found that BMI models including shares of different uses perform better than models including Shannon indices, which they explained by arguing that the presence of a particular use is what is important, not that all uses exist in equal
amounts. On the other hand, no single land use mix measure showed a superior performance for the remaining weight related outcomes investigated. The study also reports high correlations between Shannon indices with different degrees of detail in land use classification. In contrast, correlations between Shannon indices and shares of different uses, or between the different shares, were usually less high and often quite low.

4.3 Methodology
The simulation approach we adopt in this chapter builds on previous work by Karpov (2008) and Spielman and Yoo (2009). Karpov (2008) sought to compare a range of indices measuring disproportionality in proportional electoral systems. Data limitations led the author to create a synthetic database by generating and transforming random normal variables. Spearman rank correlations were then computed to test to what extent alternative measures produce similar rankings. Spielman and Yoo (2009), motivated by the literature on the link between neighbourhood attributes and health, used a simulation to investigate the effects of alternative scales in estimating spatially related variables. They created grids of equally sized cells, each of which was assigned a random value according to a predetermined autocorrelation pattern which depended on distance. Adjoining cells were grouped together and their corresponding values averaged to create a set of spatial variables. A synthetic dependent variable was generated as a linear combination of the synthetic spatial variable and a random normal variable. Spatial scale was altered by changing the number of neighbouring cells belonging to a group; subsequently, sets of spatial variables were estimated at different scales. The simulated dependent variable was regressed on variables estimated on alternative scales to test the effect spatial scale has on results.

In this study, we simulate cities to be used in the estimation of different land use mix measures. Our cities are composed of individuals and employment establishments. Individuals are represented by a set of coordinates that correspond to their residential location. Employment establishment are represented by a set of coordinates signifying location and a value corresponding to the number of employees. Various land use mix measures are computed for samples of individuals in the synthetic cities. Pearson and
Spearman correlations are calculated for the derived measures and regressions are simulated in a manner similar to Spielman and Yoo (2009). Further details of the methodology are given below.

We firstly assume the cities to be monocentric. The assumption is, of course, used to simplify matters as most cities nowadays are polycentric. However, having polycentric cities in this case adds unnecessary complexity because our analysis of land use mixing is concerned with the neighbourhood rather than metropolitan scale. Individual neighbourhoods in a monocentric city are similar to those in a polycentric city, so assuming a monocentric urban structure should not have a substantial impact on results. Population density is assumed to fall exponentially with distance from the city centre. Clark (1951) was the first author to observe such a relationship between density and distance. Such exponential relationships have since been estimated by many authors (e.g. Ingram and Carroll, 1981; Sridhar, 2007; for reviews see Anas et al, 1998; McDonald, 1989; Mieszkowski and Mills, 1993; Mills and Tan, 1980). Even models of the more recent polycentric structure assume that density decreases exponentially from each centre and use different methods to aggregate the individual effects (Anas et al, 1998). The same relationship has also been observed for employment (Anas et al, 1998).

If density $D$ decreases from the city centre according to the relationship $D = D_0 e^{-br}$, where $D_0$ and $b$ are constants, and $r$ is the distance from the city centre, then the population residing at a distance $r$ from the centre follows a Gamma $(2, b)$ distribution. Consequently, we generate random polar coordinates $(r, \theta)$, where $r \sim \text{Gamma}(2, b)$ and $\theta \sim \text{U}(0, 2\pi)$, to represent individuals’ residential locations. Employment establishments are divided into retail and non-retail, and are assigned

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17 Assume the population density $D$ at a distance $x$ from a city centre is given by $D = D_0 e^{-bx}$, where $D_0$ and $b$ are constants. Then, the population $P$ living at a distance $x$ from the city centre is given by $P = 2\pi x D_0 e^{-bx}$. The total population $P_{\text{total}}$ of the city is

$$P_{\text{total}} = \int_0^{\infty} 2\pi x D_0 e^{-bx} dx = 2\pi D_0 \left[ x \int e^{-bx} dx - \int \left( \int e^{-bx} dx \right) dx \right]_0^\infty$$

$$= 2\pi D_0 \left( \left. \frac{xe^{-bx}}{-b} \right|_0^\infty - \int_0^\infty \frac{e^{-bx}}{-b} dx \right) = \frac{2\pi D_0}{b^2}$$

Therefore, the proportion of population living at a distance $x$ from the city centre is $\frac{P}{P_{\text{total}}} = b^2 xe^{-bx}$, which is the probability density function of a Gamma$(2, b)$ distribution.
polar coordinates in the same way, albeit using larger values of b, as employment should be more concentrated near the centre. Initially, a medium-sized city with a population of 100,000, 212 retail outlets, and 5,140 non-retail businesses is assumed. We base these numbers on the ratio of business or retail outlets to population that is found in Greater London. Employees are also assigned to the various establishments using the distributions for Greater London\textsuperscript{18}. The parameter b is set to $0.25 \text{m}^{-1}$ for population, and $0.35 \text{m}^{-1}$ for employment. A neighbourhood is defined as a circular buffer of radius 1km around an individual’s residential location. A set of 20 cities are created and a random sample of 500 individuals (i.e. set of coordinates) is drawn from each city, creating a total sample of 10,000 individuals. The following land use mix measures are calculated for the neighbourhoods of all individual belonging to the sample:

- Minimum distance to a retail outlet (straight line distance)
- Number of retail outlets
- Total employment
- Employment per capita
- Balance index
- Share of population $= \frac{\text{population}}{\text{population} + \text{employment}}$
- Shannon index
- $\text{accessibility}_i = \sum_j \frac{\text{employment}_j}{\text{distance}_{ij}}$

The measures are chosen to represent the categories presented in section 2.2.2 Dummy variables are not considered due to their simplicity and the Gini coefficient is excluded because it is not suitable for use at the neighbourhood scale. The Shannon and balance indices are defined for two land uses, residential and non-residential, measured by population and employment respectively.

\textsuperscript{18} Based on 2008 data from the Annual Business Inquiry. Only retail outlets covering every day needs are considered: non-specialised retail stores, stores specialising in the sale of food, beverages and tobacco, stores specialising in the sale of pharmaceutical and medical goods, cosmetic and toilet articles. The London area is selected simply due to ease of access to the data.
We proceed to create a synthetic dataset of travel outcomes for all individuals sampled. For each individual $i$, we generate a random normal variable $X_i \sim N(1, 0.1)$, which is assumed to sum the effect of all exogenous variables except land use diversity on travel. Travel outcome $T$ is assumed to be a function of land use mix and $X$. Initially, minimum distance is used as a base case, so that $T$ is simulated as a function of minimum distance to retail and $X$. For every individual $i$, we generate a random normal variable $T_i \sim N(\alpha \cdot \text{minimum distance}_i + X, 0.5)$, where $\alpha = \frac{1}{\text{mean(minimum distance)}}$, so that $X$ and minimum distance account for an equal share in the variation in $T$. The variances in the generation of $T$ and $X$ are chosen by trial and error so that, despite the variability they introduce in the model, regressing $T$ on minimum distance and $X$ gives significant results for $\alpha$ and a corresponding elasticity close to 0.5 as expected from the formulation of $T$. Subsequently, for each of the six datasets, $T$ is regressed on the remaining land use mix measures in turn to examine whether using alternative measures affects results. The regression equation explains $T$ as a linear function of land use mix and $X$:

$$T = \alpha_1 \cdot \text{land use mix} + \alpha_2 \cdot X + \varepsilon,$$

where $\varepsilon$, the error term, satisfies $E(\varepsilon / X, \text{land use mix}) = 0$ and $E(\varepsilon \cdot / X, \text{land use mix}) = \sigma^2 \cdot I$ for a constant $\sigma$.

Since the choice of minimum distance as a base case is arbitrary, we repeat the procedure using alternative measures as base cases. $T$ is recreated using in turn each of the various measures in the place of minimum distance and regressions are rerun each time as in the initial process.

The analysis described above considers the Shannon and balance indices when defined for two land uses, in particular population and employment, so that they are readily comparable to the remaining measures. However, the main advantage of the two indices is that they can be defined for multiple uses. So, what happens if we split one land use class into two distinct categories? To investigate the issue, we split employment into retail and non-retail, and define the Shannon and Balance indices for three land uses. Subsequently, regressions are simulated as before.

The entire process is replicated for urban areas with alternative configurations. Two further sets of cities are generated, identical to the original but with different density decay factors: $b_{\text{population}} = 0.35m^{-1}$ and $b_{\text{employment}} = 0.5m^{-1}$, and $b_{\text{population}} = 0.25m^{-1}$ and
b_{employment}=0.5m^{-1}. The majority of neighbourhoods sampled from the constructed cities have more population than employment. To include more neighbourhoods with high employment concentration in the analysis, we create two final sets of cities which include, in addition to urban areas with the initial configuration\(^\text{19}\), two further types of urban areas with higher overall employment to population ratio. The first has 180,000 residents, 1,011 retail outlets, 47,145 non-retail businesses, \(b=0.2m^{-1}\) for population and \(b=0.3m^{-1}\) for employment. The second has 8,000 residents, 170 retail outlets, 15,350 non-retail businesses, \(b=0.2m^{-1}\) for population and \(b=0.3m^{-1}\) for employment. The number of residents and the ratio of businesses/retail outlets to population are chosen according to data for existing areas, Westminster Borough and the City of London respectively, both parts of central London. Employees are also assigned to the various establishments using the distributions for Westminster Borough and the City of London\(^\text{20}\).

### 4.4 Results
Pearson correlations and Spearman rank correlations\(^\text{21}\) are calculated for all pair of land use mix measures, separately for each dataset. Pearson correlations are shown below and Spearman rank correlations above the diagonal of table 3.1. In both cases, the minimum and maximum values from the five datasets are given. Pearson correlations show how closely the relationship between two land use mix measures can be represented by a linear function. Spearman rank correlations illustrate the extent to which two land use mix measures rank neighbourhoods as being more mixed in the same order. The elasticities obtained from the regressions are given in table 3.2. As measures differ in scale, elasticities rather than coefficients are shown for comparisons to be made. Once more, the minimum and maximum values from the five datasets are given. The elasticity with respect to the measure used to generate T is

\(^{19}\) 100,000 population, 212 retail outlets, 5,140 non-retail businesses, \(b_{population}=0.2m^{-1}\) and \(b_{employment}=0.3m^{-1}\).

\(^{20}\) Based on 2008 data from the Annual Business Inquiry. Data from existing areas are chosen to ensure the businesses to people ratio is realistic. Areas of London are chosen due to ease of access to the data.

\(^{21}\) The Spearman rank correlation for two variables X and Y is defined as \(\frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2(y_i - \bar{y})^2}}\), where \(x\) and \(y\) are the ranks of X and Y when the variables are arranged in increasing order. It measures how closely the relationship between the two variables can be expressed by a monotonic function. Its value ranges from -1 to 1. If no observations are repeated in the sample, the two extrema arise when each variable is a monotonic function of the other.
0.5 due to the way the simulation is set up. Results illustrate that with few exceptions the various measures are not equivalent. Typically, the strength, and often even the direction of association, is not stable across datasets. The elasticities derived when substituting one measure for another can be equally variable between datasets.
<table>
<thead>
<tr>
<th></th>
<th>Minimum Distance</th>
<th>Number of Shops</th>
<th>Employment</th>
<th>Employment per Capita</th>
<th>Balance Index</th>
<th>Population Share</th>
<th>Shannon Index</th>
<th>Accessibility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum Distance</td>
<td>-</td>
<td>-0.89 to -0.85</td>
<td>-0.84 to -0.66</td>
<td>-0.79 to -0.34</td>
<td>-0.74 to -0.22</td>
<td>0.34 to 0.79</td>
<td>-0.74 to -0.22</td>
<td>-0.87 to -0.4</td>
</tr>
<tr>
<td>Number of Shops</td>
<td>-0.42 to -0.27</td>
<td>-</td>
<td>0.67 to 0.88</td>
<td>0.32 to 0.79</td>
<td>0.14 to 0.72</td>
<td>-0.79 to -0.32</td>
<td>0.14 to 0.72</td>
<td>0.41 to 0.9</td>
</tr>
<tr>
<td>Employment</td>
<td>-0.39 to -0.23</td>
<td>0.49 to 0.94</td>
<td>-</td>
<td>0.8 to 0.98</td>
<td>-0.06 to 0.89</td>
<td>-0.98 to -0.8</td>
<td>-0.06 to 0.89</td>
<td>0.66 to 0.97</td>
</tr>
<tr>
<td>Employment per Capita</td>
<td>-0.35 to -0.07</td>
<td>-0.01 to 0.7†</td>
<td>0.28 to 0.83</td>
<td>-</td>
<td>-0.25 to 0.92</td>
<td>-1</td>
<td>-0.25 to 0.92</td>
<td>0.75 to 0.91</td>
</tr>
<tr>
<td>Balance Index</td>
<td>-0.6 to -0.25</td>
<td>-0.13 to 0.64†</td>
<td>-0.3 to 0.68</td>
<td>-0.53 to 0.59</td>
<td>-</td>
<td>-0.92 to 0.25</td>
<td>1</td>
<td>-0.32 to 0.84</td>
</tr>
<tr>
<td>Population Share</td>
<td>0.3 to 0.55</td>
<td>-0.71 to -0.17</td>
<td>-0.78 to -0.51</td>
<td>-0.86 to -0.53</td>
<td>-0.91 to 0.31†</td>
<td>-</td>
<td>-0.92 to 0.25</td>
<td>-0.91 to -0.75</td>
</tr>
<tr>
<td>Shannon Index</td>
<td>-0.72 to -0.28</td>
<td>-0.03 to 0.52</td>
<td>-0.39 to 0.54</td>
<td>-0.61 to 0.55</td>
<td>0.93 to 0.96</td>
<td>-0.86 to 0.36</td>
<td>-</td>
<td>-0.32 to 0.84</td>
</tr>
<tr>
<td>Accessibility</td>
<td>-0.54 to -0.12</td>
<td>0.3 to 0.87</td>
<td>0.41 to 0.91</td>
<td>0.16 to 0.86</td>
<td>-0.51 to 0.75</td>
<td>-0.87 to -0.52</td>
<td>-0.58 to 0.73</td>
<td>-</td>
</tr>
</tbody>
</table>

† includes values not significant at the 5% level
Table 4.2 Elasticities of T with respect to Land Use Diversity

<table>
<thead>
<tr>
<th>Measure used to generate T</th>
<th>Minimum Distance</th>
<th>Number of Shops</th>
<th>Employment</th>
<th>Employment per Capita</th>
<th>Balance Index</th>
<th>Population Share</th>
<th>Shannon Index</th>
<th>Accessibility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum Distance</td>
<td>-</td>
<td>-0.3 to -0.13</td>
<td>-0.27 to -0.1</td>
<td>-0.26 to -0.02</td>
<td>-1.08 to -0.22</td>
<td>0.3 to 1.81</td>
<td>-1.92 to -0.33</td>
<td>-0.87 to -0.09</td>
</tr>
<tr>
<td>Number of Shops</td>
<td>-0.18 to -0.13</td>
<td>-</td>
<td>0.18 to 0.42</td>
<td>0 to 0.48†</td>
<td>-0.2 to 0.81†</td>
<td>-1.79 to -0.15</td>
<td>-0.07 to 0.97</td>
<td>0.2 to 1.1</td>
</tr>
<tr>
<td>Employment</td>
<td>-0.18 to -0.13</td>
<td>0.33 to 0.55</td>
<td>-</td>
<td>0.1 to 0.65</td>
<td>-0.42 to 0.89</td>
<td>-2.13 to -0.62</td>
<td>-0.52 to 1.03</td>
<td>0.33 to 1.2</td>
</tr>
<tr>
<td>Employment per Capita</td>
<td>-0.15 to -0.06</td>
<td>-0.01 to 0.27†</td>
<td>0.2 to 0.36</td>
<td>-0.87 to 0.54</td>
<td>-1.95 to -0.78</td>
<td>-1.44 to 0.7</td>
<td>0.16 to 0.8</td>
<td></td>
</tr>
<tr>
<td>Balance Index</td>
<td>-0.14 to -0.06</td>
<td>-0.02 to 0.13†</td>
<td>-0.07 to 0.13</td>
<td>-0.14 to 0.16</td>
<td>-1.02 to 0.18†</td>
<td>0.6 to 0.69</td>
<td>-0.23 to 0.43</td>
<td></td>
</tr>
<tr>
<td>Population Share</td>
<td>0.04 to 0.08</td>
<td>-0.1 to -0.05</td>
<td>-0.11 to -0.07</td>
<td>-0.19 to -0.04</td>
<td>-0.25 to 0.13†</td>
<td>-</td>
<td>-0.34 to 0.2</td>
<td>-0.3 to -0.16</td>
</tr>
<tr>
<td>Shannon Index</td>
<td>-0.13 to -0.06</td>
<td>0 to 0.09†</td>
<td>-0.07 to 0.08</td>
<td>-0.12 to 0.12†</td>
<td>0.31 to 0.37</td>
<td>-0.8 to 0.15†</td>
<td>-</td>
<td>-0.19 to 0.34†</td>
</tr>
<tr>
<td>Accessibility</td>
<td>-0.11 to -0.04</td>
<td>0.11 to 0.3</td>
<td>0.13 to 0.27</td>
<td>0.04 to 0.43</td>
<td>-0.28 to 0.44</td>
<td>-0.93 to -0.45</td>
<td>-0.44 to 0.57</td>
<td>-</td>
</tr>
</tbody>
</table>

† includes values not significant at the 5% level
The Shannon and the balance indices are the only pair of measures with consistently high correlations. Consequently, swapping the two measures also leads to similar regression results. The relationship between the two measures will be discussed in more detail in the next section. Population share and employment per capita have a rank correlation of -1. This reflects the fact that there is a monotonic relationship between the two measures. On the other hand, their Pearson correlation appears to be more modest ranging from -0.86 to -0.53. The value of the Pearson correlation depends on the range of values of the two measures available in the dataset. Regarding elasticities, in addition to the Shannon and balance indices, substituting employment with the number of shops in the regression models also produces satisfactory elasticities.

Both the Shannon and the balance index appear to compare poorly with the remaining measures. The corresponding Pearson correlations and Spearman rank correlations vary widely between samples, not only in magnitude, but most frequently in sign as well. In some cases, the results include values that are not significantly different from zero. Elasticities obtained when the Shannon or the balance index is substituted by another measure also exhibit the same variability. The variation in sign is easily understood when we consider the effects of an increase in employment or the number of shops in a neighbourhood. Employment per capita and accessibility also increase; population share decreases. The change in the Shannon and balance indices, however, can be positive or negative depending on the initial values of population and employment. Essentially, the Shannon and balance indices measure how evenly uses are distributed; the remaining metrics measure magnitude of use.

With the further exception of employment per capita and the number of shops, the remaining pairs of measures have Pearson correlations that are always significant and consistent in sign, albeit varying in magnitude. Several measures appear to be highly correlated in some cases, but the correlations change when alternative datasets are used. For instance, the Pearson correlation for accessibility and employment per capita varies from 0.16 to 0.86; the elasticities obtained from the corresponding substitutions are similarly variable. On the other hand, several measures with variable Pearson correlations have consistently high Spearman rank correlations. Accessibility
and employment per capita that were mentioned above have a Spearman rank correlation that ranges from 0.75 to 0.91.

The above analysis considers the Shannon and balance indices when defined for two land uses classes, in particular population and employment. What happens if we define them for three land use categories by dividing employment into retail and non-retail? The results are presented in Table 3.3. As before, only the minimum and maximum values from the five datasets used are given. Our simulation experiment suggests that indices defined over three uses are highly correlated with their two-class counterparts. This is consistent with Brown et al (2009) who found high correlations in their dataset for Shannon indices with different degrees of detail. Subsequently, the simulated regressions suggest that using a three-use measure in the place of a two-use measure produces similar elasticities. Brown et al (2009) suggest that for their models, more detailed Shannon indices improved fit.

<table>
<thead>
<tr>
<th></th>
<th>Pearson correlation</th>
<th>Spearman rank correlation</th>
<th>Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Balance index</td>
<td>0.93 to 0.97</td>
<td>0.91 to 0.98</td>
<td>0.45 to 0.49</td>
</tr>
<tr>
<td>Shannon index</td>
<td>0.94 to 0.98</td>
<td>0.91 to 0.97</td>
<td>0.53 to 0.55</td>
</tr>
</tbody>
</table>

**4.5 A discussion of the Shannon and balance indices**

As discussed in the previous section, the simulation results suggest that the Shannon and balance indices are consistently highly correlated. The finding is not surprising as the two measures share common properties that none of the other metrics considered do. As explained in section 4.2, both achieve their maximum value when all land uses are equally distributed and are minimized when only a single land use is present. Furthermore, both measures fail to distinguish the individual effect of each land use as any permutation of land uses leaves the indices unaffected. The properties hold when the indices are defined for any number of uses. When they are defined for two land uses in particular, there is a monotonic increasing relationship between the two variables (see figure 3.1), which explains the Spearman rank correlation of 1.
Are the two measures highly correlated when defined for more detailed land use classifications? When employment is split into retail and non-retail in the simulation, the Pearson correlation between the two indices remains high, ranging from 0.96 to 0.98. Likewise, the Spearman rank correlation ranges from 0.96 to 0.99. To further test the extent to which the two variables are correlated for any number of uses, we create a sequence of random variables to simulate shares of different land uses and compute Pearson and Spearman rank correlations for the resulting Shannon and balance indices. We initially generate a set of 1,000 uniform random variables \( p_1 \sim U(0, 1) \); we assume each \( p_1 \) to represent the share of residential uses in an area. These are used to compute the Shannon and balance indices for two land use categories. To split the first category into two distinct classes, we generate for each \( p_1 \) a random uniform variable \( p_2 \sim U(0, p_1) \). Proceeding in this manner we estimate the two indices for three, four, five and six distinct land use categories. The indices estimated using this approach appear to be highly correlated regardless of the number of land uses considered; both the Pearson and Spearman rank correlations are above 0.95 in all cases. However, the analysis assumes that all possible values for the proportion of residential uses in a neighbourhood are equally probable; the assumption is somewhat restrictive and unrealistic. Consequently, we repeat the analysis using various approaches to generate \( p_1 \):
We restrict $p_1$ to be below a fixed value $\alpha$ by generating $p_1 \sim U(0, \alpha)$, $\alpha \in (0,1)$.
The following values are tested for $\alpha$: 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9.

We generate three random numbers $\alpha \sim U(0,1)$, $\beta \sim U(0,1)$ and $q \sim U(0,1)$.
Subsequently, we generate $n$ random variables $p_1 \sim U(0, \alpha)$ and $m$ random variables $p_1 \sim U(\beta,1)$, where $n=1000q$ and $m=1000-n$. We repeat the approach for 1,000 sets of random numbers $\alpha, \beta$ and $q$.

We generate random numbers $\alpha \sim U(0,1)$, $\beta \sim U(\alpha,1)$, $\gamma \sim U(\beta,1)$, $q_1 \sim U(0,1)$, $q_2 \sim U(0,1-q_1)$ and $q_3 \sim U(0,1-q_1-q_2)$. Next, we generate $n_1$ random variables $p_1 \sim U(0, \alpha)$, $n_2$ random variables $p_1 \sim U(\alpha, \beta)$, $n_3$ random variables $p_1 \sim U(\beta, \gamma)$ and $n_4$ random variables $p_1 \sim U(\gamma,1)$, where $n_1=1000q_1$, $n_2=1000q_2$, $n_3=1000q_3$ and $n_4=1000-(n_1+n_2+n_3)$. We repeat the approach for 1,000 sets of random numbers $\alpha, \beta, \gamma, q_1, q_2$ and $q_3$.

Results again suggest that the Shannon and balance indices are correlated irrespective of the number of land uses considered in their definition. For the first two approaches, both the Pearson and the Spearman correlations never fall below 0.91. The last approach produces slightly lower correlations; the minimum is 0.75, however the vast majority of estimated correlations are still higher than 0.9. Analytical results are presented in Table 3.4. Are there any criteria for selecting between the two measures? The two metrics are affected differently by small variations in the relative shares of population and employment. In the case of two land use categories, the change in the balance index is independent of the original shares of uses, where as the Shannon index is more sensitive to changes the more imbalanced the original shares were. The choice of measure can be guided by which of the two properties the researcher considers desirable in the specific context. Based on this criterion, we recommend use of the Shannon index in the travel behaviour context: the launch of a new retail unit in an entirely residential area should have a greater effect than a new addition in a neighbourhood with substantial existing retail development. For more than two uses, the balance index has the disadvantage that some changes to the distribution of uses leave its value unaltered. For example, the following two cases both have a balance index of 0.6 when the balance index is defined for three uses: $p_1 = 0.2$, $p_2 = 0.2$, $p_3 = 0.6$ and $p_1 = 0.1$, $p_2 = 0.3$, $p_3 = 0.6$. 
Table 4.4 Pearson correlations and Spearman rank correlations between the Shannon and balance indices defined for various land use classifications

<table>
<thead>
<tr>
<th>Number of land uses</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pearson</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>minimum</td>
<td>0.90</td>
<td>0.86</td>
<td>0.95</td>
<td>0.92</td>
</tr>
<tr>
<td>maximum</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>% of estimated correlations that is lower than 0.9</td>
<td>0.2%</td>
<td>0.2%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Spearman</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>minimum</td>
<td>1</td>
<td>0.75</td>
<td>0.88</td>
<td>0.90</td>
</tr>
<tr>
<td>maximum</td>
<td>1</td>
<td>1.00</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>% of estimated correlations that is lower than 0.9</td>
<td>0%</td>
<td>2.2%</td>
<td>0.1%</td>
<td>0.1%</td>
</tr>
</tbody>
</table>

Note: All correlations were significant at the 5% level

4.6 Conclusion

In this chapter we presented a short discussion of the properties of land use mix measures commonly employed in the travel behaviour literature. Subsequently, we used a simulation to explore how different measures affect our understanding of the links between travel demand and land use mix. The results show that, all else being equal, use of an alternative measure rarely produces equivalent results. Furthermore, we demonstrated that the relationship between the various measures can often vary significantly between datasets. The findings suggest that researchers should be cautious when comparing results from studies that use different measures and, if data is available, should test alternative measures when estimating travel behaviour models. As an exception, the Shannon and the balance indices appear to produce roughly equivalent results. Further simulations suggested that the two measures are highly correlated regardless of the number of land use categories used in their definition. Although the analysis does not constitute proof of the hypothesis, it does provide strong support. In light of this conclusion, we have discussed the two measures’ common properties and identified where the Shannon index performs better.

The measurement of land use mix merits further attention. Our analysis has looked at how the mixing of uses is measured. Two relevant issues deserve further study. First, which land uses are pertinent in the travel behaviour context? The land uses
considered vary vastly between studies; few researchers have sought to test their chosen measure for different land uses (exceptions include Brown et al, 2009 and Cao, Handy and Mohktarian, 2007). Second, how do we measure land use itself? Again, researchers have used several approaches: counts of activities such as population, employment or the number of retail outlets (e.g. Cervero and Duncan’s, 2003, balance index; Vance and Hedel’s, 2007, Shannon index,), land area (e.g. Crane and Crepeau’s, 1998, shares of land uses, Van Acker and Witlox’s, in press, balance index) and building floor area (e.g. Frank et al’s, 2006, Shannon index). In the next chapter we apply various land use mix measures in an empirical model of public transport demand; the analysis also addresses the second of the questions posed here.
Chapter 5: An empirical investigation of the measurement of land use mix in the context of public transport demand

5.1 Introduction

As discussed in the previous chapter, a shortcoming of the literature is that it fails to adequately address how the choice of land use mix measure affects our understanding of the link between mixed uses and travel behaviour. In the previous chapter, we used simulation analyses to demonstrate how different measures can lead to different conclusions regarding the relationship between land use mix and travel behaviour.

An empirical model of travel demand that tests the wide range of measures used in past studies of travel behaviour is absent in the literature. In the medical literature, on the other hand, Brown et al (2009) have tried various land use mix measures in modelling outcomes relating to body weight. However, most measures examined in the study are not relevant in the context of personal travel (e.g. the presence of parks in a neighbourhood) and the study covers only few of the measures used in the travel behaviour literature.

In this chapter, we take advantage of a detailed dataset of addresses for the United Kingdom, OS MasterMap Address Layer 2, to construct different land use mix measures and then apply these in a model of public transport trip frequency in London. We also consider measures that define land use mix in terms of land area rather than counts of establishments, and examine whether the unit of measurement of land uses affects model results.

The empirical testing of a wide range of land use mix measures is the main contribution of the paper. A further contribution is the presentation of evidence on the link between travel and urban form in London. To our knowledge, this is the first such

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22 Brown et al (2009) find that there is no measure that best predicts all outcomes considered, but also conclude that it is the presence of various land uses rather than how equal their shares are that relates to healthy weight.
study conducted in the context of London and in fact only a few similar studies exist for UK as a whole (Guiliano and Narayan, 2003; Aditjandra, 2009, 2010; Stead, 2001). Studies from diverse geographical areas are valuable because, as demonstrated in the work of Giuliano and Narayan (2003) and Buehler (2010, in press), the relationship between urban form and travel can differ between countries/geographical areas due to factors such as culture or policies.

The chapter is structured as follows. The next section describes the data used in estimation. Section 5.3 explains the model specification. Results are presented in section 5.4 before some concluding remarks are made in section 5.5.

5.2 Data
The main data source for the study is the London Travel Demand Survey (LTDS) administered by Transport for London (TfL)23, a personal travel survey covering the Greater London Area. Starting in 2005, the LTDS is run on a rolling basis with an aim of sampling 8,000 households with a complete coverage of the Greater London area per financial year (from April to March). All members of eligible households aged 5 years or older are required to complete a 24-hour travel diary on an assigned day, and to attend a face-to-face personal interview. The dataset includes information on all trips performed on the assigned day, including origin and destination, travel time, mode used and trip purpose, as well as a wealth of personal information. Response rates for each financial year range from 51.5% to 52.6%.24 Table 5.1 presents the sample sizes and response rates achieved in each financial year.

In our sample, we include all participants who are permanent members of the surveyed households rather than visitors, who spent the travel night inside the survey area and whose profession does not involve driving as a major part of the job.25 Visitors are excluded for consistency as they were not asked to complete the survey in all years. Data on work/school location was not collected from all respondents and

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23 Government body responsible for transport in Greater London.
24 The figures exclude the financial year 2008/9, for which no data on response rates were available.
25 Professions that were excluded include drivers of taxis, minicabs, public transport, emergency, patrol or goods vehicles; car, motor or pedal cycle couriers; door to door sellers; home delivery (e.g. postman, milkman); home service workers (e.g. plumber).
this greatly reduces the number of observations in our final sample. We also had to
exclude individuals living close to the Greater London boundary because we did not
have data to construct the corresponding land use mix measures. The final sample
used for model estimation includes 25,508 observations. Table 5.2 presents
descriptive statistics for some basic socio-demographic characteristics both for the
sample and the entire population of the Greater London area. Children under 18 are
slightly overrepresented in the sample, and adults aged 18 to 60 slightly
underrepresented. However, in general, sample characteristics compare well with
population characteristics.

Table 5.1 LTDS Response rates
(source: LTDS Technical Review, provided by TfL)

<table>
<thead>
<tr>
<th>Financial year</th>
<th>Sample Size (household)</th>
<th>Sample Size (individuals)</th>
<th>Response Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>LTDS 2005/06</td>
<td>5,008</td>
<td>11,583</td>
<td>52.4%</td>
</tr>
<tr>
<td>LTDS 2006/07</td>
<td>8,006</td>
<td>18,242</td>
<td>52.6%</td>
</tr>
<tr>
<td>LTDS 2007/08</td>
<td>7,873</td>
<td>17,926</td>
<td>51.5%</td>
</tr>
</tbody>
</table>

Table 5.2 Sample versus population characteristics
(London data source: 2001 Census; Key Statistics)

<table>
<thead>
<tr>
<th>% population over 4 years old that is</th>
<th>London</th>
<th>Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>male</td>
<td>0.48</td>
<td>0.46</td>
</tr>
<tr>
<td>aged &lt;18</td>
<td>0.17</td>
<td>0.23</td>
</tr>
<tr>
<td>aged 18 to 60</td>
<td>0.65</td>
<td>0.60</td>
</tr>
<tr>
<td>aged &gt;60</td>
<td>0.18</td>
<td>0.17</td>
</tr>
<tr>
<td>employed</td>
<td>0.48</td>
<td>0.47</td>
</tr>
<tr>
<td>student aged over 16</td>
<td>0.08</td>
<td>0.07</td>
</tr>
<tr>
<td>homemaker</td>
<td>0.06</td>
<td>0.08</td>
</tr>
<tr>
<td>average household size</td>
<td>2.38</td>
<td>2.62</td>
</tr>
</tbody>
</table>

Land use mix variables are estimated using data from two sources, the Ordnance
Survey\(^\text{26}\) (OS) MasterMap Address Layer 2 and the General Land Use Database for
England 2005 (GLUD). OS MasterMap Address Layer 2 is a comprehensive database
of postal and non-postal addresses in Great Britain. It is compiled using the addresses

\(^{26}\) National Mapping Agency of Britain
available in the UK national postal service, supplemented by data on non-postal premises (e.g. depots, churches etc) collected by Ordnance Survey and the Valuation Office Agency, a government agency responsible for property valuations relating to taxes. Each address is georeferenced and associated with a use. In total, 456 uses are identified. We classify them into six categories: residential, retail, services, education, leisure and eating/drinking establishments. We exclude from the classification certain uses that we do not deem relevant in the context of personal travel (e.g. farming, wholesale retailers etc). The georeferenced locations and detailed classification of uses make the dataset ideal for constructing several different land use mix measures. We have available 2009 data for the London Government Office Region. Figure 5.1 shows a screenshot of part of the dataset as portrayed in the Mapinfo GIS software.

**FIGURE 5.1** Screenshot of part of the OS MasterMap Address Layer 2 dataset in the Mapinfo Software showing features as red points with their use as a label. (Source: OS Address Layer 2 Ordnance Survey © Crown Copyright. All rights reserved.)

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27 The OS Address Layer 2 uses that are included in each of the six categories considered in this study can be found in the appendix.
The GLUD is provided by the Department of Communities and Local Government\textsuperscript{28}. The database specifies the area covered by various land uses in different statistical geographical boundaries used by the UK Census. Nine land use categories are considered: domestic buildings, non-domestic buildings, domestic gardens, roads, paths, rail, greenspace, water and ‘other’, where ‘other’ largely refers to areas of hardstanding such as tarred car parks, estate roads or hard tennis courts. The GLUD is the result of the linking of OS MasterMap Address Layer, a precursor to OS MasterMap Address Layer 2 described above, and the OS MasterMap topography layer, a map of spatially referenced polygons that correspond to fixed objects of the landscape such as buildings, fields, water or roads. In addition to land use mix, GLUD is also used to construct measures of road supply.

Data on public transport supply are available from the National Public Transport Access Node (NaPTAN) database\textsuperscript{29}. NaPTAN provides an up-to-date identification of all the points of access to public transport in the UK; the exact location is given in terms of National British Grid coordinates. The database is maintained centrally by a contractor to the UK’s Department for Transport and includes data on all modes of public transport: rail, underground, tram, bus, coach, ferry, air travel and taxis.

Finally, the 2001 UK Census supplies data on population and on aggregate demographics. The latter are used to construct instruments to deal with endogeneity between public transport use, public transport accessibility and urban form.

A possible issue with our dataset is the various years for which different data items were collected. First, the LTDS survey is a rolling survey. Participants in our sample were surveyed in different years (from 2005 to 2009). We address this by adding in our model binary dummy variables representing the year of collection of travel data. Second, urban form variables are constructed from datasets compiled in various years, which do not necessarily match the LTDS survey years. However, we believe that the induced measurement error will be small as urban form is persistent over time.


\textsuperscript{29} Available online from http://data.gov.uk/dataset/naptan (accessed April 2011).
5.3 Model specification

5.3.1 Econometric model

We model public transport demand as the number of trips made per person by public transport in a 24 hour period. Hence, a model specification suitable for count dependent variables is required. The fundamental model for count data is based on the Poisson distribution. The Poisson model defines the probability of observing a specific count for variable $y$ given a parameter $\mu$ as $P(y/\mu) = \frac{e^{-\mu} \mu^y}{y!}$, where $\mu = E(y/x) = \exp(x'\beta)$. $x$ is a vector of factors affecting $y$ and $\beta$ is a vector of parameters to be estimated. An innate feature of the Poisson distribution is that the variance equals the mean: $\text{Var}(y) = E(y) = \mu$. This is a rather restrictive assumption; real data tend to be overdispersed, that is $\text{Var}(y) > E(y)$.

The negative binomial model is a widely used alternative to the Poisson that incorporates overdispersion. Negative binomial models treat the parameter $\mu$ as random; it is defined as the product of two independent components, where the first is deterministic on $x$ while the second is random. In particular, $\mu = \lambda \nu$, where $\lambda = \exp(x'\beta)$ and $\nu$ is an iid random variable that follows a $\text{Gamma}(\frac{1}{a}, a)$ distribution ($a > 0$). Then, $E(\nu) = 1$, $\text{Var}(\nu) = a$, $E(y/x, a) = \mu$ and $\text{Var}(y/x, a) = \mu (1 + a \mu)$. Since $a > 0$, $\text{Var}(y/x, a) > E(y/x, a)$ as required. A popular specification for negative binomial models treats $a$ as a parameter to be estimated. This is commonly referred to as the NB2 model. Alternatively, we can set $a = \frac{\gamma}{\mu}$ where $\gamma$ is a parameter to be estimated, so that the variance of $y$ is a scale multiple of $\mu$. This model it often called NB1. We will use both terms NB1 and NB2 from now on. Note that the Poisson model can be seen as a special case of the Negative Binomial model with $a = 0$. Note also that the conditional expectation of $y$ is the same for the Poisson and Negative Binomial models, so that results can be interpreted in the same way.

An advantage of the Poisson and NB2 models is that the parameter estimates for $\beta$ are consistent even if the distributional assumptions on $y$ are wrong, provided that the conditional mean of $y$ is correctly specified. This is not true for NB1 models. For both

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30 $x$ denotes a column vector and $x'$ a row vector.

31 Underdispersion, that is $\text{Var}(y) < E(y)$, is also possible.
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the Poisson and negative binomial models, elasticities \( e_{y,x_i} \) of \( y \) with respect to \( x_i \), the \( i \)th component of the vector \( x \), can be derived as follows.

\[
e_{y,x_i} = \frac{x_i}{E(y/x)} \frac{\partial E(y/x)}{\partial x_i} = \frac{x_i}{e^{x'\beta}} \frac{\partial (e^{x'\beta})}{\partial x_i} = \frac{x_i}{e^{x'\beta}} e^{x'\beta} \beta_i = x_i \beta_i
\]

We estimate Poisson, NB1 and NB2 models where \( y \) is individual public transport trip frequency in a 24 hour period and \( x \) is a vector of factors that affect travel demand, which includes variables describing demographics, urban form, transit supply, road supply, the cost of public transport use, the cost of car use and controls relating to the travel day. The models are estimated using maximum likelihood (see Cameron and Trivedi, 1998, pp. 61, 71, 73). We define a public transport trip as any trip that uses a public transport mode for at least one of its stages. Our definition of public transport includes buses, coaches, tramway, rail and underground. Several different land use mix measures are created; separate models are estimated for each measure to investigate whether the choice of measure affects our understanding of the relationship between land use mix and public transport trip frequency. We now describe in detail the hypotheses underpinning the selection of covariates for the public transport demand model, including the different land use mix measures considered.

5.3.2 Land use mix measures
As explained in section 5.2, two distinct data sources are used for the estimation of land use mix measures. The following metrics, selected to represent the categories identified in section 4.2 of chapter 4, are estimated using the OS Address Layer 2 dataset. Dummy variables and the Gini coefficient are not considered for the reasons given in chapter 4 (see section 4.2).

1. Minimum distance from an individual’s residence to a retail outlet measured as a straight line distance
2. Retail density \( D = \frac{\text{# of retail establishments}}{\text{area}} \)
3. Ratio of non-residential to residential uses \( R = \frac{\text{# of non-residential establishments}}{\text{# of residential establishments}} \)
4. The share of non-residential establishments \( S = \frac{\text{# of non-residential establishments}}{\text{total # of establishments}} \)
5. Shannon index \( S = -\sum_{i=1}^{n} p_i \ln p_i \), where \( p_i \) is the proportion of establishments with use \( i \) and \( n \) is the total number of land uses considered. We define the Shannon index both for two land use categories (residential and non-residential) and for six (residential, retail, services, leisure, eat/drink and education).

6. Balance index \( B = 1 - \frac{\sum_{i=1}^{n} |p_i - 1|}{2(n-1)} \), where \( p_i \) and \( n \) are defined as for the Shannon index. Again, we define the Balance index both for two land use classes (residential and non-residential) and for six (residential, retail, services, leisure, eat/drink and education).

7. Retail accessibility defined as \( \text{accessibility}_i = \sum_j X_j e^{-\beta d_{ij}} \), where \( X_j \) is the number of retail establishments at a distance \( d_{ij} \) from the residence of \( i \), \( \beta \) is a fixed parameter and the sum runs over all retail establishments that are located at a maximum distance of 500m from the residence. Retail establishments located at a distance of more than 500m from a residence are not taken into account because the OS address layer 2 dataset we have available is limited to the Greater London area; extending the limit beyond 500m will cause problems with calculating accessibility measures for respondents living close to the Greater London boundary. In addition, retail establishments rather than retail employment is used because georeferenced data on retail employment are not available. Choosing a value for \( \beta \) is difficult, as most studies that have employed a similar accessibility measure in the urban form-travel behaviour literature define accessibility in terms of travel time rather than distance or do not present the parameter value used. We tried \( \beta = 1, 0.1, 0.05, 0.01 \) and 0.001. The estimated elasticities are equal to two decimal places for all values of \( \beta \) and therefore, we only present results for \( \beta = 1 \).

The fact that OS Address Layer 2 features are georeferenced gives us complete freedom regarding the choice of spatial unit for the measurement of land use mix. We estimate all land use mix measures (apart from minimum distance) for a circular buffer of radius 500m around each individual’s neighbourhood. We choose to use

\[ \text{balance index is not a widely used term. It has been utilized by Cervero and Duncan (2003) and we will also use it in the paper.} \]
circular buffers of fixed radii rather than existing administrative or statistical entities, for a number of reasons. First, administrative or statistical geographical entities vary in size. Larger spatial units are more likely to have multiple uses simply due to their large size; in other words, the size of a unit can influence the measurement of land use mix. Consequently using equally sized geographical units are preferable. Second, circular buffers have the intuitive meaning that they comprise all area up to a maximum distance from a residence. This distance can be perceived as the maximum distance an individual is willing to walk to reach a destination such as their workplace, a shop or a transit station. Although this is a rather simplistic definition of what constitutes a neighbourhood, it is nevertheless more intuitive than administrative or statistical boundaries, which have been delineated for unrelated purposes. A household might be located near the border of an administrative/statistical unit; then the unit is likely to be a poor approximation of the household’s neighbourhood. Last, circular buffers introduce more variability in the dataset. Since our data is from a single city, different households in the dataset will inevitably fall in the same administrative/statistical unit, and will hence have the same observation for land use mix. Circular buffers produce distinct land use mix observations for each household in the dataset, with the rare exception of households living within the same building. Circular buffers of various sizes have been used in the literature, ranging from 300 feet (approximately 91 metres; e.g. Cervero, 1996a) to a mile (approximately 1600 metres; e.g. Greenwald and Boarnet; 2001). We choose to use an intermediate value, 500 metres.

In defining land use mix using the OS Address Layer 2 data, due to the nature of the data, we used count of establishments as a unit of measurement for land use. Authors have also defined land uses in terms of other units, such as land area or building floor area. For instance, while Vance and Hedel (2007) use counts of various types of establishments to estimate the Shannon index, Brown et al (2009) use land area and Frank et al (2006) use building floor area. Cervero and Duncan (2003) measure the share of residential uses as the ratio of housing units to housing units and employment, while Crane and Crepeau (1998) use the proportion of land area that is residential. Cervero and Duncan (2003) use employment and population to construct

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33 The comment does not apply to minimum distance measures and to retail density.
the balance index, while Van Acker and Witlox (in press) use land area, and Sohn and Shim (2010) use building floor area.

The GLUD dataset provides the opportunity to redefine some of the measures constructed with OS Address Layer 2 data using land area instead of counts of establishments and investigate the effect on model results. We estimate the ratio of non-residential to residential uses as \( R = \frac{\text{land area allocated to non-residential uses}}{\text{land area allocated to residential uses}} \) and the share of non-residential uses as \( S = \frac{\text{area allocated to non-residential uses}}{\text{total area}} \). The Shannon and the balance indices defined above are estimated in terms of \( p_i \) = the proportion of area allocated to use \( i \). Two uses are considered, residential and non-residential. The GLUD measures are estimated at the Lower Super Output Area level (LSOA)\(^{34}\).

In chapter 4, we noted that a limitation of the balance index is that it advocates an equal distribution of land uses as the optimum, when in fact there may be no reason why this should be the case. For example, Bhat and Guo (2007) defined the balance index for the following three uses: residential, commercial/industrial and other. There is no basis to justify why residential uses should comprise exactly one third of a neighbourhood; likewise for commercial/industrial and other land uses. In the case of two land uses, we propose a modification of the balance index that is maximized at a chosen level. Let \( p_i \) and \( q_i = 1 - p_i \) be the proportions of two distinct classes of land uses in neighbourhood \( i \), and let \( P \) and \( Q = 1 - P \) be the corresponding optimal shares. Then we define the index

\[
H = \begin{cases} 
\frac{p_i}{P} & \text{if } p_i \leq P \\
\frac{1-p_i}{1-P} & \text{if } p_i > P
\end{cases}
\]

The index takes values in the range 0 to 1. It achieves the minimum value of 0 when a neighbourhood contains only one use and the maximum value of 1 when the shares of land uses \( p_i \) and \( q_i = 1 - p_i \) are equal to \( P \) and \( Q = 1 - P \) respectively. The index increases linearly as \( p_i \) increases from 0 to \( P \), and decreases linearly as \( p_i \) increases

\(^{34}\) Statistical geographical entity used in the UK for census output. LSOAs have a minimum of 1,000 residents and 400 households, but an average size of 1,500 residents.
from \( P \) to 1. The balance index (defined for two land uses) is a special case of the index \( H \) for \( P = \frac{1}{2} \). In this study, we define the index \( H \) setting \( P \) to be the share of the non-residential uses in the entire Greater London area. The choice of \( P \) relies on the assumption that a uniform distribution of non-residential uses across London is the optimum. We estimate the index using both OS Address Layer 2 and GLUD.

5.3.3 Factors affecting public transport trip frequency

Table 5.3 lists the explanatory variables included in the model besides land use mix. The model includes a rich set of demographic variables. The data are available in the LTDS. Various demographic variables have been associated with public transport demand in the past: income, car ownership, possession of a driving license, age, education level, employment status, household structure (e.g. Kitamura, Mokhtarian and Laidet, 1997; Graham et al, 2009; Taylor et al, 2008; Frondel and Vance, 2011).

Income was included in our model as in any demand model. Regarding public transport, it can have a twofold effect: On one hand, wealth can increase demand for travel in general and as a result demand for public transport travel as well. On the other hand, public transport might be considered an inferior good; increased affluence could lead to public transport being substituted by the private vehicle.

Age can also have a complex effect on public transport demand with children and the elderly likely to behave differently than the rest of the population. The elderly are expected to travel less in total as they are less mobile, but might also use public transport more frequently as they are often unable to drive. Children are often transported by car when they are young, but are expected to be frequent public transport users once they start travelling independently. In London, children under 18 and adults aged 60 and over receive free or discounted travel depending on their age, which could encourage public transport trips. The age categories included in the model are chosen to reflect the various categories of age related passes offering travel discounts.
Table 5.3 Explanatory variables included in the model (apart from land use mix)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td>0-1 dummy variable indicating the respondent is male</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td>0-1 dummy variables identifying the age of respondents i</td>
</tr>
<tr>
<td></td>
<td>aged 5-10</td>
</tr>
<tr>
<td></td>
<td>aged 11-15</td>
</tr>
<tr>
<td></td>
<td>aged 16-17</td>
</tr>
<tr>
<td></td>
<td>aged 18-59 (base case, excluded from model)</td>
</tr>
<tr>
<td></td>
<td>aged 60-64</td>
</tr>
<tr>
<td></td>
<td>aged 65-69</td>
</tr>
<tr>
<td></td>
<td>aged 70-74</td>
</tr>
<tr>
<td></td>
<td>aged 75-79</td>
</tr>
<tr>
<td></td>
<td>aged 80+</td>
</tr>
<tr>
<td><strong>Income</strong></td>
<td>0-1 dummy variables identifying a household's income category</td>
</tr>
<tr>
<td></td>
<td>&lt; £5,000</td>
</tr>
<tr>
<td></td>
<td>£5,000 - £9,999</td>
</tr>
<tr>
<td></td>
<td>£10,000 - £14,999</td>
</tr>
<tr>
<td></td>
<td>£15,000 - £19,999</td>
</tr>
<tr>
<td></td>
<td>£20,000 - £24,999</td>
</tr>
<tr>
<td></td>
<td>£25,000 - £34,999</td>
</tr>
<tr>
<td></td>
<td>£35,000 - £49,999</td>
</tr>
<tr>
<td></td>
<td>£50,000 - £74,999</td>
</tr>
<tr>
<td></td>
<td>£75k or more (base case, excluded from the model)</td>
</tr>
<tr>
<td><strong>Economic activity</strong></td>
<td>0-1 dummy variables indicating the status of the economic activity of respondents</td>
</tr>
<tr>
<td></td>
<td>employed ii</td>
</tr>
<tr>
<td></td>
<td>student 18 years old or over</td>
</tr>
<tr>
<td><strong>Homemaker</strong></td>
<td>0-1 dummy variables relating to the travel day v</td>
</tr>
<tr>
<td></td>
<td># of cars/vans/lorries per adult the household owns or has access to</td>
</tr>
<tr>
<td></td>
<td># number of motorcycles the hhld owns or has access to divided by # of hhld members over 16</td>
</tr>
<tr>
<td><strong>License holding</strong></td>
<td>0-1 dummy variables indicating possession of</td>
</tr>
<tr>
<td></td>
<td>a car license</td>
</tr>
<tr>
<td></td>
<td>a motorcycle license</td>
</tr>
<tr>
<td><strong>Disability</strong></td>
<td>0-1 dummy variable indicating the individual has a disability a disability iii</td>
</tr>
<tr>
<td><strong>Household structure</strong></td>
<td>household size</td>
</tr>
<tr>
<td></td>
<td># of children under 10</td>
</tr>
<tr>
<td></td>
<td># of adults over 70</td>
</tr>
<tr>
<td></td>
<td># of household members with a car driving license</td>
</tr>
<tr>
<td></td>
<td># of household members with a motorcycle driving license</td>
</tr>
<tr>
<td></td>
<td># of employed household members</td>
</tr>
<tr>
<td></td>
<td># of adult students in the household</td>
</tr>
<tr>
<td></td>
<td># of visitors staying over on the travel day</td>
</tr>
<tr>
<td><strong>Road supply</strong></td>
<td>road area per capita in the household home location</td>
</tr>
<tr>
<td><strong>Transit supply</strong></td>
<td>minimum distance from home to a rail, metro or underground station</td>
</tr>
<tr>
<td><strong>Population density</strong></td>
<td>population density at the household home location</td>
</tr>
<tr>
<td><strong>Public transport cost</strong></td>
<td>0-1 dummy variables indicating possession of</td>
</tr>
<tr>
<td></td>
<td>a staff pass for TfL or police workers allowing free travel on public transport</td>
</tr>
<tr>
<td></td>
<td>a New Deal pass providing discounted travel</td>
</tr>
<tr>
<td><strong>Work location/cost of car use</strong></td>
<td>0-1 dummy variable indicating the respondent resides outside the CCZ iv, but works inside</td>
</tr>
<tr>
<td><strong>Travel day controls</strong></td>
<td>0-1 dummies to control for survey year</td>
</tr>
<tr>
<td></td>
<td>2005</td>
</tr>
<tr>
<td></td>
<td>2006</td>
</tr>
<tr>
<td></td>
<td>2007</td>
</tr>
<tr>
<td></td>
<td>2008</td>
</tr>
<tr>
<td></td>
<td>2009 (base case, excluded from model)</td>
</tr>
<tr>
<td></td>
<td>travel day was in a weekend</td>
</tr>
<tr>
<td></td>
<td>travel day was New Year's day</td>
</tr>
<tr>
<td></td>
<td>travel day was another bank holiday</td>
</tr>
<tr>
<td></td>
<td>travel day was in the summer (June, July, August)</td>
</tr>
</tbody>
</table>

i No data was available on trips made by children under 5, ii includes both full-time and part time workers and both employees and self-employed individuals, but excludes unpaid voluntary work, iii includes mobility disabilities, visual and hearing impairments, learning difficulties, age related mobility difficulties, long-term illness and mental health problems, iv CCZ-Congestion Charging Zone, v No observations for Christmas Day or Boxing Day
Economic activity can have a bearing on an individual’s travel as it determines the activities he/she participates in. Three 0-1 dummy variables are included indicating whether respondents are employed, students or homemakers. Students aged 18 or over are specifically considered to reflect the fact that they receive different travel discounts compared to younger students. We also wanted to include a 0-1 dummy variable for students aged 16 to 17, but it was found to be correlated with the corresponding dummy variable for age. For children aged 5 to 16 school attendance is compulsory, so no variable is needed other than the corresponding age variable.

Vehicle ownership and possession of a driving license are also taken into account as they determine whether a feasible alternative to public transport exists. Motorcycles are included separately from other vehicles, both with regard to ownership and license holding, because they are excluded from paying the congestion charge that other vehicles are required to pay to enter the central London area during some specified time. Naturally, the congestion charge is a significant deterrent to vehicle use.

An individual’s travel is usually planned in conjunction with other household members. Hence, detailed variables describing household structure and attributes are necessary to ensure observations from members of the same household can be treated as independent. Finally, controls are also included for gender and the presence of a disability that can affect mobility.

In addition to land use mix, several other attributes of the home neighbourhood can have a bearing on public transport demand. First and foremost, accessibility to public transport clearly affects its use. We use minimum distance to a rail, underground or tram station as a measure of public transport accessibility. This is derived using the NapTan dataset described in section 2. Road supply can negatively influence public transport demand as improved road provision reduces the generalised cost of driving. Road supply is represented in the model using road area per capita. It is measured at the LSOA level using data on road area from GLUD and data on population from the 2001 UK Census. We chose to use road area per capita rather than per total area as we want a measure that represents the road space available for each resident. Finally, we also include another widely used measure of urban form, population density. This is calculated also at the LSOA level from population data in the 2001 UK Census. It can
be argued that population density is highly correlated with land use mix. However, the correlations of population density with each of the land use mix measures applied in this study does not exceed 0.32 in absolute value.

The decision to make a public transport trip can be undoubtedly affected by its cost as well as the cost of alternative modes. The fare for a given public transport trip is the same for all Londoners unless they have purchased a monthly or annual pass allowing unlimited travel, or if they qualify for free or discounted travel. Binary dummy variables were included for possession of a police or TfL staff pass that allows free public transport travel, and for possession of a ‘New Deal’ pass whose holders qualify for fare discounts. Children, seniors, students and disabled individuals are also entitled to either free or discounted travel, but the variables included for age, student status and disability account for the effect.

Possession of a monthly or annual pass is extremely endogenous. On one hand, possession of a pass can induce further public transport use as the marginal cost of a trip for pass holders is zero. On the other hand, people purchase passes only if they plan to use public transport extensively. We believe the latter effect to be more significant and subsequently, we decided not to include a variable indicating possession of a monthly or annual pass in the model. The decision was reinforced by the fact that finding a suitable instrument is difficult as the intention to make extensive use of public transport is the sole reason for obtaining a pass.

Possession of various passes for rail travel across the UK also provides some discounts on the London public transport network. A relevant dummy variable for this effect may, or may not be endogenous, because although such passes are not free, they are mainly purchased for rail travel outside the study area. We estimated models with and without the relevant dummies; results were almost identical and we subsequently decided to exclude them.

London is divided into fare zones; a trip’s fare depends on the zones in which its origin and destination lie. We tried using the fare zone of the home location as a

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35 Government programme to tackle unemployment
rough proxy of the average fare an individual is likely to face for a trip. However, we found it to be correlated with the urban form variables used and thus excluded it from the final model.

Regarding the cost of the main alternative mode, the car, we assumed fuel prices and car maintenance costs to be equal across London. A dummy for individuals that reside outside London’s congestion charging zone, but work or go to school/university inside the zone was included to indicate individuals that face increased costs if they wish to commute by car\textsuperscript{36}. Residents living outside the congestion charging zone were only considered, as residents in the congestion charging zone receive a large discount on the charge. Not all survey participants were asked questions regarding their work location so that inclusion of this variable greatly reduced the number of observations available for estimation. We estimated models with and without the variables and used AIC and BIC to choose the best model. Including the variable was clearly preferred\textsuperscript{37}.

Finally, trip making depends on the day considered. For instance, travel patterns may differ between weekends and weekdays or between weekdays and bank holidays. Similarly, travel patterns can vary between winter and summer months due to differences in weather conditions. To control for the travel day, we include 0-1 dummy variables for the different survey years and 0-1 dummy variables indicating whether the assigned travel day was on a weekend, on bank holiday or in the summer. Ideally, we would also include dummy variables indicating that the travel day was during the school holidays. However, this was not possible as term dates differ between schools and are only available on school internet sites for the current and upcoming years.

5.3.4 Endogeneity
As remarked in section 2.4.2 of chapter 2, a widely acknowledged estimation issue is endogeneity between urban form and travel demand. Our model includes two

\textsuperscript{36} Construction of the variable took account of changes in the congestion charging zone’s boundaries during the survey years.

\textsuperscript{37} We also calculated mean values for all explanatory variables used in the model before and after dropping the observations that did not have work location data. Dropping the observations results in a slight reduction in the number of employed participants in the sample, from 53% to 47%. The remaining explanatory variables however did not experience a significant change.
variables relating to urban form that are treated as endogenous, population density and land use mix. Similarly, to urban form, distance to transit is also endogenous. Individuals who prefer to travel with public transport naturally choose to live close to public transport stations. To eliminate endogeneity we use the instrumental variable approach that was explained in chapter 3. Since the models are non-linear and have an exponential mean we use the GMM approach proposed by Mullahy (1997), which was described in section 3.3. This is implemented using the IVPOIS command in STATA (Nichols, 2007a). It should be noted that Mullahy’s estimator ignores the count nature of the data, which leads to a loss in efficiency.

In selecting instruments we follow Boarnet and Sarmiento (1998), Greenwald and Boarnet (2001) and Vance and Hedel (2007) and use neighbourhood attributes that are not related to transport: the percentage of residents that are over 65 years old, the percentage of residents that are single, the percentage of residents that were born outside the EU and the percentage of residents that have a professional occupation. The attributes are expected to affect the choice of neighbourhood and thus be correlated with urban form, but not to influence travel behaviour. In addition, we use the percentage of dwellings that do not have sole use of a bathroom. In London, these are usually small studio apartments with shared use of a bathroom that are generally intended for students or young single people. Hence, they are often located in areas with good public transport accessibility and diverse uses, which are attributes valued by young people. All instruments are measured at the LSOA level.

5.4 Results
First, in table 5.4 we present Pearson correlations between the land use mix measures employed in the study. All but two correlations are significant at the 0.1% level. However, many are modest in value and a few are very low. For instance, correlations of minimum distance with the remaining measures do not exceed 0.39 in magnitude. On the other hand, the share of non-residential uses, the ratio of non-residential to residential uses, the Shannon index and the balance index are highly correlated when measured using the OS Address Layer 2 dataset (0.89 and above). In contrast, the corresponding correlations tend to be lower when land use mix is measured in terms of land area. Correlations between measures estimated using
different units of measurement for land use mix never exceed 0.52 in absolute value, and in some cases are very low (e.g. the correlation between the ratio of non-residential to residential uses calculated using GLUD, and the modified balance index calculated using OS MasterMap Address Layer 2, is -0.01 and significant only at the 5% level). Importantly, even when the same measure is considered correlations are modest (they range from 0.25 to 0.44).
Table 5.4 Pearson correlations for the land use mix measures employed in the study

<table>
<thead>
<tr>
<th>OS MasterMap Address Layer 2</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
<th>(11)</th>
<th>(12)</th>
<th>(13)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) minimum distance</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2) retail density</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3) ratio non-residentials uses/residentials uses</td>
<td>-0.27</td>
<td>0.74</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4) share of non-residential uses</td>
<td>-0.32</td>
<td>0.75</td>
<td>0.97</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(5) Shannon (2 uses)</td>
<td>-0.39</td>
<td>0.69</td>
<td>0.86</td>
<td>0.96</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(6) Shannon (6 uses)</td>
<td>-0.38</td>
<td>0.70</td>
<td>0.89</td>
<td>0.97</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>(7) balance (2 uses)</td>
<td>-0.32</td>
<td>0.76</td>
<td>0.95</td>
<td>1.00</td>
<td>0.96</td>
<td>0.97</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>(8) balance (6 uses)</td>
<td>-0.34</td>
<td>0.72</td>
<td>0.92</td>
<td>0.99</td>
<td>0.98</td>
<td>0.99</td>
<td>0.99</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(9) modified balance (2 uses)</td>
<td>0.29</td>
<td>-0.05</td>
<td>0.01</td>
<td>-0.03</td>
<td>-0.17</td>
<td>-0.03</td>
<td>-0.04</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(10) ratio non-residentials uses/residentials uses</td>
<td>-0.22</td>
<td>0.52</td>
<td>0.43</td>
<td>0.44</td>
<td>0.40</td>
<td>0.41</td>
<td>0.44</td>
<td>0.43</td>
<td>0.01</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(11) share of non-residential uses</td>
<td>-0.31</td>
<td>0.51</td>
<td>0.40</td>
<td>0.44</td>
<td>0.45</td>
<td>0.44</td>
<td>0.44</td>
<td>0.44</td>
<td>-0.08</td>
<td>0.86</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(12) Shannon (2 uses)</td>
<td>-0.37</td>
<td>0.39</td>
<td>0.30</td>
<td>0.35</td>
<td>0.41</td>
<td>0.40</td>
<td>0.36</td>
<td>0.37</td>
<td>-0.18</td>
<td>0.54</td>
<td>0.86</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(13) balance (2 uses)</td>
<td>-0.27</td>
<td>0.22</td>
<td>0.20</td>
<td>0.25</td>
<td>0.31</td>
<td>0.30</td>
<td>0.25</td>
<td>0.27</td>
<td>-0.18</td>
<td>0.22</td>
<td>0.54</td>
<td>0.85</td>
<td></td>
</tr>
<tr>
<td>(14) modified balance (2 uses)</td>
<td>-0.31</td>
<td>0.15</td>
<td>0.13</td>
<td>0.18</td>
<td>0.24</td>
<td>0.23</td>
<td>0.18</td>
<td>0.20</td>
<td>-0.23</td>
<td>0.06</td>
<td>0.34</td>
<td>0.72</td>
<td>0.85</td>
</tr>
</tbody>
</table>

Notes: † Not significant.
‡ Significant at the 5% level.

Remaining correlations are significant at the 0.1% level.
For each model specification discussed in section 5.3.1 (Poisson, NB1, NB2, Poisson with IV), we estimated fifteen models, each including a different land use mix variable. Presentation of the full set of results for the sixty models is impractical and would involve a great deal of repetition of information. Instead, we start by presenting the full results for the models that include minimum distance to assess model fit and then present results for land use mix variables only for the remaining models.

Table 5.5 presents the estimated coefficients for models using minimum distance as a land use mix measure. In general, results are consistent with prior expectations.

Young children appear to travel less by public transport than adults, where as older children appear to travel more as we hypothesized in section 5.3.3. There appears to be an increase in public transport trip frequency for people aged 70 to 74, probably because people start finding driving difficult due to age. The effect is not apparent for older individuals, presumably because total trip making declines as mobility decreases with age. Moreover, old age does not appear to play any role according to the IV model.

Individuals in the middle income range appear to travel less by public transport than high earners, but this does not seem to be true for the lower income range. As explained in section 5.3.3, this could mean that wealthy individuals travel more in total and at the same time low income groups choose public transport for a larger share of their trips than wealthier income groups. Students and employed individuals appear to travel more by public transport than economically inactive individuals, possibly because they engage in more travel in total. However, the effect is not significant in the IV model.

Vehicle availability and the ability to drive a car or a motorcycle appear to have the expected negative association with public transport trip frequency.

Not all variables describing household structure are significant in the models. Specifically in the IV model, no variable relating to household structure is significant. In the remaining models, household size and the number of elderly appear to decrease the number of trips made by public transport. The presence of elderly people in the
household that are likely to require care could decrease the freedom to travel. The number of employed household members seems to have a positive effect on public transport usage, possibly because it increases competition for access to the household’s vehicles. Contrary to prior expectations, the number of visitors present on the travel day does not appear to affect the household’s travel patterns.

As expected, possession of a staff pass that allows free travel on the public transport network appears to increase public transport use. On the other hand, having a disability reduces the number of trips made by public transport. As anticipated, having to pay the congestion charge to commute by car seems to encourage public transport use. Similarly, proximity to a rail or underground station appears to have the expected positive effect on public transport trip making. Population density is positively associated with increased public transport use but not when instrumental variables are used suggesting that the apparent effect may not be causal. A surprising result is that the number of motorcycle license holders in a household appears to be positively associated with public transport trip making. A possible explanation is that both public transport and the motorcycle are seen as more environmentally friendly than the car, so that households which are environmentally conscious make substantial use of both. Another unexpected result is that road provision does not appear to have a bearing on public transport use. Finally, people appear to travel less by public transport on weekends and bank holidays.

A single measure of goodness of fit equivalent to $R^2$ in OLS does not exist for count models. Instead, several different measures, called pseudo- $R^2$ have been proposed; they do however lack the intuitive interpretation of the OLS $R^2$ and are not so widely used. For the Poisson, NB1 and NB2 models, we calculate three distinct pseudo- $R^2$ measures. No values are available for the IV model as the pseudo- $R^2$ measures presented are based on likelihoods, and the IV model is estimated using GMM. The pseudo- $R^2$ values appear to be low. Unfortunately, we are not aware of any studies estimating count models of public transport trip frequency that present pseudo- $R^2$ measures to compare with our findings. Kitamura, Mokhtarian and Laidet (1997) develop an OLS model of public transport trip frequency with a similarly low $R^2$, however pseudo- $R^2$ cannot be directly compared to $R^2$. The pseudo- $R^2$ values for the Negative Binomial models are slightly lower than the corresponding Poisson values.
However, pseudo- $R^2$ values are not a valid method for comparing different models. To examine the suitability of the Negative Binomial specification versus the Poisson we use instead a likelihood-ratio test for the null hypothesis of no overdispersion. The test statistic is $LR = 2 (\ln L_{NB} - \ln L_{poisson})$, where $L_{NB}$ and $L_{poisson}$ denote the log-likelihood functions of the Negative Binomial and Poisson models respectively, and follows a $\chi^2(1)$ distribution. The test concludes in favour of the Negative Binomial specification both for NB1 and NB2.
<table>
<thead>
<tr>
<th></th>
<th>Poisson</th>
<th>NB1</th>
<th>NB2</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>male</td>
<td>-0.0085</td>
<td>-0.01</td>
<td>-0.0037</td>
<td>-0.043</td>
</tr>
<tr>
<td>aged 5 to 10</td>
<td>-1.4    ***</td>
<td>-1.4 ***</td>
<td>-1.4 ***</td>
<td>-1.6 ***</td>
</tr>
<tr>
<td>aged 11 to 15</td>
<td>0.13    **</td>
<td>0.22 ***</td>
<td>0.12</td>
<td>0.098</td>
</tr>
<tr>
<td>aged 16 to 17</td>
<td>0.50    ***</td>
<td>0.61 ***</td>
<td>0.51 ***</td>
<td>0.57 ***</td>
</tr>
<tr>
<td>aged 60 to 64</td>
<td>-0.024</td>
<td>-0.045</td>
<td>0.0056</td>
<td>-0.11</td>
</tr>
<tr>
<td>aged 64 to 69</td>
<td>0.033</td>
<td>0.0014</td>
<td>0.075</td>
<td>-0.094</td>
</tr>
<tr>
<td>aged 70 to 74</td>
<td>0.24    **</td>
<td>0.25 *</td>
<td>0.31 ***</td>
<td>0.38</td>
</tr>
<tr>
<td>aged 75 to 79</td>
<td>0.0099</td>
<td>-0.024</td>
<td>0.1</td>
<td>0.15</td>
</tr>
<tr>
<td>aged 80 and over</td>
<td>-0.043</td>
<td>-0.07</td>
<td>0.026</td>
<td>-0.064</td>
</tr>
<tr>
<td>income &lt; £5,000</td>
<td>0.077</td>
<td>0.055</td>
<td>0.075</td>
<td>-0.20</td>
</tr>
<tr>
<td>income £5,000 - £9,999</td>
<td>-0.073</td>
<td>-0.092</td>
<td>-0.070</td>
<td>0.10</td>
</tr>
<tr>
<td>income £10,000 - £14,999</td>
<td>-0.049</td>
<td>-0.072</td>
<td>-0.046</td>
<td>-0.16</td>
</tr>
<tr>
<td>income £15,000 - £19,999</td>
<td>-0.046</td>
<td>-0.062</td>
<td>-0.052</td>
<td>-0.20</td>
</tr>
<tr>
<td>income £20,000 - £24,999</td>
<td>-0.16 ***</td>
<td>-0.17 ***</td>
<td>-0.19 ***</td>
<td>-0.700 *</td>
</tr>
<tr>
<td>income £25,000 - £34,999</td>
<td>-0.070 *</td>
<td>-0.074 *</td>
<td>-0.094 *</td>
<td>-0.27 *</td>
</tr>
<tr>
<td>income £35,000 - £49,999</td>
<td>-0.057 *</td>
<td>-0.051</td>
<td>-0.076 *</td>
<td>-0.34 *</td>
</tr>
<tr>
<td>income £50,000 - £74,999</td>
<td>-0.0079</td>
<td>-0.016</td>
<td>-0.022</td>
<td>-0.24</td>
</tr>
<tr>
<td>employed</td>
<td>0.13    **</td>
<td>0.22 ***</td>
<td>0.10</td>
<td>0.058</td>
</tr>
<tr>
<td>student</td>
<td>0.39    ***</td>
<td>0.48 ***</td>
<td>0.42 ***</td>
<td>0.30</td>
</tr>
<tr>
<td>homemaker</td>
<td>-0.39    ***</td>
<td>-0.47 ***</td>
<td>-0.4 **</td>
<td>-0.44 *</td>
</tr>
<tr>
<td># of cars</td>
<td>-0.55    ***</td>
<td>-0.61 ***</td>
<td>-0.59 ***</td>
<td>-0.77 ***</td>
</tr>
<tr>
<td># of motorcycles</td>
<td>-0.48    ***</td>
<td>-0.53 ***</td>
<td>-0.41 ***</td>
<td>4.00E-01</td>
</tr>
<tr>
<td>car license</td>
<td>-0.52    ***</td>
<td>-0.62 ***</td>
<td>-0.58 ***</td>
<td>-0.67 ***</td>
</tr>
<tr>
<td>motocycle license</td>
<td>-0.41    ***</td>
<td>-0.53 ***</td>
<td>-0.40 ***</td>
<td>-0.48</td>
</tr>
<tr>
<td>disability</td>
<td>-0.22    ***</td>
<td>-0.25 ***</td>
<td>-0.21 ***</td>
<td>-0.073</td>
</tr>
<tr>
<td>hhld size</td>
<td>-0.078    ***</td>
<td>-0.083 ***</td>
<td>-0.079 ***</td>
<td>-0.044</td>
</tr>
<tr>
<td># of children</td>
<td>-0.00089</td>
<td>-0.015</td>
<td>-0.0093</td>
<td>-0.08</td>
</tr>
<tr>
<td># of elderly</td>
<td>-0.11    **</td>
<td>-0.12 **</td>
<td>-0.14 **</td>
<td>-0.18</td>
</tr>
<tr>
<td># of car licenses in hhld</td>
<td>0.011</td>
<td>0.025</td>
<td>-0.0037</td>
<td>0.0018</td>
</tr>
<tr>
<td># of motorcycle licenses in hhld</td>
<td>0.12    **</td>
<td>0.14 **</td>
<td>0.10</td>
<td>-0.072</td>
</tr>
<tr>
<td># of employed hhld members</td>
<td>0.046    **</td>
<td>0.037</td>
<td>0.056 **</td>
<td>0.033</td>
</tr>
<tr>
<td># of adult students in hhld</td>
<td>-0.010</td>
<td>-0.029</td>
<td>0.0046</td>
<td>-0.053</td>
</tr>
<tr>
<td># of visitors</td>
<td>-0.050</td>
<td>-0.065</td>
<td>-0.028</td>
<td>0.097</td>
</tr>
<tr>
<td>distance to station</td>
<td>-0.13    ***</td>
<td>-0.16 ***</td>
<td>-0.14 ***</td>
<td>-6.7 **</td>
</tr>
<tr>
<td>road per capita</td>
<td>-1.0    -0.83</td>
<td>-9.40E-01</td>
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<tr>
<td>density</td>
<td>7.1E-06 ***</td>
<td>8.0E-06 **</td>
<td>1.1E-05 ***</td>
<td>-1.0E-04</td>
</tr>
<tr>
<td>minimum distance</td>
<td>-0.52    ***</td>
<td>-0.51 ***</td>
<td>-0.60 ***</td>
<td>-8.9 **</td>
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<td>staff pass</td>
<td>0.37    ***</td>
<td>0.40 ***</td>
<td>0.40 ***</td>
<td>0.46 ***</td>
</tr>
<tr>
<td>New Deal pass</td>
<td>0.45    0.55</td>
<td>0.48</td>
<td>-0.56</td>
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<tr>
<td>congestion charging</td>
<td>0.78    ***</td>
<td>0.91 ***</td>
<td>0.84 ***</td>
<td>0.99 ***</td>
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</table>
Table 5.5 (continued) Coefficient estimates for the public transport trip frequency model with minimum distance measuring land use mix

<table>
<thead>
<tr>
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<th>NB1</th>
<th>NB2</th>
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<tr>
<td>2005</td>
<td>-0.038</td>
<td>-0.039</td>
<td>-0.064</td>
<td>-0.21</td>
</tr>
<tr>
<td>2006</td>
<td>-0.035</td>
<td>-0.022</td>
<td>-0.050</td>
<td>-0.18</td>
</tr>
<tr>
<td>2007</td>
<td>-0.058</td>
<td>-0.050</td>
<td>-0.079</td>
<td>-0.30</td>
</tr>
<tr>
<td>2008</td>
<td>0.020</td>
<td>0.020</td>
<td>0.0049</td>
<td>-0.25</td>
</tr>
<tr>
<td>weekend</td>
<td>-0.71***</td>
<td>-0.82***</td>
<td>-0.70***</td>
<td>-0.64***</td>
</tr>
<tr>
<td>bank holiday</td>
<td>-0.73***</td>
<td>-0.91**</td>
<td>-0.81**</td>
<td>-1.4*</td>
</tr>
<tr>
<td>new year</td>
<td>0.033</td>
<td>0.44</td>
<td>-0.0072</td>
<td>-1.3</td>
</tr>
<tr>
<td>summer</td>
<td>-0.0017</td>
<td>-0.019</td>
<td>0.018</td>
<td>-0.015</td>
</tr>
<tr>
<td>pseudo-R² (McFadden's)</td>
<td>0.12</td>
<td>0.10</td>
<td>0.07</td>
<td></td>
</tr>
<tr>
<td>pseudo-R² (Cox-Snell)</td>
<td>0.24</td>
<td>0.19</td>
<td>0.13</td>
<td></td>
</tr>
<tr>
<td>pseudo-R² (Cragg-Uhler)³⁸</td>
<td>0.26</td>
<td>0.21</td>
<td>0.15</td>
<td></td>
</tr>
</tbody>
</table>

³⁸ All pseudo-R² metrics employed attempt to construct a measure of the level of improvement over a constant-only model offered by the estimated model. McFadden’s pseudo-R² is defined as \( R^2 = 1 - \frac{\ln \hat{L}(M_{\text{full}})}{\ln \hat{L}(M_{\text{constant}})} \), where \( \hat{L}(M_{\text{full}}) \) is the estimated likelihood of the full model (i.e. a model that includes all explanatory variables) and likewise \( \hat{L}(M_{\text{constant}}) \) is the likelihood of a model with no explanatory variables apart from a constant. Since likelihoods range from 0 to 1, log-likelihoods are always negative. In addition, the larger \( \hat{L}(M_{\text{full}}) \) is, the smaller \( \ln \hat{L}(M_{\text{full}}) \) and consequently \( \frac{\ln \hat{L}(M_{\text{full}})}{\ln \hat{L}(M_{\text{constant}})} \) are in magnitude, and thus the larger \( R^2 \) is. Using the same notation, the Cox-Snell pseudo-R² is defined as \( R^2 = 1 - \left( \frac{\hat{L}(M_{\text{intercept}})}{\hat{L}(M_{\text{full}})} \right)^{2/N} \), where \( N \) is the number of observations in the sample. The measure conceives the \( N^{1/2} \) root of the likelihood \( \hat{L}(M) \) of a model \( M \), that is \( \hat{L}(M)^{1/N} \), as an approximation for the likelihood of a single observation of the dependent variable. Cox-Snell pseudo-R²’s maximum value is less than 1. The Cragg-Uhler pseudo-R² divides the Cox-Snell pseudo-R² by its maximum value to achieve a measure whose maximum value is 1. It is thus defined as \( R^2 = \frac{1 - \left( \frac{\hat{L}(M_{\text{intercept}})}{\hat{L}(M_{\text{full}})} \right)^{2/N} }{1 - \hat{L}(M_{\text{intercept}})^{2/N}} \).
As a rough test of model fit, we also compare observed and predicted probabilities. The observed probability of value \( i \) is estimated as the proportion of observations with value \( i \). To estimate the predicted probability of value \( i \), we calculate the probability of \( i \) predicted by the model for each observation and take the mean value over all observations in the sample. The estimated probabilities are presented in table 5.6. We limit the discussion to counts of 4 trips or less as probabilities for 4 trips or more drop significantly. The probability of making no trips is best predicted by the NB1 model. The probabilities of making 3 and 4 trips are low and predicted well by all models. However, all models fail to accurately predict the probabilities of 1 and 2 trips. Due to the nature of the data, the observed probability of making 1 trip is very low, but the probability of making 2 is significant higher. If an individual makes one public transport trip, he is most likely to make at least one more to return to his original location. This is a feature of the data that is difficult to model. Regarding the choice between Poisson, NB2 and NB1 specifications, based on the likelihood ratio test and the predicted probabilities the NB1 model appears to be preferable. However, as will also be explained later on, results relating to land use mix do not vary significantly between models.

**Table 5.6 Observed and predicted probabilities**

<table>
<thead>
<tr>
<th># of trips</th>
<th>Observed</th>
<th>Poisson</th>
<th>NB2</th>
<th>NB1</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.70</td>
<td>0.59</td>
<td>0.66</td>
<td>0.68</td>
<td>0.59</td>
</tr>
<tr>
<td>1</td>
<td>0.04</td>
<td>0.28</td>
<td>0.2</td>
<td>0.17</td>
<td>0.26</td>
</tr>
<tr>
<td>2</td>
<td>0.22</td>
<td>0.09</td>
<td>0.07</td>
<td>0.07</td>
<td>0.10</td>
</tr>
<tr>
<td>3</td>
<td>0.02</td>
<td>0.03</td>
<td>0.03</td>
<td>0.04</td>
<td>0.03</td>
</tr>
<tr>
<td>4</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>5</td>
<td>1.4E-03</td>
<td>2.6E-03</td>
<td>7.2E-03</td>
<td>8.7E-03</td>
<td>5.0E-03</td>
</tr>
<tr>
<td>6</td>
<td>4.7E-04</td>
<td>8.1E-04</td>
<td>3.9E-03</td>
<td>4.4E-03</td>
<td>2.1E-03</td>
</tr>
<tr>
<td>7</td>
<td>8.0E-05</td>
<td>2.6E-04</td>
<td>2.2E-03</td>
<td>2.3E-03</td>
<td>9.3E-04</td>
</tr>
<tr>
<td>8</td>
<td>0</td>
<td>8.2E-05</td>
<td>1.3E-03</td>
<td>1.2E-03</td>
<td>4.4E-04</td>
</tr>
<tr>
<td>9</td>
<td>4.0E-05</td>
<td>3.0E-05</td>
<td>7.7E-04</td>
<td>6.2E-04</td>
<td>2.1E-04</td>
</tr>
</tbody>
</table>

Table 5.7 presents results relating to land use mix. It is remarkable that in the IV model, no land use mix variable apart from minimum distance to a shop is significant. However, the results from the IV model could be unreliable.
Table 5.7: Model coefficients and estimated elasticities for land use mix

<table>
<thead>
<tr>
<th>land use mix measure</th>
<th>Poisson coefficient</th>
<th>Poisson elasticity</th>
<th>NB1 coefficient</th>
<th>NB1 elasticity</th>
<th>NB2 coefficient</th>
<th>NB2 elasticity</th>
<th>IV coefficient</th>
<th>IV elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>minimum distance</td>
<td>-0.52 ***</td>
<td>-0.08</td>
<td>-0.51 ***</td>
<td>-0.08</td>
<td>-0.6 ***</td>
<td>-0.09</td>
<td>-8.9 **</td>
<td>-1.4</td>
</tr>
<tr>
<td>retail density</td>
<td>0.00044 ***</td>
<td>0.03</td>
<td>0.00044 ***</td>
<td>0.03</td>
<td>0.00054 ***</td>
<td>0.04</td>
<td>0.0068</td>
<td>0.5</td>
</tr>
<tr>
<td>ratio non-residential uses/residential uses</td>
<td>0.092</td>
<td>0.00</td>
<td>0.062</td>
<td>0.00</td>
<td>0.13</td>
<td>0.00</td>
<td>-7.6</td>
<td>-0.3</td>
</tr>
<tr>
<td>share of non-residential uses</td>
<td>0.097</td>
<td>0.00</td>
<td>0.035</td>
<td>0.00</td>
<td>0.15</td>
<td>0.01</td>
<td>-10</td>
<td>-0.3</td>
</tr>
<tr>
<td>Shannon (2 uses)</td>
<td>0.034</td>
<td>0.00</td>
<td>0.0021</td>
<td>0.00</td>
<td>0.053</td>
<td>0.01</td>
<td>-5.1</td>
<td>-0.7</td>
</tr>
<tr>
<td>Shannon (6 uses)</td>
<td>0.024</td>
<td>0.00</td>
<td>-0.00013</td>
<td>0.00</td>
<td>0.039</td>
<td>0.01</td>
<td>-3.3</td>
<td>-0.6</td>
</tr>
<tr>
<td>balance (2 uses)</td>
<td>0.056</td>
<td>0.00</td>
<td>0.025</td>
<td>0.00</td>
<td>0.084</td>
<td>0.01</td>
<td>-5.2</td>
<td>-0.4</td>
</tr>
<tr>
<td>balance (6 uses)</td>
<td>0.014</td>
<td>0.00</td>
<td>-0.057</td>
<td>0.00</td>
<td>0.06</td>
<td>0.00</td>
<td>-8.2</td>
<td>-0.3</td>
</tr>
<tr>
<td>modified balance (2 uses)</td>
<td>-0.045</td>
<td>-0.02</td>
<td>-0.037</td>
<td>-0.02</td>
<td>-0.050</td>
<td>-0.02</td>
<td>0.35</td>
<td>0.20</td>
</tr>
<tr>
<td>accessibility</td>
<td>0.00044 ***</td>
<td>0.03</td>
<td>0.00044 ***</td>
<td>0.03</td>
<td>0.00054 ***</td>
<td>0.04</td>
<td>0.0068</td>
<td>0.46</td>
</tr>
<tr>
<td>ratio non-residential uses/residential uses</td>
<td>0.13 ***</td>
<td>0.02</td>
<td>0.14 ***</td>
<td>0.03</td>
<td>0.16 ***</td>
<td>0.03</td>
<td>-0.15</td>
<td>0.0</td>
</tr>
<tr>
<td>share of non-residential uses</td>
<td>0.38 ***</td>
<td>0.04</td>
<td>0.38 ***</td>
<td>0.04</td>
<td>0.45 ***</td>
<td>0.05</td>
<td>-0.84</td>
<td>-0.1</td>
</tr>
<tr>
<td>Shannon (2 uses)</td>
<td>0.19 ***</td>
<td>0.05</td>
<td>0.18 **</td>
<td>0.05</td>
<td>0.25 ***</td>
<td>0.07</td>
<td>-0.15</td>
<td>0.0</td>
</tr>
<tr>
<td>balance (2 uses)</td>
<td>0.073 *</td>
<td>0.03</td>
<td>0.065</td>
<td>0.03</td>
<td>0.096 *</td>
<td>0.04</td>
<td>0.32</td>
<td>0.1</td>
</tr>
<tr>
<td>modified balance (2 uses)</td>
<td>0.035</td>
<td>0.02</td>
<td>0.026</td>
<td>0.01</td>
<td>0.051</td>
<td>0.03</td>
<td>0.78</td>
<td>0.38</td>
</tr>
</tbody>
</table>
due to the problem of weak instruments. Although there are no well-established tests for weak identification as in the case of linear models, a number of reasons support this claim. First, the elasticity for minimum distance is inflated compared with the Poisson model and rather high when compared to results from past studies. Then, as shown in table 2, several exogenous regressors that were significant in the original model, are insignificant in the IV; inflated standard errors can be a symptom of weak identification.

Stock and Yogo (2002) suggest that model estimates that are sensitive to changes in the sample can be an indication of weak instruments. As a check, we re-estimated the IV models for a random subset of the original sample. In some cases endogenous variables that were significant in the original model turned insignificant when a subsample was used or vice versa (e.g. minimum distance to a shop, distance to transit in models including the share of non-residential establishments and the balance index defined for residential and non-residential establishments). In addition, there were changes in the significance of some exogenous regressors, although this regards only a few variables per model. Finally, results for the two endogenous variables that are common to all IV models estimated, distance to transit and population density, are not consistent across all IV models; although parameter estimates are significant in some models, they are insignificant in others.

As a result, our conclusions are mostly based on the original models without instrumentation. Given that our aim is to compare how well each land use mix measure relates to public transport demand rather than estimating the actual causal effects, the conclusions drawn are still meaningful. Interestingly, results for all three models, the Poisson, NB2 and NB1, are similar.

As a first note, we remark that not all measures predict a significant effect for land use mix. However, all measures calculated using the GLUD, apart from the modified balance index we proposed, are significant in the models. On the other hand, the equivalent measures calculated using OS MasterMap Address Layer 2 have insignificant coefficients. The observation suggests that estimating measures in terms of the area allocated to various uses rather than in terms of counts of different types of establishment with particular uses is preferable. The modification of the balance index
that we proposed did not perform well; it proved insignificant both when calculated using GLUD and OS MasterMap Address Layer 2.

Regarding the measures constructed using OS Address Layer 2, only minimum distance to a shop, retail density\(^{39}\) and retail accessibility produce significant results. Since other measures incorporating additional types of non-residential uses proved insignificant, the result could imply that retail is a particularly relevant land use category in relation to public transport demand. Consequently, data on retail outlets or retail employment could be adequate for the construction of suitable land use mix measures. The significance of retail accessibility is consistent with the reviews of Ewing and Cervero (2010) and Badoe and Biller (2001), who observe that accessibility measures based on gravity models of trip attraction, are significant in most studies employing them.

Minimum distance to a shop, retail density and retail accessibility indicate the presence or intensity of retail uses in an area. They do not depend on the scale of other uses, such as residential development. In contrast, measures such as the Shannon and balance indices, the share of non-residential uses or the ratio of non-residential to residential uses incorporate in their definition more than one use and attempt to capture how evenly distributed different uses are. Consequently, results for the OS MasterMap Address Layer 2 measures could indicate that it is the presence of land uses rather than how balanced their mixture is that has a bearing on public transport demand. A similar conclusion was reached by Brown et al (2009).

Using OS MasterMap Address Layer 2, we have defined the Shannon index and the balance index both for two (residential, non-residential) and six land uses (residential, retail, services, education, leisure, eating/drinking establishments). The intention was to investigate whether defining the indices for more detailed land use categories has an effect on results, but unfortunately, we are unable to draw any conclusions. Parameter estimates for all three measures are insignificant both for the two uses and the six uses definition. The insignificance could be due to the unsuitability of OS

\(^{39}\text{Since retail density was measured for areas of equal size for all observations, the measure is equivalent to the number of retail outlets in the neighbourhood.}\)
MasterMap Address Layer 2 data for constructing the indices, which hinders the forming of general conclusions.

A further remark on the results is that elasticities for the measures with significant parameter estimates are comparable in value\textsuperscript{40}. This is in contrast to the outcomes of chapter 4, where we found that elasticities can vary substantially between measures. However, the analysis in chapter 4 is based on a broad range of synthetic city configurations rather than a single city. The elasticities with respect to land use mix that are estimated in this chapter, range in magnitude from 0.03 to 0.09. They are positive in value, except in the case of minimum distance. The negative sign for minimum distance is not surprising; an increase in the distance to the nearest store implies less land use mix and in turn less transit travel.

The estimated elasticities with respect to land use mix are low. The elasticities with respect to population density are also small; they range from 0.05 to 0.11. The analytical results are presented in table 5.8. Note that population density is significant in all models at least at the 5\% level. The small elasticities estimated are consistent with the results of Ewing and Cervero’s (2010) meta-analysis. The authors calculate, based on results from existing studies, weighted elasticities of transit use that are similarly low: 0.12 with respect to land use mix, 0.07 with respect to population/residential density and 0.01 with respect to employment density. Note however, that Ewing and Cervero’s (2010) are based both on studies investigating transit trip frequency and transit mode choice.

Our elasticities provide new evidence on the relationship between urban form and public transport use in London, a geographical area that has not been studied before. Results suggest that there is an association, albeit a small one, both between land use mix and transit use, and between population density and transit use. However, since our IV model results appear to be unreliable, we cannot establish whether these relationships are causal.

\textsuperscript{40} As remarked earlier in the section, the conclusion does not take into account the IV model results, which were considered unreliable.
Table 5.8 Elasticities of public transport demand with respect to population density

<table>
<thead>
<tr>
<th>model including:</th>
<th>Poisson</th>
<th>NB1</th>
<th>NB2</th>
</tr>
</thead>
<tbody>
<tr>
<td>minimum distance</td>
<td>0.05</td>
<td>0.06</td>
<td>0.08</td>
</tr>
<tr>
<td>retail density</td>
<td>0.05</td>
<td>0.06</td>
<td>0.08</td>
</tr>
<tr>
<td>ratio non-residentials uses/residentials uses</td>
<td>0.07</td>
<td>0.08</td>
<td>0.11</td>
</tr>
<tr>
<td>share of non-residential uses</td>
<td>0.07</td>
<td>0.08</td>
<td>0.11</td>
</tr>
<tr>
<td>Shannon (2 uses)</td>
<td>0.07</td>
<td>0.08</td>
<td>0.11</td>
</tr>
<tr>
<td>Shannon (6 uses)</td>
<td>0.07</td>
<td>0.08</td>
<td>0.11</td>
</tr>
<tr>
<td>balance (2 uses)</td>
<td>0.07</td>
<td>0.08</td>
<td>0.11</td>
</tr>
<tr>
<td>balance (6 uses)</td>
<td>0.07</td>
<td>0.08</td>
<td>0.11</td>
</tr>
<tr>
<td>modified balance (2 uses)</td>
<td>0.07</td>
<td>0.08</td>
<td>0.10</td>
</tr>
<tr>
<td>modified balance (6 uses)</td>
<td>0.07</td>
<td>0.08</td>
<td>0.10</td>
</tr>
<tr>
<td>retail accessibility</td>
<td>0.05</td>
<td>0.06</td>
<td>0.08</td>
</tr>
<tr>
<td>ratio non-residentials uses/residentials uses</td>
<td>0.06</td>
<td>0.07</td>
<td>0.09</td>
</tr>
<tr>
<td>share of non-residential uses</td>
<td>0.06</td>
<td>0.07</td>
<td>0.09</td>
</tr>
<tr>
<td>Shannon (2 uses)</td>
<td>0.06</td>
<td>0.07</td>
<td>0.09</td>
</tr>
<tr>
<td>balance (2 uses)</td>
<td>0.07</td>
<td>0.08</td>
<td>0.11</td>
</tr>
<tr>
<td>modified balance (2 uses)</td>
<td>0.07</td>
<td>0.07</td>
<td>0.09</td>
</tr>
</tbody>
</table>

As noted in section 5.3.3, household members often plan their travel jointly. To ensure observations from members of the same household are independent, we included detailed variables relating to household structure and attributes. To check the validity of our analysis we re-estimated our models using a sample that includes only one randomly chosen member per household. The results for the model that includes minimum distance are comparable to the original model, although there are some differences mainly in variables regarding age, income and employment status. The predicted probabilities also do not change significantly. More importantly, the results for the various land use mix measures are comparable to the results from the original model with few exceptions: The Shannon index is not significant at the 5% level for the NB1 and NB2 specifications as in the original model, and the balance index is not significant at the 5% level for the Poisson and NB2 specifications as in the original model. However, these two changes do not affect the general conclusions reached. The full results are given in the appendix.

---

41 IV models were not estimated, since the original models were considered unreliable.
5.5 Conclusion

In this chapter, we estimated a series of models of public transport trip frequency in which several distinct land use mix measures were tested with the aim of examining the effect the choice of measure has on results. We attempted to use instrumental variables to control for the endogeneity between three model regressors, -land use mix, population density and transit accessibility-, and public transport demand. However, results suggest that the chosen instruments are weak. Hence, our conclusions are drawn primarily from the base models without instrumentation. Since we are interested in comparing how well each land use mix measure relates to public transport demand as opposed to predicting the actual causal effects, the conclusions drawn are still meaningful.

Not all measures are significant in explaining public transport demand. However, elasticities for those measures that are significant in the model are, with one exception, comparable. An important finding is that it is measures constructed in terms of land area rather than counts of establishments that show significance in relation to public transport demand. A possible interpretation is that land area captures the size and possibly the quality of facilities, and therefore is able to explain better the number of trips they attract.

We also find evidence suggesting the use of public transport is encouraged by the presence of land uses rather than an equal mix. Furthermore, retail appears to be the non-residential land use most relevant in the public transport demand context. It should be noted that the findings could be particular to public transport demand. An interesting question for further work is whether similar conclusions will be reached if other aspects of urban form, such walking trip frequency or distances travelled by car, are considered.

Results from chapters 4 and 5 highlight the importance of testing alternative specifications of land use mix measures when modelling travelling demand. Doubtless, data limitations often hinder the estimation of various land use mix measures; however, when data is available investigating diverse measures should not be neglected.
This chapter examined various land use mix measures in a study of the effect of 
neighbourhood environment on individual public transport use. The next chapter 
extends this work to investigate a further aspect of land use mix measurement: 
geographical scale. In chapter 7, we further investigate public transport use, but focus 
on the effects of the structure of the entire urban area rather than the local 
neighbourhood environment.
Chapter 6: Land use mix and the modifiable areal unit problem

6.1 Introduction

The use of spatial data raises a significant issue: at which spatial scale should the data be measured? It is widely acknowledged that the spatial resolution of the data can affect the results of a statistical analysis, an issue commonly known as the Modifiable Areal Unit Problem (MAUP). The issue was first identified by Gehlke and Biehl (1934), who observed that the correlation coefficient between male delinquency and median monthly equivalent rent tended to increase in magnitude as the census tracts used in the original estimation were aggregated into larger areas. The authors made a similar observation using experimental data produced through coin tosses.

The term ‘Modifiable Areal Unit Problem’ was coined by Openshaw and Taylor (1979), who examined the link between the percentage of Republican voters and the proportion of population over sixty. The authors found that both the magnitude and the sign of the correlation coefficient between the two variables could change when the geographical area used to measure the variables changed. MAUP has been examined extensively in various empirical contexts. For instance, Yule and Kendall (1950) demonstrated that the correlation coefficient between potato and wheat yields in England increases as the counties used in the original estimation are aggregated into larger units. Thomas (1995) showed that descriptive statistics relating to accidents vary with the length of the road segment considered. Flowerdew et al (2008) used various zoning systems created using specialized software to demonstrate the presence of MAUP when estimating the effect of various socio-economic characteristics on the proportion of population with a long-term limiting illness. Briant et al (2010) demonstrated MAUP in the context of multivariate regression analysis of wages and trade flows.

In addition to empirical studies, certain authors have studied MAUP using simulation analyses. For example, Amrhein (1995) randomly allocated points in a unit square and
assigned to each point two random values to represent two variables. The point variables were aggregated in various ways and the presence of MAUP in correlation coefficients and regression coefficients demonstrated. Spielman and Yoo (2009) assumed a grid and assigned to each cell a random value according to a predetermined autocorrelation pattern which depended on distance. A set of spatial variables was created by taking the mean of the values assigned to groups of adjacent cells. For each spatial variable, a synthetic dependent variable was created. This was the sum of a fixed multiple of the spatial variable and a random element. Spatial scale was changed by varying the number of adjoining cells forming a group. The simulated dependent variable was regressed on spatial variables created at various scales, to test whether they reproduced the original relationship used to generate it. The authors concluded that altering spatial scale can affect results and that R-square measures cannot be used to determine the ‘correct’ spatial scale.

Given the spatial nature of urban form measurements, an investigation of MAUP in the urban form-travel behaviour context is pertinent. Defining what constitutes a neighbourhood is hard as the definition is likely to depend on the characteristics of the neighbourhood itself. In addition, perceived neighbourhood boundaries could differ between people. For instance, elderly, and hence less mobile, individuals might perceive their neighbourhood to be smaller than their younger neighbours. The spatial scale used in the literature to measure urban form varies widely between studies; undoubtedly, the choice might often depend on data availability. Authors have both used existing administrative or statistical boundaries, and defined their own geographical units. Geographical units defined by researchers typically take the form either of a grid (e.g. Krizek, 2003; Zhang, 2004; Zhang and Kukadia, 2005) or of circles of fixed radius around residences, workplaces or transit stations (e.g. Crane and Crepeau, 1998; Estupinan and Rodriguez, 2008; Greenwald and Boarnet, 2001). A circular geographical unit around a residence represents the area that is located up to a maximum distance from the residence. Some researchers define neighbourhoods in a similar way, but measuring distance along the street network rather than along a straight line (e.g. Frank et al, 2007; Wells and Yang, 2008). Table 2.2 of chapter 2 provided an illustration of the variety of geographical units used to measure urban form in past studies.
Despite the large variation in the geographical units used for urban form measurement in the literature, few studies have examined the sensitivity of results to spatial scale. Moreover, few land use mix measures are included in the analyses. The literature shows that the influence of spatial scale differs for distinct urban form measures. Therefore, studying the effects of scale on the various land use mix measures is pertinent. In this chapter, we re-estimate the models of chapter 6 altering the geographical area at which land use mix is measured, to test whether the conclusions reached are dependent on the geographical scale used. The next section reviews studies examining MAUP in the urban form-travel behaviour context. Section 6.3 presents the various spatial units that are tested. Section 6.4 presents the results and section 6.5 some final remarks.

6.2 MAUP in the urban form-travel behaviour literature

Despite the potential importance of the area of measurement of urban form, few studies have attempted to measure urban form at multiple geographical units. To our knowledge, MAUP has been systematically examined in the urban form-travel behaviour context by two studies only (Zhang and Kukadia; 2005; Mitra and Buliung; 2011). In addition, Boarnet and Sarmiento (1998) and Greenwald and Boarnet (2001) present separate models for two distinct levels of measurement of urban form variables. Finally, Handy, Cao and Mohktarian (2005), Handy, Cao and Mohktarian (2006) and Cao, Mohktarian and Handy (2007) measure their urban form variables for circular buffers of three distinct radii. However, they do not compare the results from the different spatial scales, but rather include in the final models the measure that provided the best fit.

Zhang and Kukadia (2005) investigate MAUP in the context of the urban form - mode choice relationship in Boston, US. They estimate multinomial mode choice models that include population density, the percentage of cul-de-sac intersections in a given area and the Shannon index for land use mix as covariates. These urban form variables are measured for grid cells of various sizes \(\frac{1}{16}, \frac{1}{4}, \frac{1}{2}, 1\) and 2-mile
Mitra and Buliung (2011) focus on children’s travel to school in Toronto, Canada. They estimate discrete choice models for the probability of travelling to school by an active (walking, cycling) versus a passive mode (car, public transport, school bus). They investigate a number of built environment variables: the ratio of employment to population, the number of street blocks divided by area, the proportion of four-way intersections, and the proportion of intersections with street lights. Urban form variables are measured for circular buffers of various radii (250m, 400m, 800m, 1000m) and for two distinct statistical units: Census Dissemination Areas, - the smallest geographical unit for which census data is available in Canada-, and Transportation Analysis Zones, -small geographical units defined for transportation purposes. Separate models are estimated for each spatial unit. The authors find that the spatial definition of urban form affects both the significance and the magnitude of the estimated effects, but the impact of the various spatial units is not consistent for all urban form variables considered. Consequently, no optimal unit could be singled out.

Boarnet and Sarmiento (1998) estimate two models for the number of non-work car trips using data from Southern California. The first model considers urban form, - population density, retail job density and service job density-, at the census tract or block group level. The second considers the same variables at the Zip Code level. Service job density at the Zip Code level is the only significant urban form variable in the final models.

Greenwald and Boarnet (2001) develop models for non-work walking trips. Similarly to Boarnet and Sarmiento (1998), they measure two of their urban form variables, population density and retail employment density, both at a local (US block group or census tract) and at a regional (US Zip Code) level. The authors estimate separate urban form models for each spatial unit. The authors find population density to be significant in all models; however, the magnitude of the effect is not stable. The percentage of cul-de-sac intersections is insignificant in all models and results for land use mix vary both in significance and magnitude.

Census blocks, block groups, census tracts, Zip Codes and transportation analysis zones are US geographical entities delineated for various purposes.
models for each scale, and find that both population and retail employment density affect walking only at the local level.

The studies reviewed above highlight the fact that the spatial resolution at which urban form is measured can have an effect on our understanding of the link between urban form and travel. Regarding land use mix in particular, Zhang and Kukadia (2005) find that both the significance and the size of the estimated impact of the Shannon index on mode choice depends on the spatial units used to evaluate the index. The finding raises the question of whether the results of the previous chapter are also dependent on the spatial units considered.

6.3 Spatial units
In the previous chapter, land use mix measures based on the OS Address Layer 2 data were estimated for a circular buffer of radius 500 metres around individuals’ residences. Since OS Address Layer 2 features are georeferenced, it is possible to estimate land use mix measures for any spatial unit. In this chapter, we additionally estimate, using OS Address Layer 2, land use mix measures for circular buffers of the following radii: 100m, 250m, 750m and 1000m. These are chosen to span a large part of the range of radii used in the literature. We also estimate measures for three spatial units used by the UK Census: Lower Super Output Areas (LSOA), Middle Super Output Areas (MSOA) and Census Area Statistics (CAS) wards.

LSOAs and MSOAs are geographical entities used for census data output. They were created to ensure consistency regarding size and stability over time. LSOAs have a minimum population of 1,000 and 400 households, and a mean population of 1,500. Their delineation involved criteria of social homogeneity relating to issues such as dwelling types and housing tenure. MSOAs have at least 5,000 residents and 2,000 households, and a mean population of 7,200. Their definition entailed consultations with local authorities to ensure local requirements are met. CAS wards are also used.

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43 Information on LSOAs and MSOAs were retrieved from the website of the Office of National Statistics, in particular from the following links: http://www.neighbourhood.statistics.gov.uk/dissemination/Info.do;jsessionid=ZCvGTVtJ7Pn62M03nYSvJh7kTN4HypTDzBTpmswzWn3YGHKZjL-
for census output. They are based on electoral wards\textsuperscript{44}, namely the primary units of UK administrative geography that are used in the election of local government councillors. In contrast to electoral wards, CAS wards are required to have a minimum of 100 residents and 40 households\textsuperscript{45,46}. Figures 6.1, 6.2 and 6.3 show the boundaries of LSOAs, MSOAs and CAS wards respectively, for the Greater London Area.

\textsuperscript{44}Electoral wards are known as electoral divisions in some parts of the UK.

\textsuperscript{45}The comment applies to CAS wards in England.

FIGURE 6.1 Boundaries of Lower Super Output Areas (LSOAs) in the Greater London Area
FIGURE 6.2 Boundaries of Middle Super Output Areas (MSOAs) in the Greater London Area
FIGURE 6.3 Boundaries of CAS wards in the Greater London Area
The GLUD does not allow the same flexibility in the use of spatial units as OS Address Layer 2. Nevertheless, in addition to the LSOA level that was used in the previous chapter, GLUD data are also available for MSOAs and CAS wards. Consequently, we further estimate measures at these levels.

In this chapter, the models presented in chapter 5 are re-estimated for each of the spatial units described above. As in chapter 5, we estimate Poisson, NB1 and NB2 models. We do not, however, estimate IV models, as the evidence in chapter 5 suggested that our instrumental variables were not suitable. Since we seek to compare model results based on different geographical units for land use mix rather than to estimate precise causal effects, meaningful conclusions can still be drawn even if endogeneity is not treated.

6.4 Results
Tables 6.1-6.4 show the elasticities of public transport trip frequency estimated for the various land use mix measures and the various spatial scales considered. Tables 6.1-6.3 present results for measures calculated using OS Address Layer 2; they show results for the Poisson, NB1 and NB2 models respectively. Table 6.4 presents results for measures calculated using GLUD.
Table 6.1 Elasticities of public transport trip frequency with respect to land use mix for various land use mix measures and various spatial scales, based on Poisson models (OS Address Layer 2 data).

<table>
<thead>
<tr>
<th>land use mix measure</th>
<th>100m elasticity</th>
<th>Coef.</th>
<th>Sig.</th>
<th>250m elasticity</th>
<th>Coef.</th>
<th>Sig.</th>
<th>500m elasticity</th>
<th>Coef.</th>
<th>Sig.</th>
<th>750m elasticity</th>
<th>Coef.</th>
<th>Sig.</th>
<th>1000m elasticity</th>
<th>Coef.</th>
<th>Sig.</th>
<th>LSOA elasticity</th>
<th>Coef.</th>
<th>Sig.</th>
<th>MSOA elasticity</th>
<th>Coef.</th>
<th>Sig.</th>
<th>CAS ward elasticity</th>
<th>Coef.</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>retail density</td>
<td>0.02</td>
<td>***</td>
<td>0.02</td>
<td>***</td>
<td>0.03</td>
<td>***</td>
<td>0.04</td>
<td>***</td>
<td>0.05</td>
<td>***</td>
<td>0.02</td>
<td>***</td>
<td>0.03</td>
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<td>0.03</td>
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<td>0.03</td>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ratio non-res. uses/res. uses</td>
<td>0.01</td>
<td>*</td>
<td>0.01</td>
<td>0.00</td>
<td>0.03</td>
<td>*</td>
<td>0.04</td>
<td>**</td>
<td>0.03</td>
<td>***</td>
<td>0.04</td>
<td>***</td>
<td>0.04</td>
<td>***</td>
<td>0.04</td>
<td>**</td>
<td>0.02</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>share of non-residential uses</td>
<td>0.01</td>
<td>**</td>
<td>0.01</td>
<td>*</td>
<td>0.00</td>
<td>0.03</td>
<td>*</td>
<td>0.04</td>
<td>**</td>
<td>0.03</td>
<td>0.03</td>
<td>**</td>
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<td>0.03</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Shannon (2 uses)</td>
<td>0.02</td>
<td>**</td>
<td>0.03</td>
<td>**</td>
<td>0.00</td>
<td>0.03</td>
<td>0.04</td>
<td>0.05</td>
<td>***</td>
<td>0.05</td>
<td>0.05</td>
<td>**</td>
<td>0.05</td>
<td>**</td>
<td>0.03</td>
<td>**</td>
<td>0.03</td>
<td>*</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Shannon (6 uses)</td>
<td>0.02</td>
<td>**</td>
<td>0.03</td>
<td>**</td>
<td>0.00</td>
<td>0.03</td>
<td>0.04</td>
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<td></td>
</tr>
<tr>
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<td>**</td>
<td>0.02</td>
<td>*</td>
<td>0.00</td>
<td>0.03</td>
<td>*</td>
<td>0.03</td>
<td>**</td>
<td>0.03</td>
<td>0.03</td>
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<td></td>
</tr>
<tr>
<td>balance (6 uses)</td>
<td>0.01</td>
<td>**</td>
<td>0.02</td>
<td>*</td>
<td>0.00</td>
<td>0.03</td>
<td>0.04</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>modified balance (2 uses)</td>
<td>0.01</td>
<td></td>
<td>0.05</td>
<td>***</td>
<td>-0.02</td>
<td></td>
<td>0.01</td>
<td></td>
<td>-0.02</td>
<td></td>
<td>0.05</td>
<td>***</td>
<td>0.02</td>
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<td>-0.01</td>
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</tr>
</tbody>
</table>

Note: * significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Table 6.2 Elasticities of public transport trip frequency with respect to land use mix for various land use mix measures and various spatial scales, based on NB1 models (OS Address Layer 2 data).

<table>
<thead>
<tr>
<th>land use mix measure</th>
<th>100m</th>
<th>250m</th>
<th>500m</th>
<th>750m</th>
<th>1000m</th>
<th>LSOA</th>
<th>MSOA</th>
<th>CAS ward</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>elasticity</td>
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<td>elasticity</td>
<td>elasticity</td>
<td>elasticity</td>
<td>elasticity</td>
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</tr>
<tr>
<td></td>
<td>Sig.</td>
<td>Sig.</td>
<td>Sig.</td>
<td>Sig.</td>
<td>Sig.</td>
<td>Sig.</td>
<td>Sig.</td>
<td>Sig.</td>
</tr>
<tr>
<td>retail density</td>
<td>0.02</td>
<td>0.02</td>
<td>0.03</td>
<td>0.04</td>
<td>0.05</td>
<td>0.02</td>
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<td>***</td>
<td>***</td>
<td>***</td>
</tr>
<tr>
<td>ratio non-res. uses/res. uses</td>
<td>0.01</td>
<td>0.01</td>
<td>0.00</td>
<td>0.03</td>
<td>0.05</td>
<td>0.03</td>
<td>0.04</td>
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<td></td>
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<td>0.04</td>
<td>0.03</td>
<td>0.04</td>
<td>0.03</td>
</tr>
<tr>
<td>share of non-residential uses</td>
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<td>0.02</td>
<td>0.00</td>
<td>0.03</td>
<td>0.05</td>
<td>0.03</td>
<td>0.04</td>
<td>0.03</td>
</tr>
<tr>
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<td>0.03</td>
<td>0.00</td>
<td>0.03</td>
<td>0.04</td>
<td>0.04</td>
<td>0.05</td>
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</tr>
<tr>
<td>Shannon (6 uses)</td>
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<td>0.03</td>
<td>0.00</td>
<td>0.03</td>
<td>0.04</td>
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<td>balance (2 uses)</td>
<td>0.01</td>
<td>0.02</td>
<td>0.00</td>
<td>0.03</td>
<td>0.04</td>
<td>0.03</td>
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</tr>
<tr>
<td>balance (6 uses)</td>
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<td>0.02</td>
<td>0.00</td>
<td>0.03</td>
<td>0.04</td>
<td>0.03</td>
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<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>modified balance (2 uses)</td>
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<td>-0.02</td>
<td>0.01</td>
<td>-0.02</td>
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<td>***</td>
<td>***</td>
<td>***</td>
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<td>***</td>
</tr>
</tbody>
</table>

Note: * significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Table 6.3 Elasticities of public transport trip frequency with respect to land use mix for various land use mix measures and various spatial scales, based on NB2 models (OS Address Layer 2 data).

<table>
<thead>
<tr>
<th>land use mix measure</th>
<th>100m elasticity</th>
<th>250m elasticity</th>
<th>500m elasticity</th>
<th>750m elasticity</th>
<th>1000m elasticity</th>
<th>LSOA elasticity</th>
<th>MSOA elasticity</th>
<th>CAS ward elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>retail density</td>
<td>0.02 ***</td>
<td>0.03 ***</td>
<td>0.04 ***</td>
<td>0.05 ***</td>
<td>0.06 ***</td>
<td>0.03 ***</td>
<td>0.04 ***</td>
<td>0.04 ***</td>
</tr>
<tr>
<td>ratio non-res. uses/res. uses</td>
<td>0.01 *</td>
<td>0.01</td>
<td>0.00</td>
<td>0.03</td>
<td>0.04 *</td>
<td>0.04 ***</td>
<td>0.04 ***</td>
<td>0.03 *</td>
</tr>
<tr>
<td>share of non-residential uses</td>
<td>0.02 *</td>
<td>0.02 *</td>
<td>0.01</td>
<td>0.03</td>
<td>0.04 *</td>
<td>0.06 ***</td>
<td>0.04 **</td>
<td>0.04</td>
</tr>
<tr>
<td>Shannon (2 uses)</td>
<td>0.02 **</td>
<td>0.03 **</td>
<td>0.01</td>
<td>0.03</td>
<td>0.04</td>
<td>0.06 ***</td>
<td>0.05 *</td>
<td>0.03</td>
</tr>
<tr>
<td>Shannon (6 uses)</td>
<td>0.02 **</td>
<td>0.03 **</td>
<td>0.01</td>
<td>0.03</td>
<td>0.04</td>
<td>0.06 ***</td>
<td>0.05 *</td>
<td>0.04</td>
</tr>
<tr>
<td>balance (2 uses)</td>
<td>0.02 *</td>
<td>0.02 *</td>
<td>0.01</td>
<td>0.03</td>
<td>0.04 *</td>
<td>0.04 ***</td>
<td>0.04 **</td>
<td>0.03</td>
</tr>
<tr>
<td>balance (6 uses)</td>
<td>0.02 **</td>
<td>0.02 *</td>
<td>0.00</td>
<td>0.03</td>
<td>0.04</td>
<td>0.04 ***</td>
<td>0.04 **</td>
<td>0.03</td>
</tr>
<tr>
<td>modified balance (2 uses)</td>
<td>0.02 *</td>
<td>0.05 ***</td>
<td>-0.02</td>
<td>0.01</td>
<td>-0.03</td>
<td>0.06 ***</td>
<td>0.02</td>
<td>-0.01</td>
</tr>
</tbody>
</table>

Note: * significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Table 6.4 Elasticities of public transport trip frequency with respect to land use mix for various land use mix measures and various spatial scales, based on Poisson models (GLUD).

<table>
<thead>
<tr>
<th>land use mix measure</th>
<th>Poisson</th>
<th>Negative Binomial 1</th>
<th>Negative Binomial 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LSOA</td>
<td>MSOA</td>
<td>CAS ward</td>
</tr>
<tr>
<td>ratio non-res. uses/res. uses</td>
<td>0.02</td>
<td>0.03</td>
<td>0.05</td>
</tr>
<tr>
<td>share of non-residential uses</td>
<td>0.04</td>
<td>0.04</td>
<td>0.03</td>
</tr>
<tr>
<td>Shannon (2 uses)</td>
<td>0.05</td>
<td>0.06</td>
<td>0.08</td>
</tr>
<tr>
<td>balance (2 uses)</td>
<td>0.03</td>
<td>0.03</td>
<td>0.04</td>
</tr>
<tr>
<td>modified balance (2 uses)</td>
<td>0.02</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Note: * significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Does scale influence findings regarding the land use mix-public transport demand link?

The results show that scale can influence both the significance and the magnitude of the estimated effects of land use mix on public transport use. However, different land use mix measures are not affected to the same extent. Notably, the significance of retail density is not affected by scale, although the magnitude of the corresponding elasticity is. The dependence of results on scale, particularly regarding significance, is an important concern, as it implies that the choice of scale can lead researchers to draw different conclusions and in turn different policy recommendations.

Results for retail density, that is significant at all spatial scales, suggest that elasticity estimates increase with scale. The pattern is similar for other measures when only significant results are taken into account. Nonetheless, the estimated elasticities are small irrespective of the scale, or measure, applied, suggesting that the impact of land use mix on public transport trip making is low.

What is the neighbourhood extent that influences public transport use?

The concept of neighbourhood is difficult to define and can vary in different contexts (Spielman and Yoo, 2009). In this study, we aimed to investigate the geographical extent at which land use mix affects public transport use. In the discussion that follows, we employ as a criterion for the selection of the ‘right’ spatial scale, the consistency with which the various land use mix measures show significance in relation to land use mix in the estimated models.

In the previous chapter, reasons were given to support our choice of a circular buffer rather than existing administrative or statistical boundary to measure land use mix. Contrary to our hypotheses, LSOAs appear to be the spatial units for which land use mix measures more consistently show significance in relation to public transport use. MSOAs are also highly consistent in giving significant results for different land use mix measures. It appears that geographical entities delineated for administrative or statistical purposes might be able to capture the effect of land use mix on travel, despite being defined for entirely different purposes. If the various circular buffers are
only considered, smaller units (100m and 250m radii) appear to give more consistent results than larger entities.

The area of LSOAs, MSOAs and CAS wards is not fixed. Table 6.5 presents descriptive statistics for the land area of these geographical entities in the Greater London Area. For each area value in the table, the radius of the circle with that area is also given. Half of the LSOAs in London have a land area smaller than the area of a circle of radius 260m. Three-quarters have an area smaller than the area of a circle of radius approximately 320m. MSOAs are, by definition, larger than LSOAs. CAS wards are, in general, larger than MSOAs.

Table 6.5: Land area of LSOAs, MSOAs and CAS wards: Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>LSOA</th>
<th>MSOA</th>
<th>CAS Ward</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>area (thousands m²)</td>
<td>Radius of circle of same area (m)</td>
<td>area (thousands m²)</td>
</tr>
<tr>
<td>mean</td>
<td>335</td>
<td>326</td>
<td>1622</td>
</tr>
<tr>
<td>minimum</td>
<td>18</td>
<td>76</td>
<td>294</td>
</tr>
<tr>
<td>1st quartile</td>
<td>137</td>
<td>209</td>
<td>745</td>
</tr>
<tr>
<td>median</td>
<td>208</td>
<td>257</td>
<td>1158</td>
</tr>
<tr>
<td>3rd quartile</td>
<td>326</td>
<td>322</td>
<td>1746</td>
</tr>
<tr>
<td>maximum</td>
<td>15797</td>
<td>2242</td>
<td>22430</td>
</tr>
</tbody>
</table>

It appears that smaller spatial units give more consistent results regarding the land use mix-transit demand link. This is true both when statistical entities and circular units around residences are used. The finding suggests that it is the immediate environment around a residence, up to approximately 300m, that plays a role in determining transit use. The finding is a potential indication that people are not willing to walk far to use public transport. Choosing small geographical units, with a land area equivalent to the area of a circle of up to 250-300m radius, is recommended to capture the relation between land use mix and transit use.

The delineation of LSOAs involves homogeneity criteria, including a criterion relating to dwelling type, which is particularly relevant in the context of land use.
MSOAs are formed by aggregating LSOAs and could also have relatively homogeneous characteristics in relation to land use. The circular spatial units of 100m and 250m used in the study should also be more homogeneous with regard to land use than larger units (500, 750 and 1000m radii) simply due to their size. It appears that homogeneity of geographical entities with respect to land use is also a potential criterion for choosing a scale that captures the land use mix-transit demand link.

Are results consistent with the conclusions of chapter 5?
In chapter 5, we concluded that retail is a particularly relevant land use category in relation to public transport demand. The fact that retail density is highly significant for all spatial units considered in this chapter strengthens the conclusion.

In the previous chapter, we also found that it is land use mix measures constructed in terms of land area rather than counts of establishments that show significance in relation to public transport use. Indeed, land use mix measures based on area are, with few exceptions, consistently significant for all spatial units considered in this chapter. Nevertheless, since only three distinct geographical units are considered, we should be cautious in assuming that the finding can be generalized. In particular, the fact that land use mix measures calculated in terms of counts of establishments also appear to be consistently significant when estimated at the LSOA level and, with few exceptions, at the MSOA level, weakens our finding. It is true, however, that at the CAS wards level, several measures are only significant when constructed in terms of land area.

Further conclusions regarding land use mix metrics
The analysis in this chapter leads to some further conclusions regarding the selection of land use mix metrics, in addition to those reached in the previous chapter. An important observation is that the significance of retail density in the model is not affected by geographical scale, an advantage that researchers can take into account when choosing land use mix measures. Of course, minimum distance and accessibility measures (as defined in the previous chapter) that are, by definition, independent of scale, also offer the same benefit. It should be noted that the robustness of retail density to spatial scale (in relation to significance) might be particular to the context of the study.
Using OS MasterMap Address Layer 2, we have calculated the Shannon index and the balance index both for two and six land use categories. Our aim was to investigate whether results are robust to the number of land use classes applied in the calculation of the indices. In the previous chapter we were unable to reach any conclusions, as all relevant measures were insignificant. Results in this chapter suggest that, in general, the level of detail in land use classification when defining the Shannon or the balance index does not affect model outcomes. The same conclusion was reached using simulation analysis in chapter 4. The conclusion is also consistent with Brown et al (2009), who found high correlations between Shannon indices defined over different numbers of land use classes.

6.5 Conclusions

In this chapter, we have re-estimated the models presented in chapter 5 using land use mix measures calculated at various geographical units, in order to investigate how spatial scale affects estimates of the link between land use mix and public transport trip making. We found that spatial units do, in general, affect results, but that not all measures are affected to the same extent. For instance, retail density is the only measure which is consistently significant irrespective of spatial scale, although the size of the corresponding elasticity varies slightly. The robustness of retail density to scale is a significant advantage.

In contrast to our hypothesis, LSOAs and MSOAs, namely statistical entities used for census output, appear to be the geographical units that most consistently capture the link between land use mix and transit demand. In addition, circular buffers of 100m and 250m radii are more consistent at capturing the link than buffers of larger radii. Based on these findings, we recommended that researchers use small spatial scales to measure land use mix, with land area equivalent to the area of a circle of up to 250m-300m radius, and prefer spatial units that are homogeneous in relation to land use.

The findings in this chapter provide further support for conclusions reached in previous chapters. In particular, they strengthen the finding of chapter 5 regarding the relevance of retail in connection with public transport use. They also support the
conclusion of chapter 4 that defining the Shannon and balance indices for more detailed classifications does not significantly alter model results.

Chapters 4 and 5 highlighted the importance of trying different land use mix measures when modelling the relationship between land use mix and travel. Similarly, this chapter illustrates the value of investigating, whenever possible, various spatial scales in the measurement of land use mix.
Chapter 7: Measuring the effect of urban form on public transport demand using aggregate travel data

7.1 Introduction
The effect of urban form on public transport use is most commonly investigated in the context of mode choice, either with discrete choice models or continuous models for the share of trips by transit. Trip frequency by public transport has received less attention\textsuperscript{47}. However, it is an important outcome as the number of trips made by public transport determines the viability of a public transport system. Mode choice models can capture changes in the relative shares of different modes, but not changes in trip making in absolute terms.


Taylor et al (2009) find evidence of a link between an urban area’s population density and public transport patronage. Similarly, Estupinan and Rodriguez (2008), Sohn and Shim (2010), Kuby et al (2004), Sung and Oh (2011), Cervero (2006) and Parsons and Brickenhoff (1996) suggest there is an association between the built environment around a station and station boardings. On the other hand, Kitamura et al (1997), Meurs and Haaijer (2001) and Chatman (2008) find, in general, little evidence that the built environment affects public transport trip use. The conflicting conclusions could be due to the fact that the latter studies control for endogeneity, in contrast with most

\textsuperscript{47} Some studies also look at the distance travelled by public transport (e.g. Schwanen and Mokhtarian, 2005b, Bangley and Mokhtarian, 2002).
of the studies mentioned formerly. Furthermore, transit accessibility and urban form at the neighbourhood level could be highly correlated and the models might be failing to distinguish between the two effects.

This chapter investigates the effect of city structure on city-wide public transport patronage and aims to extend the study by Taylor et al (2009). Taylor et al’s (2009) motivation is the lack of aggregate public transport demand studies that examine multiple transport systems and test a large number of covariates. In fact, to our knowledge, Taylor et al (2009) is the only aggregate level public transport demand model that uses data from multiple urban areas, and hence from multiple transport systems, and includes an urban form measure as a covariate. Considering multiple transport systems is important to reach general conclusions. As Brownstone (2008) points out, studies relying on data from small geographical areas can be misleading because results could depend on characteristics specific to the area, such as local culture.

While Taylor et al’s (2009) study makes important contributions to the literature, it also suffers from two key limitations. First, although the authors acknowledge that various aspects of urban form could have an effect on transit demand, the only relevant measure employed in the model is population density, which provides only a general indication of urban structure. For instance, a city with a dense urban core and low-density outlying areas could have the same density as a city with constant medium population density. Furthermore, population density conveys no information on the distribution of employment.

Second, while Taylor et al (2009) do address endogeneity between transport demand and supply through use 2SLS\(^{48}\), it is not clear in the paper which variables they use as instruments. Furthermore, they do not provide theoretical justifications for their instruments and do not perform appropriate tests for instrument relevance and exogeneity. As discussed in chapter 3, failure to meet the requirements regarding instrument validity and relevance can have serious consequences; in such cases using instrumental variables can do more harm than good.

\(^{48}\) See chapter 3.
In this chapter, we estimate an aggregate model of public transport patronage using the same data as Taylor et al (2009), which are taken from the National Transit Database (NTD) compiled by the US Federal Transit Administration (FTA). Our model includes three distinct measures of urban form that represent both population and employment distribution. The measures will be presented in more detail in section 7.3.2. Furthermore, we carefully select instruments and ensure that our choice is supported by the relevant tests. Taylor et al (2009) only consider transit supply as endogenous. In contrast, we also estimate models that treat both transit supply and urban form as endogenous. We also experiment with several functional forms that have been employed in the literature to model transit demand. Last, we estimate separate models for transit in general, and bus transit only, to investigate whether the link between urban form and patronage varies for different modes.

This chapter is structured as follows. The next section presents the data used for estimation. Section 7.3 deals with model specification: the choice of dependent and independent variables, the functional form of the model and the issues of endogeneity and heteroskedasticity are discussed. Section 7.4 presents the results before some concluding remarks in section 7.5.

7.2 Data
The empirical analysis of the transit demand-urban form relationship uses an aggregate city-level dataset compiled from a range of sources. The main transit variables are collected from the National Transit Database (NTD) published by the US Federal Transit Administration (FTA), the operating administration of the U.S. Department for Transportation that manages funding to local public transport systems. Since 1979, all transit agencies operating local services and receiving funding from the FTA are required by law to report annually to the NTD on various aspects of their operations. Data are provided by transit operator, but each operator has to report the urbanized area (UZA) where it primarily functions and thus data can be aggregated.

49 Transit agencies operating less than nine vehicles in maximum service are exempted.
50 According to the US Census, an urbanized area is a densely settled area with a population of at least 50,000. In general, an urbanized area is composed of a geographic core of block groups or blocks that
by urbanized area. We use cross-sectional data for the year 2000 on transit patronage, transit supply and fare revenues. Further details on the variables used are provided in section 7.3. The year 2000 is chosen as the most recent year that can be coupled with data from the decennial census. Unfortunately, the available panel transit data cannot be exploited because the urban form variables used for the study cannot be constructed for various years. Besides, urban form is highly persistent over time, which can introduce problems in panel estimators with individual time invariant effects (Baltagi, 2005).

In our study, we consider the following modes: bus, trolley bus, commuter rail, heavy rail, light rail, monorail, automated guideway and cable car. Detailed definitions of all modes included in the NTD can be found in the appendix. The Alaska railroad is included in the dataset because part of its services is eligible for FTA funding. However, it does not constitute local transit and is thus excluded from the model. Vanpool and demand response services are also excluded because although they receive FTA funding they do not constitute public transport in the traditional sense. They represent something between public transport and private services as they have no fixed schedules, routes or stops. Demand response services often have the characteristics of a taxi service. In addition, several demand response services are open only to specific groups rather than the general public (e.g. seniors, individuals with mobility difficulties or other special needs etc). Vanpool agencies are usually simply facilitating ridesharing arrangements including vehicle leasing; the vans are typically driven by members of the public that participate in the ridesharing arrangements rather than by paid drivers. Ferryboat is also excluded as its use should depend mainly on the presence of water barriers in a city rather than the factors generally thought to affect public transport usage. Furthermore, ferryboats are also used by private vehicles and thus patronage figures might reflect its usage as a

have a population density of at least 1,000 people per square mile, and adjoining block groups and blocks with a density of at least 500 people per square mile. This chapter uses a number of terms relating to US geography. Brief definitions of such terms, including definitions of census blocks and block groups, can be found in the appendix. More information on urbanized areas can be found at http://www.census.gov/geo/www/tiger/glossry2.html#UR or http://www.census.gov/geo/www/GARM/Ch12GARM.pdf (accessed 4th September 2011).
crossing by private vehicles rather than usage by individuals who chose public transport as an alternative to car travel\textsuperscript{51}.

The socio-economic variables included in the model are taken from the 2000 US decennial census. The 2000 decennial census also provides population data that are used in the construction of urban form variables, and data on housing age that are used as instruments. Data on population, race and age are taken from Summary File 1. Summary File 1 includes results from questions asked on the short form of the census, that is completed by all households/individuals in the US. Data on income, student status, car ownership and housing age are taken from Summary File 3. Summary File 3 contains results from questions that are asked in the long form of the census, that is completed by approximately 1 in 6 households. The Census Bureau also provides historic census data that are used as instruments\textsuperscript{52}.

Employment data used to construct urban form variables are taken from the Zip Code Business Patterns dataset, also published by the US Census Bureau. The database contains information on the total number of establishments, employment by industry type and total payroll at the five-digit Zip Code Tabulation Area\textsuperscript{53} level. It is available on an annual basis and covers most of the country's economic activity, although it excludes self-employed individuals, employees of private households, railroad and agricultural production employees and certain government employees.

Transit and demographic data are supplemented with road supply data from the Federal Highway Administration’s (FHA) Highway Statistics, which are published yearly, and fuel price data from the Bureau of Labour Statistics (BLS). The BLS also provides wage data that are used to construct instruments.

\textsuperscript{51} Publico is also included in the NTD. The mode is however specific to Puerto Rico which was not included in the study. Jitneys and aerial tramways are also regarded as public transit. However, there were no agencies operating more than nine vehicles in maximum service in the year of interest.

\textsuperscript{52} Historic census data are available at http://www.census.gov/population/www/censusdata/hiscendata.html (accessed on 7th September 2011)

\textsuperscript{53} A Zip Code Tabulation Area is a statistical entity created by the US Census as an approximation to the US Postal Service 5-digit Zip Code delivery areas. http://www.census.gov/geo/ZCTA/zcta.html (accessed on 9th January 2010)
Construction of the urban form variables employed in the study requires the use of GIS maps for various Census geographical entities. These can be derived either from the US Census Bureau website\(^ {54}\) or from the Esri website\(^ {55}\). Furthermore, the Missouri Data Centre offers an online facility that provides the correspondence between different geographical entities\(^ {56}\).

The US Census Bureau recognizes 460 urbanized areas for 2000, of which only 369 have public transport systems. After removing observations with missing or inconsistent data, our final sample contains 235 urbanized areas. Table 7.1 presents mean values for some basic demographic characteristics for the urbanized areas in the sample, the set of all urbanized areas with transit systems and the set of all urbanized areas in the US. The only characteristic that differs significantly between the three sets is population: the mean urbanized area population is highest in the sample and lowest when all 460 urbanized areas are considered. However, this is anticipated as the urbanized areas without public transport systems should be the least populated. Furthermore, many small urbanized areas only have demand response systems, and so are not included in the final sample.

Table 7.1 Sample versus population: Mean values for basic demographic characteristics of urbanized areas.

<table>
<thead>
<tr>
<th></th>
<th>sample (235 UZAs)</th>
<th>UZAs with transit systems (369)</th>
<th>all UZAs (460)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population</td>
<td>599153</td>
<td>505295</td>
<td>425218</td>
</tr>
<tr>
<td>% male</td>
<td>0.49</td>
<td>0.49</td>
<td>0.49</td>
</tr>
<tr>
<td>% aged under 14</td>
<td>0.21</td>
<td>0.21</td>
<td>0.21</td>
</tr>
<tr>
<td>% aged over 65</td>
<td>0.13</td>
<td>0.13</td>
<td>0.13</td>
</tr>
<tr>
<td>% African American</td>
<td>0.12</td>
<td>0.12</td>
<td>0.11</td>
</tr>
<tr>
<td>% students</td>
<td>0.09</td>
<td>0.08</td>
<td>0.08</td>
</tr>
<tr>
<td>annual income per capita ($)</td>
<td>20383</td>
<td>20336</td>
<td>20116</td>
</tr>
<tr>
<td>car ownership per capita</td>
<td>0.64</td>
<td>0.64</td>
<td>0.63</td>
</tr>
</tbody>
</table>

\(^ {54}\) http://www.census.gov/geo/www/cob/bdy_files.html, accessed on 7\(^ {th}\) September 2011


\(^ {56}\) http://mcdc.missouri.edu/websas/geocorr2k.html, accessed on 9\(^ {th}\) January 2010
7.3 Model specification

7.3.1 The dependent variable

The model takes the form \( y = f(x) \), where the dependent variable \( y \) is unlinked passenger trips per capita measured at the urbanized area level, and \( x \) is a vector of factors affecting transit demand. Information on unlinked passenger trips is available in the NTD. Trips per capita rather than the absolute number of trips is used to account for the fact that cities with larger populations naturally have a larger transit patronage. The NTD defines unlinked passenger trips as ‘the number of passengers who board public transportation vehicles. Passengers are counted each time they board vehicles no matter how many vehicles they use to travel from their origin to their destination.’ On the other hand, a linked trip is a trip from origin to destination on the transit system irrespective of the number of transfers. Linked trips clearly provide a more accurate measure of transit ridership. However, no data on linked trips is provided in the NTD and, to our knowledge, no data suitable for the estimation of linked trips from unlinked trips at the urbanized level, such as estimates of the number of transfers involved in the average trip by operator, urbanized area or Metropolitan Statistical Area, are available. Taylor et al (2009) also acknowledges the issue.

7.3.2 Urban form variables

Population and employment density can be rather crude measures for urban form at the city level as they do not convey information on the distribution of population and employment within the city, and the balance between them. Cities with similar population and employment densities can have very different structures. We therefore employ three more carefully constructed urban form measures.

Perceived population density

Perceived population density, estimated as density weighted by actual population, aims to capture how many people experience each density level in a city, distinguishing thus between cities with strong urban cores and cities with more homogeneous density distributions. To calculate perceived density the urban area must be divided into zones and the density of each zone computed. Perceived density is the sum of the individual zone densities weighted by the proportion of the population living in each zone (Richardson et al, 1998). To compute perceived density following this approach, we consider the population living in the various census
tracts within an urbanized area. Perceived population density has the further advantage that it is less dependent than actual population density to the metropolitan boundaries used for estimation, as the addition in the calculations of practically vacant ‘ambiguous’ areas in the outskirts of a city is unlikely to significantly change results.

A rough illustration of the perceived density measure can be provided by considering two cities A and B, both of which have a population of 100,000 living in an area of 100 square miles. City A has a central urban core of 10 square miles with a population of 90,000. The remaining 10,000 inhabitants live in suburbs which cover 90 square miles. In contrast, City’s B inhabitants are equally distributed within the city. The actual density for both cities is 1,000 people per square mile, although they clearly have a very different structure. In contrast, the perceived density for city A is $0.9 \times \frac{90,000}{10} + 0.1 \times \frac{10,000}{90} = 8,111$ compared to 1,000 for city B.

**Jobs-housing balance**

We measure the balance between population and employment using a Gini coefficient, a measure previously employed by Bento et al (2005), that has its origins in the residential segregation literature (Massey and Denton, 1988). We calculate the Gini coefficient by ordering the zip codes of each city in increasing employment numbers and plotting the cumulative proportion of jobs against the cumulative proportion of population. The Gini coefficient is the area between the resulting Lorenz curve and the 45-degree line representing equal distributions of employment versus population. It takes values in the 0-1 range, with lower values representing a more uniform distribution.

Total mid-march employment by ZTCA is available from the Zip Code Business Patterns dataset that is described in the data section. However, data for some ZTCAs are withheld for confidentiality reasons. Withheld employment values are estimated using data on the number of establishments by employment size class available by

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57 Geographical entity used by the US Census Bureau. Census tracts are defined to have a population of between 1,000 and 8,000, with an optimum size of 4,000 people, and to be relatively homogeneous with regard to population characteristics, economic status, and living conditions. More details on US geographical entities can be found in the appendix.

58 A ZTCA (Zip Code Tabulation Area) is a statistical entity created by the US Census as an approximation to the US Postal Service 5-digit Zip Code delivery areas. [http://www.census.gov/geo/ZCTA/zcta.html](http://www.census.gov/geo/ZCTA/zcta.html) (accessed on 9th January 2010)
ZTCA from the same source. The employment class sizes used are 1-4; 5-9; 10-19; 20-49; 50-99; 100-249; 250-499; 500-999 and 1000 or more (numbers refer to number of employees). Employment is estimated as the sum of the product of the number of establishments in each class times the midpoint of the class. In the case of establishments with 1000 or more employees, it is rather simplistic to assume that all establishments have 1000 employees. Luckily, withheld employment values are complemented with the employment size class of the confidential data; the classes considered for the case of more than 1000 employees are: 1,000-2,499; 2,500-4,999; 5,000-9,999; 10,000-24,999; 25,000-49,999 and 50,000-99,999. In the small number of cases where more than one establishment in a ZTCA with withheld data have ‘1000 or more’ employees, we assume that all establishments belong to the indicated employment class size.

Population centrality
To account for the distribution of population in a city, we use a measure proposed by Bento et al (2005) that represents population concentration around the central business district. It is defined as

$$\frac{1}{N} \sum_{n=1}^{N} \frac{\sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} P_i} - \frac{\sum_{i=1}^{N} P_i d_i}{\sum_{i=1}^{N} P_i d_i}$$

where $i=1,\ldots, N$ are indices for a sequence of annuli around the central business district that are located at fixed proportions of the distance from the centre to the outer boundary of the city. Each annulus is located at a distance $d_i$ from the city centre and has population $P_i$. Larger values of the measure indicate a higher concentration around the urban core. Table 7.2 depicts two examples of the measure as found in Bento et al (2005).
Table 7.2 Examples of the population centrality measure (Source: Bento et al, 2005)

<table>
<thead>
<tr>
<th>City</th>
<th>Distance from CBD</th>
<th>% of total distance</th>
<th>Actual population</th>
<th>Distance-weighted population</th>
<th>Cumulative actual population</th>
<th>Cumulative distance-weighted population</th>
<th>Measure of population centrality</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>2</td>
<td>20</td>
<td>5</td>
<td>10</td>
<td>50</td>
<td>21</td>
<td>0.1694</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>60</td>
<td>3</td>
<td>18</td>
<td>80</td>
<td>58</td>
<td></td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>100</td>
<td>2</td>
<td>20</td>
<td>100</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>1</td>
<td>20</td>
<td>2</td>
<td>2</td>
<td>20</td>
<td>6</td>
<td>0.113</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>60</td>
<td>3</td>
<td>9</td>
<td>50</td>
<td>31</td>
<td></td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>100</td>
<td>5</td>
<td>25</td>
<td>100</td>
<td>100</td>
<td></td>
</tr>
</tbody>
</table>

A challenge in estimating the population centrality measure is identifying the central business district (CBD). The US Census Bureau defines a CBD as ‘an area of very high land valuation characterized by a high concentration of retail businesses, service businesses, offices, theatres, and hotels, and by a very high traffic flow’\(^\text{59}\). The US Census Bureau last identified CBDs in the 1982 Census of Retail Trade; these followed census tract boundaries. However, we chose not to use the 1982 definitions for two reasons. First, the 1982 Census of Retail Trade identifies CBDs for each Place\(^\text{60}\). Each urbanized area, the geographical level for which we define our transit and urban form data, can contain more than one Place, making it difficult to identify a single CBD. In addition, many urbanized areas do not contain any of the places included in the 1982 Retail Trade report, therefore we would have to drop a large number of observations. Instead, we define as the city centre the census tract with the highest population density\(^\text{61}\).

To estimate the measure, we construct three annuli around the central census tract, located at 20%, 60% and 100% of the maximum distance from the central census tract to the boundary of each urbanised area. To estimate the population living in each annulus, we use data on census block\(^\text{62}\) population from the US Census. Naturally,

\(^{59}\) \url{http://www.census.gov/geo/www/cbd.html} (accessed 18\textsuperscript{th} November 2011)

\(^{60}\) Geographical entity used by the US Census Bureau. Places can be broadly defined as a concentration of population; the entities that are commonly recognized as cities, towns, villages or boroughs. The precise definition varies by state. In 2000, the US Census Bureau recognised approximately 25,000 places.

\(^{61}\) To our knowledge, data for employment are not available at the census tract level, or indeed at any level smaller than ZTCAs, so we could not use employment density.

\(^{62}\) The smallest geographical entity for which the US Census tabulates statistics. For more details, see the appendix.
census blocks do not necessarily fall entirely within or outside the annuli boundaries. A census block is assumed to fall within an annulus if its centroid falls inside the annulus.

7.3.3 Additional covariates

The factors affecting public transport demand were discussed in chapter 5. In addition to urban form metrics, we include the following explanatory variables in our models: income per capita, vehicle revenue miles per capita, road length per capita, fuel price per gallon, average public transport fare, car ownership per capita, the percentage of the population that is African-American, the percentage of the population that is below 14 years of age, the percentage of population that is above 65 years of age and the percentage of the population that is currently enrolled in college or university. The variables are less detailed than those considered in chapter 5. We did not, for instance, include as detailed age categories. We tried to make the model parsimonious due to the modest number of observations in the sample. Moreover, the use of aggregate data along with the small number of observations in the sample gave rise to multicollinearity issues between some potential covariates.

Income per capita and car ownership data are available from the 2001 US Census Summary File 3. We also considered introducing variables on unemployment rates and poverty status, but they were highly correlated with income per capita and thus excluded from the final model. The remaining demographic variables were obtained from the 2001 US Census Summary File 1. All demographic variables are measured at the urbanized area level.

In chapter 5, race was not included as a covariate as it was not considered relevant to public transport use in the London context. However, it may be important in the US context as it is commonly accounted for in US studies of travel behaviour (e.g. Taylor et al, 2009). African-Americans are expected to travel more by public transport than the average American; according to the 2000 US Census, the percentage of African Americans that commute by public transport is 12% compared to 5% for the entire population. Although the difference could be explained by differences in
income\textsuperscript{63} or by the fact that African-Americans are concentrated in denser and more centrally located areas, it may also be due to cultural differences. For example, as African-Americans were originally banned from the first residential suburbs, they may be, in general, less accustomed to a suburban car dependent lifestyle. Consequently, the percentage of the population that is African-American is included as a separate regressor in the model.

Fuel price per gallon, available from the BLS, is used as a proxy for motoring costs as, to our knowledge, data on total motoring costs by urbanized area are not available. The price considers all gasoline types and is an average of monthly data for all months of 2000. Fuel price data are not available by urbanized area. The BLS provides data for certain Metropolitan Statistical Areas (MSA)\textsuperscript{64}, and then for different categories of MSAs based on region and size\textsuperscript{65}. We assign to each urbanized area the value of the MSA in which it belongs\textsuperscript{66} or of the category in which the corresponding MSA belongs if no data are available specifically for the MSA. We need to acknowledge that the fuel price variable constructed in this way is a rough proxy for actual fuel prices, and does not exhibit large variation in the dataset. An insignificant result in relation to fuel prices could indicate attenuation to the null due to measurement error rather than a true null effect.

The average fare for a public transport trip is calculated by dividing total fare revenues by the total number of unlinked trips (both available in the NTD). Unfortunately, in 2000 operators were not required to report fare revenues by mode\textsuperscript{67}. Hence, an average for all modes, including those excluded from the study, is used.

\textsuperscript{63} According to the US 2000 Census, mean income per capita in 1999 was $14,437 for African-Americans, $23,918 for white Americans and $21,587 for the entire population.

\textsuperscript{64} A county or group of adjoining counties that contains at least one city with a population of 50,000 or over or an urbanized area with a population of at least 100,000. A metropolitan statistical areas is composed by the county or counties that contain all or the main part of the main city or urbanized area, and all adjoining counties that fulfill certain criteria mainly regarding commuting and population concentration. Counties are the primary legal divisions of a state (except Alaska and Louisiana). For more details on US geographical entities see the appendix.

\textsuperscript{65} The regions are West, South, Midwest, Northeast as defined by the US Census. The size categories are: Metropolitan Statistical Area with population larger than 1.5 million, Metropolitan Statistical Area population with population smaller than 1.5 million, non-metropolitan.

\textsuperscript{66} There is no exact one-to-one correspondence between MSAs and urbanized areas. An urbanized area can be entirely contained in a single MSA, partly contained in a single MSA or belong to more than one MSAs. Urbanized areas were thus assigned to the MSA which contained the largest part of their area.

\textsuperscript{67} This has since changed.
Although demand response services and vanpools are generally priced higher than other modes, their relative shares are usually small, so the estimated fares for all modes are expected to be reasonably close to the actual fares for the modes included in the study. The use of unlinked trips also distorts the estimate of the true value faced by consumers for a trip, as transfers to another service are often covered by the original fare. However, as explained earlier in section 7.3.1, we did not find a way to estimate linked trips.

Vehicle revenue miles per capita are used as a measure of transit supply. Vehicle revenue miles data are available in the NTD. They are divided by each urbanized area’s population, available from the 2000 US Census, to account for the fact that larger cities are bound to have a larger public transport network. The NTD defines revenue vehicle miles as ‘the miles that vehicles are scheduled to or actually travel while in revenue service. Vehicle revenue miles include layover/recovery time, but exclude deadhead, operator training, and vehicle maintenance testing, as well as school bus and charter services.’ Vehicle revenue miles have the advantage that they are affected both by changes in the extent of a public transport network and by changes in the frequency of service, and hence incorporate both of these two diverse aspects of supply.

Road length per capita is included as a measure of road supply. Data on the total length of roads in each urbanized area are available from the FHA Highway Statistics. Instead of all roads, we also considered using the length of freeways or arterial roads. However, all three measures are highly correlated (>0.95), so we simply use road length per capita in the final model. It should also be noted that in some cases the naming of urbanized areas used in the 2000 Highway Statistics, and possibly the definition of their boundaries, does not match the naming used by the US Census and the NTD for 2000. Hence, some informed assumptions were made to join the two datasets. On the other hand, the naming used in the 2002 Highway Statistics matches, with few exceptions, the naming used in the 2000 Census. We did contemplate using 2002 road length data; however, the choice is not important as the 2000 and 2002

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68 The definition is from the 2006 manual for annual reporting. No manual is available for 2000. However, the NTD staff assured us that the data items used in this study have constant definitions over time.

69 We contacted the FHA regarding the issue but did not receive a reply.
variables are very similar and have a correlation of 0.996. In the final model we use 2000 road length per capita.

7.3.4 Functional form
A variety of functional specifications have been used in the literature to model transit demand. Most studies do not discuss their choice of functional form (Holgrem, 2007). We experiment with linear, logarithmic and Box-Cox specifications, all of which have been employed in past studies (e.g. linear: Peng et al, 1997; logarithmic: Taylor et al, 2009; Graham et al, 2009; Box-Cox: Wang and Skinner, 1984). The logarithmic specification has the advantage of reducing heteroskedasticity, which is common in cross-sectional studies, and of allowing the coefficients to be interpreted directly as elasticities. The Box-Cox transformation (Box and Cox, 1964) aims to specify a more correct functional form by making the error term of a regression model, or equivalently the dependent variable, fit a normal distribution in compliance with model assumptions. More precisely, the Box-Cox transformation for a positive variable $v$ is defined as

$$v^{(t)} = \begin{cases} \frac{v^{t-1}}{t} & \text{if } t \neq 0 \\ \ln(v) & \text{if } t = 0 \end{cases}$$

where $t$ is a parameter to be estimated\textsuperscript{70}. The transformation nests the linear ($t=1$), the logarithmic ($t=0$) and the reciprocal ($t=-1$) transformations.

Specifically, if $y$ represents public transport trips per capita, $x = (x_1, x_2, ..., x_k)'$ a vector of $k$ determinants of public transport demand, $\beta = (\beta_1, \beta_2, ..., \beta_k)'$ a set of $k$ parameters to be estimated and $\varepsilon$ an unobserved error term, we estimate the following models.

- Linear: $y = \sum_{i=0}^{k} \beta_i x_i + \varepsilon$ \hspace{1cm} (7.1)
- Logarithmic: $\ln y = \sum_{i=0}^{k} \beta_i \ln(x_i) + \varepsilon$ \hspace{1cm} (7.2)
- Box-Cox model: $y^{(\lambda)} = \beta' x^{(\mu)} + \varepsilon$ \hspace{1cm} (7.3)

where

\textsuperscript{70} The Box-Cox transformation considers $\frac{v^{t-1}}{t}$ rather than simply $v^t$ to ensure the transformation is continuous at $t = 0$. 
The parameters $\mu$ and $\lambda$ are chosen so that the normality assumptions of OLS hold, that is so that $\varepsilon$ is iid normally distributed with mean zero and constant variance $\sigma^2$. We estimate $\mu=0.20$ and $\lambda=0.19$ using the boxcox command in STATA, and subsequently set $\lambda=\mu=0.20$ in the final Box-Cox model. Likelihood ratio tests reject the linear, logarithmic and reciprocal ($\lambda=\mu=-1$) models. It should be noted that in the present context, the results of the Box-Cox application should only be considered as an indication towards a more correct functional form as the estimation of the Box-Cox parameter assumes no endogeneity is present.

### 7.3.5 Endogeneity

The concept of endogeneity was introduced in chapter 2 (section 2.4.2). According to economic theory, demand and supply are simultaneously determined. This is also true in the case of public transport: Changes in supply affect the public transport system’s attractiveness as they can, for instance, influence waiting times, alter geographical coverage or introduce crowding in public transport vehicles. Consequently, demand for public transport could also change. On the other hand, public transport operators adjust supply according to demand; for example, the frequency of an underused service might be reduced or the number of buses operating in a popular line might be increased. The simultaneous relationship introduces endogeneity in the model.

As discussed in section 2.4.2, endogeneity between public transport use and urban form can also be a concern. The assumption is that it is not only the built environment that affects people’s travel choices, but possibly their pre-determined travel preferences that make them chose a suitable residential location. The argument is well-grounded when urban form at the neighbourhood level is considered. On the
other hand, it is somewhat ambiguous when urban form at the city level is explored. Although people could choose between neighbourhoods based on their travel habits, it is harder to imagine individuals choosing between cities based on their travel preferences. Factors such as job availability or family links should play a more important role.

Several authors have assumed that urban form at the city level is not endogenous. Bento et al (2005) purposely estimate their urban form variables at the metropolitan statistical area (MSA) level to overcome the endogeneity problem in their travel behaviour models. Brownstone and Fang (2009) use MSA density as an instrument for census tract density in their vehicle ownership and utilization model, defending their choice with an argument similar to ours. Heres-Del-Valle and Niemeier (2010) use analogous reasoning to justify the absence of endogeneity between individual car use and city level transit supply. Evans, Oates and Schwab (1992) find that two-thirds of families in their dataset that moved house between 1975 and 1980 relocated within the same metropolitan statistical area; the finding strengthens our argument.

Following the discussion above, we chose to present, where possible, both models which consider urban form and transit supply to be endogenous and models that consider only supply as endogenous. However, this is not possible in all cases as the large number of endogenous variables renders adjustment for endogeneity challenging.

To eliminate endogeneity we employ the instrumental variables approach that was presented in chapter 3. Finding appropriate instruments proved difficult and we tried a number of different variables, many of which did not turn out to be suitable. The model specification discussed hitherto has four endogenous variables: transit supply and the three variables describing urban form that were presented in section 7.3.2. Prior to estimating IV models, we estimated OLS models for all functional forms presented in section 7.3.4. The population centrality measure proved to be highly insignificant in all OLS models. Since, in addition, we could not find strong instruments for all four endogenous variables, we resorted in dropping the population centrality measure from the final IV models. Below, we discuss the instruments used in the final models.
Past values of an endogenous variable are commonly used as instruments (e.g. Ciccone and Hall, 1996; Combes et al, 2008). We use scheduled miles of transit for 1984 as an instrument for transit supply. 1984 is the earliest year for which transit data is available in the NTD. Past transit supply is expected to be correlated with 2000 transit supply; for instance, rail infrastructure that was in place in 1984 is likely to still be in use in 2000. On the other hand, individuals are unlikely to consider the level of transit service sixteen years earlier when making decisions regarding their travel.

In economic theory, supply is determined by the marginal cost of producing an extra unit. On the other hand, the marginal cost of supplying an additional unit of transit should not directly affect public transport use. Transit users are unlikely to be aware of its value. Although in a competitive market the fare value will be set to equal the marginal cost, the transit market is unlikely to operate as a competitive market as it tends to be provided by one or few suppliers, which operate under increasing returns to scale and under subsidy. Consequently, marginal cost could be a potential instrument for transit supply. However, data on marginal cost for each transit operator included in the study is not available. Instead, we use the mean hourly wage for bus drivers as a proxy. The intuition behind the choice is that providing an extra unit of vehicle hours of transit requires extra labour by transit operators. Data on mean hourly wages by profession are available from the Occupational Employment Statistics (OES) Survey of Bureau of Labour Statistics[^71]. Data on hourly wages of drivers/conductors of other transit modes are only available at the state level, which is not disaggregate enough for the study. Hence, data on bus driver wages are only used.

Transit supply also depends on the objective of the transit operator. A public operator’s objective is most likely to maximize welfare (i.e. benefits of supply to users less total costs of supply); on the other hand, a private operator typically aims to maximize its profit. Consequently, we use information on the type of organization a transit operator is, to construct a further instrument for transit supply. Since an urbanized area can have more than one operators, we use a 0-1 dummy variable indicating whether an urbanized area contains at least one operator that is a state operator.

[^71]: The data is available from [http://stats.bls.gov/oeshome.htm](http://stats.bls.gov/oeshome.htm) (accessed on 16th November 2010)
Department of Transportation (DOT), a public agency or authority other than a DOT that directly operates all of its transit service, or a public agency or authority other than a DOT that contracts for some or all of its transit service.

As an instrument for urban form variables, we first consider the proportion of buildings constructed before 1940. The variable is constructed using data from the 2000 census. Patterns of urban development changed significantly in the economic expansion that took place following the second world war; it is the period when the suburbanisation of US cities started. A city with a substantial proportion built prior to 1940 is expected to have a large dense central core and hence, higher perceived density. It could also have less suburban retail centres and neighbourhoods with a more traditional mix of retail and residences and as a result, a more balanced mixture of jobs and employment. On the other hand, there is no reason to believe that the age of buildings can affect transit demand directly. Instruments relating to building age have been used for urban form by Boarnet and Sarmiento (1998), Vance and Hedel (2007, 2008) and Heres-Del-Valle and Niemeier (2010).

Using a similar line of reasoning, the presence of an early urban population is indicative of early urban development, which can imply that a substantial part of a city was built following the traditional development patterns that were prevalent in the pre-auto years. The collection of historic census data of the US Census Bureau provides information on the population of the 100 largest urban places in 1840. We construct a variable that indicates the presence of significant urban development in 1840. If an urbanized area contains at least one place that was amongst the 100 largest urban places in 1840, the variable takes the value of the population of the place or the sum of the population of the places that belong to the urbanized area and were amongst the 100 largest urban places in 1840. Otherwise, it equals zero. The variable is too distant in the past to have any direct bearing on current public transport use. The year 1840 is set during the industrial revolution in the US. Initially, we tried a later year, 1900, which is set towards the end of the industrial revolution. However, the choice proved unsuccessful, probably because by 1900 there was a large number of urban places in the US, so being amongst the 100 largest did not have the same significance as in 1840.
In addition to the above instruments, we tested a number of further variables that proved irrelevant. As well as the percentage of buildings constructed before 1940, we tried the proportion of buildings constructed in the periods 1940-1950 and 1950-1960, when the US population started leaving city centres for newly constructed suburbs. As an alternative to the proportion of pre-1940 buildings we also tried the number of multi-family housing in 1940 as well as the share of housing that was multi-family in 1940. The intuition behind the instruments is the same as for the share of pre-1940 buildings. The data is part of the historic census data available from the US Census Bureau. However, it is available by state rather than urbanized area, which most possibly explains the instrument’s failure.

Last, we tested the percentage of voters that voted for the Democrats in the 1972 election, an instrument proposed by Duranton and Turner (2008) for transit supply. Data on election results by county are available in the ‘General Election Data for the United States, 1950-1990’ dataset held by the Interuniversity Consortium for Political and Social Research (ICPSR). Duranton and Turner (2008) provide detailed arguments advocating the relevance of their instruments. One of the issues on which the 1972 election was contended, was the Democrats’ strong social agenda. Regions where the Democrats got a large share of the vote are likely to have also voted for local officials with a similarly strong social agenda. The 1972 election came shortly after the 1970 National Urban Mass Transportation Act and shortly before the 1974 National Urban Mass Transportation Act, both of which increased the level of federal funding for public transport to levels that continue to this day. The increase in transit subsidies spurred the growth of public transport networks. Such growth is likely to have been larger in regions where local government had a strong social agenda.

7.3.6 Heteroskedasticity

Heteroskedasticity, namely the violation of the assumption that the error term has the same variance for all observations included in the sample, is a common problem with cross-sectional data. Heteroskedasticity introduces bias in standard errors, which can lead to incorrect inferences. To test for heteroskedasticity we use the test proposed by

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72 County data can be aggregated to the Metropolitan Statistical Area (MSA) level. Info on changes in county boundaries/naming can be found on http://www.census.gov/geo/www/tiger/ctychng.html (accessed 6th Sept 2010). Definitions of counties and MSAs can be found in the appendix.
Pagan and Hall (1983), which is available in STATA with the command ivhettest. The test is suitable for instrumental variable models because it is valid for the equation of interest irrespective of whether there is heteroskedasticity somewhere else in the system. The null hypothesis of no homoskedasticity is rejected for the linear model, but not for the logarithmic and Box-Cox models. Therefore, for the linear model we estimate robust standard errors as proposed by White (1980). Accordingly, the variance of the estimator of $\beta$ is given by

$$(\sum_{j=1}^{N} x_j x_j')^{-1}(\sum_{j=1}^{N} \hat{u}_j^2 x_j x_j')(\sum_{j=1}^{N} x_j x_j')^{-1}$$

where $j$ denotes the observation, $x$ the vector of covariates and $u$ the residuals of the model.

For every IV model we estimate, we also present the corresponding OLS model. Testing directly for heteroskedasticity in the OLS model is not possible due to the presence of untreated endogeneity (the tests will not be valid). For the OLS models, we use a robust estimator only when the corresponding IV model is found to be heteroskedastic.

### 7.4 Results

We present two set of models. The first are estimated using transit data for all modes described in section 7.2 (bus, trolley bus, commuter rail, heavy rail, light rail, monorail, automated guideway and cable car). The latter are estimated using data for bus modes only. We were compelled to estimate both sets because we believe that the effect of urban form on rail and bus modes may differ as the two modes have very different characteristics. Bento et al (2005) investigate the effect of population centrality and the Gini index for the balance between population and employment on mode choice and find that both variables have a different effect on the probability of using the bus and the probability of using rail.

Table 7.3 presents the results for models considering all transit modes. Table 7.4 presents the tests conducted to support the legitimacy of the applied instruments. Table 7.5 presents the results for models considering bus modes only, and table 7.6
the corresponding tests for the instrumental variables of the bus models. Table 7.7 summarizes the results for transit supply and urban form variables.
### Table 7.3 Model results (all transit modes)

<table>
<thead>
<tr>
<th></th>
<th>linear</th>
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<th></th>
<th></th>
<th></th>
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<th></th>
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<td>OLS</td>
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<td>IV (2)</td>
<td>OLS</td>
<td>IV</td>
<td>OLS</td>
<td>IV</td>
<td>OLS</td>
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<td>coefficient</td>
<td>elasticity</td>
<td>coefficient</td>
<td>elasticity</td>
<td>coefficient</td>
<td>elasticity</td>
</tr>
<tr>
<td>vehicle revenue miles</td>
<td>2.06***</td>
<td>1.03</td>
<td>2.09***</td>
<td>1.04</td>
<td>2.63***</td>
<td>1.31</td>
<td>1.2***</td>
<td>1.20</td>
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<tr>
<td>perceived density</td>
<td>0.00303***</td>
<td>0.73</td>
<td>0.00377*</td>
<td>0.91</td>
<td>0.00245***</td>
<td>0.59</td>
<td>1.24***</td>
<td>1.24</td>
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<td>Gini index</td>
<td>10.3**</td>
<td>0.17</td>
<td>19.8</td>
<td>0.34</td>
<td>5.14</td>
<td>0.09</td>
<td>0.649***</td>
<td>0.65</td>
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<td>income per capita</td>
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<td>0.63</td>
<td>0.000134</td>
<td>0.17</td>
<td>0.000239</td>
<td>0.30</td>
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<td>fuel price</td>
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<td>-7.45</td>
<td>-0.72</td>
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<td>-0.87</td>
<td>-0.781</td>
<td>-0.78</td>
</tr>
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<td>average fare</td>
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<td>-0.12</td>
<td>-2.62</td>
<td>-0.10</td>
<td>-2.22</td>
<td>-0.09</td>
<td>-0.117</td>
<td>-0.12</td>
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<td>car ownership per cap</td>
<td>-28.6</td>
<td>-1.13</td>
<td>2.83</td>
<td>0.11</td>
<td>-13.4</td>
<td>-0.53</td>
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<td>road miles per capita</td>
<td>534</td>
<td>0.15</td>
<td>641</td>
<td>0.18</td>
<td>225</td>
<td>0.06</td>
<td>-0.664***</td>
<td>-0.66</td>
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<tr>
<td>% student</td>
<td>-2.9</td>
<td>-0.02</td>
<td>12.3</td>
<td>0.07</td>
<td>1.36</td>
<td>0.01</td>
<td>0.221</td>
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<td>% aged over 65</td>
<td>-44.4</td>
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<td>-16.9</td>
<td>-0.13</td>
<td>-30.6</td>
<td>-0.24</td>
<td>0.243</td>
<td>0.24</td>
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<td>% aged under 17</td>
<td>-54.4</td>
<td>-0.71</td>
<td>-10.6</td>
<td>-0.14</td>
<td>-11.2</td>
<td>-0.15</td>
<td>2.45**</td>
<td>2.45</td>
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<tr>
<td>% African-American</td>
<td>9.92*</td>
<td>0.07</td>
<td>12.2**</td>
<td>0.09</td>
<td>10.7*</td>
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<td>% male</td>
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<td>4.95</td>
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<td>constant</td>
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<td>-22.4***</td>
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<td>$R^2$</td>
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<td>0.90</td>
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<td>bus drivers' wage</td>
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<td>public operator (dummy)</td>
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<tr>
<td></td>
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<td>% pre-1940 buildings</td>
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<td>1840 urban population</td>
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</table>

Legend: * p<0.05; ** p<0.01; *** p<0.001

Coefficients presented to 3 significant figures.

Elasticities and $R^2$ presented to 2 decimal points.
### Table 7.4 Instrumental variables’ testing (models considering all transit modes)

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<tr>
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<th>Box-Cox IV</th>
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<td>1</td>
<td>1</td>
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<td><strong># of instruments</strong></td>
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<td>(equation exactly identified)</td>
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<tr>
<td>Hansen J statistic: 1.923</td>
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<td>Hansen J statistic: 0.159</td>
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<td>p-value: 0.3823 [$\chi^2(2)$]</td>
<td>p-value: 0.6905 [$\chi^2(1)$]</td>
<td>(equation exactly identified)</td>
<td>(equation exactly identified)</td>
<td></td>
</tr>
<tr>
<td><strong>identification</strong></td>
<td></td>
<td></td>
<td>Anderson canon. corr. LM statistic: 31.90</td>
<td>Anderson canon. corr. LM statistic: 36.13</td>
</tr>
<tr>
<td>Kleibergen-Paap rk LM statistic: 31.62</td>
<td>Kleibergen-Paap rk LM statistic: 37.692</td>
<td>p-value: 0.0000 [$\chi^2(1)$]</td>
<td>p-value: 0.0000 [$\chi^2(1)$]</td>
<td></td>
</tr>
<tr>
<td>p-value: 0.0000 [$\chi^2(3)$]</td>
<td>p-value: 0.0000 [$\chi^2(2)$]</td>
<td>Cragg-Donald statistic: 36.92</td>
<td>Cragg-Donald statistic: 42.69</td>
<td></td>
</tr>
<tr>
<td><strong>weak identification</strong></td>
<td></td>
<td></td>
<td>p-value: 0.0000</td>
<td>p-value: 0.0000</td>
</tr>
<tr>
<td>Kleibergen-Paap rk Wald F statistic: 7.521</td>
<td>Kleibergen-Paap rk Wald F statistic: 20.313</td>
<td>Cragg-Donald Wald F statistic: 34.72</td>
<td>Cragg-Donald Wald F statistic: 40.15</td>
<td></td>
</tr>
<tr>
<td>5% maximal IV relative bias 9.53</td>
<td>10% maximal IV size 19.93</td>
<td>10% maximal IV size 16.38</td>
<td>10% maximal IV size 16.38</td>
<td></td>
</tr>
<tr>
<td>20% maximal IV relative bias 4.99</td>
<td>20% maximal IV size 8.75</td>
<td>20% maximal IV size 6.66</td>
<td>20% maximal IV size 6.66</td>
<td></td>
</tr>
<tr>
<td>30% maximal IV relative bias 4.30</td>
<td>25% maximal IV size 7.25</td>
<td>25% maximal IV size 5.53</td>
<td>25% maximal IV size 5.53</td>
<td></td>
</tr>
<tr>
<td><strong>Weak-instrument-robust inference</strong></td>
<td>F-test: 15.35</td>
<td>F-test: 10.48</td>
<td>F-test: 30.10</td>
<td>F-test: 49.74</td>
</tr>
<tr>
<td>(Anderson-Rubin Wald test)</td>
<td>p-value: 0.0000 [$F(5,219)$]</td>
<td>p-value: 0.0000 [$F(2,220)$]</td>
<td>p-value: 0.0000 [$F(1,221)$]</td>
<td>p-value: 0.0000 [$F(1,221)$]</td>
</tr>
<tr>
<td>$\chi^2$-test: 82.38</td>
<td>$\chi^2$-test: 22.40</td>
<td>$\chi^2$-test: 32.00</td>
<td>$\chi^2$-test: 52.89</td>
<td></td>
</tr>
<tr>
<td>p-value: 0.0000 [$\chi^2(5)$]</td>
<td>p-value: 0.0000 [$\chi^2(2)$]</td>
<td>p-value: 0.0000 [$\chi^2(1)$]</td>
<td>p-value: 0.0000 [$\chi^2(1)$]</td>
<td></td>
</tr>
</tbody>
</table>
Table 7.5 Model results (bus modes)

<table>
<thead>
<tr>
<th></th>
<th>linear</th>
<th></th>
<th></th>
<th>logarithmic</th>
<th></th>
<th></th>
<th>Box-Cox</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>IV (1)</td>
<td>IV (2)</td>
<td>OLS</td>
<td>IV</td>
<td>OLS</td>
<td>IV</td>
</tr>
<tr>
<td></td>
<td>coefficient</td>
<td>elasticity</td>
<td>coefficient</td>
<td>elasticity</td>
<td>coefficient</td>
<td>elasticity</td>
<td>coefficient</td>
</tr>
<tr>
<td>vehicle revenue miles</td>
<td>1.86***</td>
<td>0.98</td>
<td>2.61***</td>
<td>1.37</td>
<td>2.49***</td>
<td>1.31</td>
<td>1.09***</td>
</tr>
<tr>
<td>perceived density</td>
<td>0.00158</td>
<td>0.43</td>
<td>0.00109**</td>
<td>0.29</td>
<td>0.00149**</td>
<td>0.40</td>
<td>.233*</td>
</tr>
<tr>
<td>Gini index</td>
<td>9.79**</td>
<td>0.19</td>
<td>8.63</td>
<td>0.17</td>
<td>5.11</td>
<td>0.10</td>
<td>.201***</td>
</tr>
<tr>
<td>income per capita</td>
<td>0.000445</td>
<td>0.64</td>
<td>0.000241</td>
<td>0.34</td>
<td>0.000201</td>
<td>0.29</td>
<td>1.08***</td>
</tr>
<tr>
<td>fuel price</td>
<td>6.74</td>
<td>0.74</td>
<td>1.41</td>
<td>0.15</td>
<td>-0.177</td>
<td>-0.02</td>
<td>1</td>
</tr>
<tr>
<td>average fare</td>
<td>-4.02*</td>
<td>-0.18</td>
<td>-2.09</td>
<td>-0.09</td>
<td>-2.74</td>
<td>-0.12</td>
<td>-372***</td>
</tr>
<tr>
<td>car ownership per capita</td>
<td>-37*</td>
<td>-1.65</td>
<td>-26.6</td>
<td>-1.18</td>
<td>-19.9</td>
<td>-0.89</td>
<td>-1.44**</td>
</tr>
<tr>
<td>road miles per capita</td>
<td>159</td>
<td>0.05</td>
<td>4.75</td>
<td>0.00</td>
<td>11.2</td>
<td>0.00</td>
<td>-0.0887</td>
</tr>
<tr>
<td>% student</td>
<td>5.97</td>
<td>0.04</td>
<td>7.52</td>
<td>0.05</td>
<td>5.95</td>
<td>0.04</td>
<td>.241*</td>
</tr>
<tr>
<td>% aged over 65</td>
<td>-33.3</td>
<td>-0.29</td>
<td>-23</td>
<td>-0.20</td>
<td>-24.9</td>
<td>-0.22</td>
<td>0.0787</td>
</tr>
<tr>
<td>% aged under 17</td>
<td>-57.2</td>
<td>-0.84</td>
<td>-16.2</td>
<td>-0.24</td>
<td>-19.3</td>
<td>-0.28</td>
<td>0.304</td>
</tr>
<tr>
<td>% African-American</td>
<td>6.9</td>
<td>0.06</td>
<td>8.36</td>
<td>0.07</td>
<td>9.67*</td>
<td>0.08</td>
<td>0.0482</td>
</tr>
<tr>
<td>% male</td>
<td>19.9</td>
<td>0.68</td>
<td>38.4</td>
<td>1.31</td>
<td>39.3</td>
<td>1.34</td>
<td>-1.7</td>
</tr>
<tr>
<td>constant</td>
<td>2.27</td>
<td>-14.9</td>
<td>-14.8</td>
<td>-13.7***</td>
<td>7.86*</td>
<td>0.794</td>
<td>0.028</td>
</tr>
<tr>
<td>R²</td>
<td>0.83</td>
<td>0.80</td>
<td>0.81</td>
<td>0.86</td>
<td>0.83</td>
<td>0.87</td>
<td>0.83</td>
</tr>
</tbody>
</table>

endogenous variables: vehicle revenue miles, perceived density, Gini index

instruments: 1984 transit supply, bus drivers' wage, public operator (dummy), % pre-1940 buildings, 1840 urban population

Legend: * p<0.05; ** p<0.01; *** p<0.001

Coefficients presented to 3 significant figures.

Elasticities and R² presented to 2 decimal points.
<table>
<thead>
<tr>
<th></th>
<th>linear IV (1)</th>
<th>linear IV (2)</th>
<th>logarithmic IV</th>
<th>Box-Cox IV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong># of endogenous variables</strong></td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td><strong># of instruments</strong></td>
<td>5</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td><strong>Instrument validity</strong></td>
<td>Hansen J statistic: 1.229, p-value: 0.5409 $\chi^2(2)$</td>
<td>Hansen J statistic: 0.260, p-value: 0.6102 $\chi^2(1)$</td>
<td>(equation exactly identified)</td>
<td>(equation exactly identified)</td>
</tr>
<tr>
<td><strong>identification</strong></td>
<td>Kleibergen-Paap rk LM statistic 35.087, p-value: 0.0000 $\chi^2(3)$</td>
<td>Kleibergen-Paap rk LM statistic 32.545, p-value: 0.0000 $\chi^2(2)$</td>
<td>Anderson canon. corr. LM statistic: 23.05, p-value: 0.0000 $\chi^2(1)$</td>
<td>Anderson canon. corr. LM statistic: 26.18, p-value: 0.0000 $\chi^2(1)$</td>
</tr>
<tr>
<td><strong>Weak identification</strong></td>
<td>Kleibergen-Paap rk Wald F statistic: 9.353</td>
<td>Kleibergen-Paap rk Wald F statistic: 9.548</td>
<td>Cragg-Donald Wald F statistic: 24.04</td>
<td>Cragg-Donald Wald F statistic: 27.70</td>
</tr>
<tr>
<td><strong>Weak-instrument-robust inference</strong></td>
<td>F-test: 4.43, p-value: 0.0007 [F(5,219)]</td>
<td>F-test: 6.01, p-value: 0.0029 [F(2,220)]</td>
<td>F-test: 30.05, p-value: 0.0000 [F(1,221)]</td>
<td>F-test: 37.70, p-value: 0.0000 [F(1,221)]</td>
</tr>
<tr>
<td>(Anderson-Rubin Wald test)</td>
<td>$\chi^2$-test: 23.75, p-value: 0.0002 [$\chi^2(5)$]</td>
<td>$\chi^2$-test: 12.83, p-value: 0.0016 [$\chi^2(2)$]</td>
<td>$\chi^2$-test: 31.95, p-value: 0.0000 [$\chi^2(1)$]</td>
<td>$\chi^2$-test: 40.09, p-value: 0.0000 [$\chi^2(1)$]</td>
</tr>
</tbody>
</table>
In addition to parameter estimates, the tables also present elasticities. For the linear model (equation 7.1),

\[ \varepsilon_{y,x_i} = \frac{x_i y}{\partial y} = \frac{x_i}{y} \]

where \( \varepsilon_{y,x_i} \) is the elasticity of \( y \) with respect to \( x_i \). For the logarithmic model (equation 7.2), the elasticities equal the parameter estimates. Our Box-Cox model takes the form of equation 7.3 with \( \mu = \lambda \). Differentiating both sides of the equation with respect to \( x_i \) gives:

\[ \mu y^{\mu-1} \frac{\partial y}{\partial x_i} = \mu \beta_i x_i^{\mu-1} \]  

Then, \( \frac{\partial y}{\partial x_i} = \beta_i x_i^{\mu-1} \) and \( \varepsilon_{y,x_i} = \frac{x_i}{y} \frac{\partial y}{\partial x_i} = \beta_i x_i^{\mu} \).

Elasticities for the linear model are calculated at the point of means of the sample data. The approach is not suitable for non-linear models, as the point of means of the data does not satisfy the estimated model equation like it does in linear models. Therefore, for the Box-Cox model, we present the mean of the individual elasticities of each observation in the sample.

Following the discussion in section 7.3.5, we aimed to estimate both models where urban form and transit supply are endogenous and models where only transit supply is endogenous. As further explained in section 7.3.5, population centrality was dropped from the final specifications because it was insignificant in the OLS models whilst it complicated the application of instrumental variables. Nevertheless, estimating models with three endogenous variables proved difficult. We only managed to find strong instruments for the linear case. We tried different combinations as well as transformations of the instruments presented in section 7.3.5, but they failed to pass the Stock and Yogo (2005) test for weak identification. Hence, for the logarithmic and Box-Cox specification we only present models where transit supply is the sole endogenous variable.

The next subsection discusses the suitability of the chosen instruments for the models presented in tables 7.3 and 7.5. Then, we discuss the results’ implications regarding the choice of functional form in transit demand modelling. We proceed to compare the fuel price, fare, income, transit supply and car ownership elasticities obtained in this study with values from the literature. Finally, we discuss the findings in relation to the link between urban structure and transit demand.
7.4.1 Suitability of instruments

Tests regarding the suitability of instruments in the models, presented in tables 7.4 and 7.6, appear to support the choice of instruments. Performing overidentification tests is only possible for the linear models, in which the number of instruments exceeds the number of endogenous variables. The Hansen J statistic is used, which is suitable for heteroskedastic models. The null hypothesis that the instruments are exogenous is not rejected for all models for which the test is possible.

To test for identification, we use the Anderson canonical correlations test and the Cragg-Donald statistic test for homoskedastic models, and the Kleibergen-Paap rank statistic test for heteroskedastic models (for details of the tests see chapter 3). All statistics are significant at the 0.0001 level in every model, which suggests all models are identified.

Tests for weak identification support the choice of instruments, albeit not so strongly in all cases. For homoskedastic models, we use the test proposed by Stock and Yogo (2005). For heteroskedastic models, we use the F-form of the Kleibergen-Paap statistic with the Stock and Yogo (2005) critical values, as suggested by Baum et al (2003). As explained in chapter 3, Stock and Yogo (2005) provide two alternative tests that are founded on distinct approaches of defining what constitutes a weak instrument, the first based on the bias of the IV estimator compared to OLS bias and the latter on the size of the Wald test derived from IV statistics. The critical values for each test depend on the number of instruments and the number of endogenous variables, and are not available in all cases. For each model, we present the critical values for the version of the test for which this is possible.

For models where only transit supply is endogenous, the test statistic passes the critical value for the 10% maximal size, suggesting the instruments are relevant, except in the case of the linear bus model. Results for the latter model are less strong; the test statistic only passes the critical value for 20% maximal size. For the linear model that treats both transit supply and urban form variables as endogenous, the corresponding statistic exceeds the critical value for 10% maximal IV relative bias, both for the model that considers all transit modes and the model that considers only bus modes. The results suggest that the bias of the IV estimator does not exceed 10% of the bias of the corresponding OLS estimator, supporting the

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73 For more details, see chapter 3.
74 Kleigerben-Paap F-statistic or Cragg-Donald F-statistic depending on the model
relevance of the instruments. However, the evidence would have been stronger if the 5% limit for relative bias was also exceeded.

7.4.2 Functional form

In general, results between functional forms differ, for instance with regard to income, fares, car ownership and urban form variables. The differences regard whether variables are significant and the size of the corresponding effect, but not the direction of the effect. The findings illustrate the importance of functional specification choices.

Results for all model specifications are reasonable with respect to the direction of significant effects. For the logarithmic model, however, some of the estimated elasticities appear high (e.g. percentage of the population under 17 in the model that considers all transit modes). It is also surprising that in the linear specification the percentage of population that is African-American appears to be the only significant socio-economic variable. Based on these limitations of the linear and logarithmic forms, we believe that the Box-Cox specification is preferable. It is true that it appears to have slightly lower explanatory power (based on the $R^2$ for the model considering all transit), but the difference is marginal.

7.4.3 Comparison of price, income, transit supply and car ownership elasticities with the literature

Before discussing the results relating to the variables of main interest, it is important to consider whether results for variables whose effect on transit demand has been studied extensively, such as transit supply, income, fares, fuel price and car ownership, compare favourably with previous literature.

Results suggest that fare values have a negative effect on transit demand, although the finding is not consistent in all specifications. The estimated (significant) elasticities range from -0.25 to -0.37. This is close to the often cited rule of thumb of -0.3 (Holgrem, 2007), despite the fact that Holgrem’s (2007) meta-analysis finds the rule of thumb not to hold when supply is treated as endogenous. Our estimated values are also close to the mean of elasticities reviewed by Holgrem (2007) and within the range of values reviewed by a number of authors (Paulley, 2006; Goodwin, 1992; Oum, 1992).

Results for income suggest that public transport, and bus transit in particular, are not inferior goods. This is in contrast to Paulley et al (2006), who concluded that although income has a
positive impact on rail travel, the effect on bus travel is negative. However, Paulley et al’s (2006) remark is based on a review of mainly British studies. The estimated elasticities go up to 2.53. However, such high values are derived from the logarithmic specification. As noted earlier, the logarithmic specification produces some unrealistically high elasticities for other variables as well (for instance, for the percentage of population over 17), which raises doubts that the true relationship follows a logarithmic form. The income elasticities are more likely to be near the values suggested by the Box-Cox form, namely in the range 0.69 to 1.09. Holgrem (2007), who focusses on bus transit, finds a very large range of elasticities in the literature (-0.82 to 1.88), which covers the range of values obtained in this study.

Fuel price is insignificant in all models estimated. This could be due, however, to measurement error arising from the fact that our fuel price variable was somewhat crude (see section 7.3.3). Furthermore, regional variations in fuel prices in a single country may not be large enough to influence transit use; the use of time-series data could be more suitable for capturing the effect. The literature includes a large range of elasticities, including zero or low values. Holgrem (2007) reviews seventeen elasticities that include zero values, and Goodwin (1992) reviews three studies that provide elasticities as low as 0.08.

Although car ownership is not significant in all specifications, elasticities for those models for which it is significant are high (-1.10 to -1.52). This suggests that car ownership has a high negative impact on transit trip making. As a comparison with the literature, Holgrem (2007) reviews eight elasticities with respect to car ownership that range from -3.37 to 0.

Results suggest that transit demand is highly elastic with respect to transit supply. Vehicle revenue miles are consistently significant irrespective of the functional form of the model, even after being instrumented. The elasticities for transit supply estimated using IV range from 1.04 to 1.96, depending on the model, but most are between 1.3 and 1.5. The elasticities of bus demand with respect to vehicle kilometres of supply that are reviewed by Holgrem (2007) range from 0.075 to 1.88, with a mean of 0.72. Holgrem (2007) finds that cross-sectional studies tend to produce higher results than time-series, which could explain why our estimates are on the higher end of the range of reviewed values.
Table 7.7 Summary of model results on urban form and transit supply
(Insignificant results are in parentheses. Grey shading indicates variables that were treated as endogenous.)

<table>
<thead>
<tr>
<th></th>
<th>all modes</th>
<th></th>
<th>bus modes</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>linear</td>
<td>logarithmic</td>
<td>Box-Cox</td>
<td>linear</td>
</tr>
<tr>
<td></td>
<td>OLS</td>
<td>IV (1)</td>
<td>IV (2)</td>
<td>OLS</td>
</tr>
<tr>
<td>vehicle revenue miles</td>
<td>1.03</td>
<td>1.04</td>
<td>1.31</td>
<td>1.20</td>
</tr>
<tr>
<td>perceived density</td>
<td>0.73</td>
<td>0.91</td>
<td>0.59</td>
<td>1.24</td>
</tr>
<tr>
<td>Gini index</td>
<td>0.17</td>
<td>(0.34)</td>
<td>(0.09)</td>
<td>0.65</td>
</tr>
</tbody>
</table>

7.4.4 Discussion of results relating to urban form

Different model specifications provide surprisingly different results in relation to urban form variables, so it is hard to draw strong conclusions. A particularly unexpected result is that in models with endogenous transit supply only, some urban form variables are insignificant, despite being significant in the corresponding OLS model. This could be due to the potential relationship between urban form and transit supply, and the effect of urban form entering the first stage regression for transit supply. Comparing the different IV models is hard because different instruments were used for each model. Using the same instruments for all models was not possible as this would result in some models being weekly identified. A finding that is consistent across specifications is that the effects of urban form variables on bus demand follow, in general, a similar pattern to the effects on general transit demand. However, the effects on bus use appear to be smaller in size.

The discussion in section 7.4.2 favoured the Box-Cox specification. However, to investigate the presence of a causal relationship between urban form and travel, it is key to look at the linear specification that treats urban form as endogenous. The fact that perceived population density is significant after instrumentation strongly supports the hypothesis that population density has a causal effect on demand. However, given the variable findings in other models, the evidence is not conclusive.

The Gini index for the balance between population and employment is significant in OLS models and IV models with endogenous transit supply. However, when instrumented in the linear model, the variable becomes significant. The finding suggests that although there is an association between transit demand and the balance between population and employment in neighbourhoods, the relationship might not be causal. However, the insignificant result could
be due to the loss in efficiency incurred due to the use of instrumental variables. Given the results of the Kleibergen-Paap statistic test, this is a likely possibility.

The Anderson-Rubin test for the model under discussion cannot provide evidence regarding the significance of urban form variables. Both forms of the test, which is robust to weak instruments, reject the hypothesis that the parameters of the endogenous variables in the structural equation are jointly equal to zero. However, the result implies that at least one of the endogenous variables is statistically significant, which does not necessarily entail that urban form is significant. On the other hand, the Anderson-Rubin test for the logarithmic and Box-Cox specifications provides strong evidence that transit supply is endogenous.

In past literature, the effect of urban form on travel is often found to be small. Several authors comment that the impact is not large enough to make land use controls an effective policy tool (e.g. Brownstone, 2008; Brownstone and Fang, 2009). Ewing and Cervero’s (2011) meta-analysis estimates an average elasticity of transit use with respect to population/residential density of 0.07, and an average elasticity of transit use with respect to land use mix of 0.12. It should be noted that these elasticities are based on a review of disaggregate studies, which mostly consider transit mode choice rather than trip frequency. Below, we discuss the findings of our study in relation to the size of the urban form effect.

Our linear model suggests that population density is likely to have a substantial impact on total transit demand. The elasticity of transit demand with respect to perceived population density is high even when the variable is instrumented (0.91). However, the finding is not supported by all model specifications. In particular, the corresponding elasticity from the Box-Cox specification is 0.33 for OLS, and 0.06 (and statistically insignificant) for IV. The results illustrate the difficulty of obtaining a precise estimate for the effect, and the dependence of the size of estimates on functional specification. Taylor et al (2009) find that population density has a considerable effect on transit demand when modelling total city public transport patronage; the estimated elasticity is 0.42.

The effect of population density on bus demand appears to be lower than the effect on general transit.

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75 The logarithmic model for OLS gives a high elasticity (1.24). However, based on past results in the literature, we believe such an estimate to be unrealistically high.
The association between the population-employment mix and transit demand appears to be modest for all model specifications.

The population centrality measure we employed appears not to be related to transit trip making. Bento et al (2005), who use the same measure, find that it has a significant positive effect on the probability of using the bus and a significant negative effect on the probability of using the rail. Our conflicting result could be due to a possible substitution effect between bus and rail; although the relative share of the two modes could be affected, the total share of transit might not. In addition, although population centrality might raise the probability of using the bus, it could reduce total trip making, so that transit trip frequency remains unaffected.

7.5 Conclusions

In this chapter, we estimated city-level public transport demand models for the US to examine the significance of urban structure in explaining public transport use. We applied three distinct urban form metrics that measure both the distribution of population within a city and the relative distribution of population and employment. To control for endogeneity between public transport demand and supply, we used instrumental variables. Instrumental variables were also used to control for endogeneity between urban form and public transport demand. Notably, we proposed and applied two new instruments for public transport supply: transit operator ownership (public versus private) and the marginal cost of producing an extra ‘unit’ of transit supply, approximated by bus drivers’ hourly wages. Nevertheless, finding legitimate instruments was not possible in all specifications, although we tested numerous combinations of a large number of variables. Our effort illustrates the difficulty of finding good instruments and the importance of performing tests for instrument validity and relevance.

Results appear to be sensitive to the functional form adopted. As an exception, public transport supply, measured by vehicle revenue miles, consistently appears to have a substantial positive impact on transit demand. Still, the exact size of the effect does depend on the model specification.
The estimated models provide evidence that population density can increase public transport patronage. Notably, in the linear model where urban form variables are instrumented, perceived population density is statistically significant. The finding strongly supports the presence of a causal link between population density and transit demand. However, given the variable findings in other model specifications, the evidence is not conclusive. The estimated size of the density effect strongly depends on model specification, making difficult to draw policy conclusions. However, the effect on bus transit is found to be lower than on general transit.

Our models support the presence of a link between the population-employment balance in neighbourhoods and transit demand, but suggest that the link is not causal. However, it is possible that the finding is due to the loss in efficiency incurred by the introduction of instruments. The link appears to be small regardless of model specification.

A limitation of this study is that it does not explicitly model all interconnections between demand, supply and urban form simultaneously. In addition to the demand-supply and demand-urban form relationships, the existence of a causal relationship between transit supply and urban form is also likely. Consequently, as well as the direct effect of urban form on public transport trip making, there could be an additional indirect effect due the potential impact of urban form on public transport supply. Ideally, to fully understand the relationship between urban form, transit demand and transit supply, the corresponding variables should be modelled jointly. However, this was not feasible due to the difficulty in defining complete structural equations for transit supply and urban form. The interrelations between demand, supply and urban form might explain why some urban form variables in our models became insignificant when only transit supply was instrumented.
Chapter 8: Conclusions

This thesis contributed to the literature on the link between urban form and travel behaviour by focussing on the relation between urban form and public transport use and on methodological issues relating to the measurement of land use mix. The thesis included four empirical chapters. Chapters 4 to 6 dealt with issues relating to land use mix measurement. Chapter 7 examined the link between public transport patronage and city structure.

This chapter attempts to pull together the findings from the empirical chapters of the thesis. The first section summarizes conclusions in relation to both land use mix measurement and the effect of urban structure on public transport demand. Section 8.2 presents the thesis’ implications for research. Section 8.3 focuses on implications for policy. Section 8.4 explains the limitations of the study. Lastly, section 8.5 sets out possible directions for future research.

8.1 Summary of findings

8.1.1 Land use mix measurement

Despite the substantial literature on the relationship between land use mix and travel behaviour, few studies have considered how the measurement of land use mix affects our understanding of the relationship per se. In this thesis, we examined how different measures influence our understanding of the links between travel demand and land use mix, using various approaches. In chapter 4, we studied the issue using simulation analysis. In chapter 5, we extended the analysis in an empirical context, by applying various land use mix metrics in a model for public transport trip frequency in London. Finally, in chapter 6, we concentrated on the geographical scale used in measuring land use mix, and repeated the analysis presented in chapter 5 for various spatial units. Although past studies have examined how spatial scale influences estimates of the urban form-travel behaviour relationship (Zhang and Kukadia, 2005; Mitra and Buliung, 2011), few land use mix measures have been included in their analyses. The literature shows that the impact of spatial scale differs for distinct urban form measures. Therefore, studying the effects of scale on the various land use mix measures is pertinent.
The simulation analysis shows that, with the exception of the Shannon and balance indices, alternative land use mix measures can produce extremely diverse results when applied in a travel behaviour model. The estimated effects can vary not only in magnitude, but also in direction. The simulation analysis considers various hypothetical city configurations and, essentially, illustrates how diverse results based on different land use mix metrics can be.

Real cities are not random and results are likely to be less diverse in reality, especially if data from a single city are considered. Indeed, when the various land use mix measures are applied in an empirical model of public transport demand in London, the estimated effects are less diverse. Although not all measures are significant in the model, measures that are significant produce comparable elasticities. Geographical scale can also affect the significance of a land use mix measure in relation to public transport trip making. Elasticities for measures that show significance appear to increase with scale. Nevertheless, the differences are small.

The following general conclusions can be reached based on the simulation and empirical analyses presented in the thesis. First and foremost, although the use of different land use mix metrics or different spatial scales does not necessarily produce dissimilar results, in many cases it will. As an exception, we find that the Shannon index and the balance index produce equivalent results. The Shannon and the balance index can be defined for multiple land use categories. We find that results based on the Shannon index are, in general, not sensitive to the number of land use classes employed in the index’s definition. The finding is consistent with Brown et al (2009), who observed high correlations between distinct Shannon indices defined with different degrees of detail in land use classification. We reach the same conclusion regarding the balance index. Correspondingly, the two indices appear to be highly correlated regardless of the number of land use categories used in their definition.

Retail appears to be a particularly relevant category in relation to public transport use. Furthermore, retail density appears not to be sensitive to changes in geographical scale. The same advantage is shared by minimum distance to a shop and retail accessibility (as defined in chapter 5). The two measures are, by definition, unaffected by spatial scale issues and appear to be linked to public transport use based on results in chapter 5.
Results suggest that it is the presence of land uses rather than an equal balance between them that affects public transport use. Brown et al (2009) reach a similar conclusion in connection with body weight outcomes. The thesis’ analysis also provides some evidence to suggest that it is measures constructed in terms of land area rather than counts of establishments that show significance in relation to land use mix. However, the evidence is not conclusive.

Model results for the various spatial units show that certain spatial entities are more consistent at capturing the land use mix-transit demand link for the various land use mix measures. In particular, the effect of land use mix on transit demand appears to be best captured by defining small ‘neighbourhoods’ that reach up to 250-300m from an individual’s residence and/or geographical entities that are homogeneous in relation to land use. Contrary to our initial hypothesis, administrative or statistical boundaries can be suitable for measuring land use mix despite being delineated for different purposes. This is possibly due to the fact that such entities are often defined to be homogeneous in relation to various characteristics that can be related to land use mix.

8.1.2 Urban structure and public transport demand

In chapter 7, we estimated city-level public transport demand models for the US to investigate the importance of urban structure in determining public transport patronage. The chapter aimed to extend a previous study on transit patronage in the US (Taylor et al, 2009) in various ways. We constructed detailed measures for urban structure that represent the distribution of population and employment in a city, rather than considering population density only. We carefully selected instruments to treat endogeneity, and checked their relevance and validity using appropriate statistical tests. As well as treating transit supply as endogenous, we estimated models that also considered urban form as endogenous. We estimated separate models for transit in general and bus modes in particular. Last, we experimented with different functional forms.

Model results suggest that population density has a causal positive effect on transit demand, although the evidence is not conclusive. The size of the effect varies substantially between different model specifications, making it hard to draw policy conclusions. The population-employment balance appears to have a modest positive association with transit patronage.
The link is found not to be causal, but the result should be treated with caution due to the possible loss in efficiency entailed in instrumental variable applications. Population ‘centrality’, namely the extent of clustering of population around a central urban core, does not appear to be linked to transit use. The effects of urban form on general transit demand are found to follow the same patterns as on bus demand; however, the effects on bus demand appears to be lower in magnitude. Last, transit supply consistently appears to have a large positive effect on transit use regardless of the model specification considered.

The analysis also highlights certain methodological issues. Finding legitimate instruments is difficult and hence, checking the validity and relevance of instruments through statistical tests is important. Moreover, model results can be particularly sensitive to the functional form adopted. The methodological implications of the thesis will be discussed further in the next section.

In addition to the public transport demand models developed in chapter 7, we also estimated disaggregate models of public transport trip frequency in relation to our study of land use mix measurement in chapters 5 and 6. As noted in the previous section, the models suggest that population density and land use mix have a positive link with public transport trip making. However, we cannot infer whether the effect is causal because we the tested instruments for transit accessibility and urban form were weak. The estimated effect is small in magnitude, in contrast with results from chapter 7. There are many potential explanations for the conflicting findings. First, different types of data (aggregate versus disaggregate) are used\(^{76}\). Then, the urban form-transit use relationship in London might be different from the US, possibly due to differences in policy or culture. Last, urban form might have a larger effect at the urban scale than at a more local scale.

8.2 Implications for research
The analysis presented in the thesis has significant implications for researchers. In chapter 2.2 we discussed three key methodological issues in the literature: endogeneity between urban form and travel, the measurement of urban form and the geographical scale of measurement of urban form. The latter two form part of the motivation of this project, and were specifically

\(^{76}\) Certain researchers have found data aggregation to increase correlation coefficients between variables (Gehlke and Biehl, 1934; Yule and Kendall, 1950).
addressed in the thesis in relation to an individual aspect of urban form, land use mix. Consequently, the relevant analysis gives rise to certain methodological conclusions regarding the metric and the scale used in land use mix measurement.

First and foremost, given the potential sensitivity of model results on the metric and scale applied, researchers should, whenever possible, test the robustness of their conclusions to different land use mix metrics and various spatial scales. Similarly, researchers should be cautious when comparing results from studies employing different metrics or measuring land use mix at different scales. It should be noted that, as an exception, the balance and Shannon indices appear to produce comparable results irrespective of the number of land uses considered in the metrics’ estimation.

The thesis’ findings lead to certain recommendations regarding the choice of metric and scale for land use mix in transit demand modelling. Nevertheless, these could be specific to the context of London or public transport use; researchers should be cautious in generalizing conclusions to other geographical areas or to other aspects of travel demand. The thesis’ results endorse the use of metrics that capture the presence of alternative uses rather than how equal the balance between them is, in particular the presence of retail. Such measures include retail density, retail accessibility measures based on gravity models and minimum distance to a retail outlet. The three suggested metrics have the further significant advantage that they are not affected by scale, the first based on the thesis’ findings and the latter two by definition. Regarding the choice of spatial scale, it is recommended that researchers measure land use mix using small geographical areas that extend up to 250-300m from an individual’s residence. It is also suggested that they use units that are homogeneous with regards to land use mix or characteristics related to land use mix. Administrative/statistical boundaries that fulfill the homogeneity criterion can be suitable.

Endogeneity is the most widely acknowledged and researched issue in the urban form-travel demand literature. Despite not forming part of the motivation of the thesis, some conclusions regarding the treatment of endogeneity in the thesis’ context have been reached. To treat urban form and transit supply as endogenous in transit demand models, we employed an instrumental variables approach. In many models, our chosen instruments proved to be weak despite theoretical arguments justifying their legitimacy, illustrating the difficulty in finding appropriate instruments and the importance of instrument testing. In chapter 5, our
instruments, selected based on past literature, were weak. Although direct comparisons between the thesis and previous studies are not possible as the full set of instruments used in each case are not identical, the finding still raises the question of whether results from studies not testing instrument validity are reliable. On the other hand, the thesis also proposed certain new instruments for transit supply, namely transit operator ownership (public versus private) and the marginal cost of producing an extra ‘unit’ of transit supply, approximated by bus drivers’ hourly wages.

In addition, the thesis highlighted the importance of functional form choice (chapter 7), an issue that is somewhat overlooked in the context of transit demand modelling. The variation of results, both in significance and in magnitude, questions the reliability of models testing a single functional form: Would conclusions be different if another functional form was employed? This is especially important when policy implications are considered as these depend on the size of the urban form effect, which appears to vary significantly with functional form. Testing different functional forms in transit demand modelling is therefore pertinent. Regarding the models estimated in chapter 7, we concluded that the Box-Cox specification is closer to the real functional form of the modelled relationship.

As a last note, the thesis’ analysis draws attention to the fact that transit demand, transit supply and urban form should ideally be modelled jointly. In chapter 7, we estimated models where only transit supply was instrumented. Surprisingly, the population-employment mix became insignificant despite being significant in the corresponding OLS model. We believe this could be due to the potential relationship between urban form and transit supply, and the effect of urban form entering the first stage regression for transit supply. Moreover, when the three variables are not modelled jointly, the full effect of urban form on public transport trip making could be underestimated as the potential indirect effect due to the impact of urban form on public transport supply is not taken into account. Unfortunately, estimating a joint model for demand, supply and urban form was not feasible due to the difficulty in defining complete structural equations for transit supply and urban form.

8.3 Implications for policy
As explained in the introductory chapters of the thesis, the general motivation guiding research on the urban form-travel behaviour relationship is to assess whether land use
policies can be effective in reducing car dependence and promoting the use of active transport modes, namely public transport, walking and cycling. Planners and researchers often advocate policies aimed at increasing residential densities and intermixing retail, offices and residences (e.g. Newman and Kenworthy, 1989, Calthorpe, 1993; Katz, 1994). However, the efficacy of land use policies in shaping travel behaviour remains debatable. Although it is generally accepted that there is a correlation between land use characteristics and travel patterns, whether land use policy measures can successfully influence travel demand depends on the direction of the causality and the size of the effect. If it is travel choices that affect residential choices rather than the converse, then clearly the introduction of land use policies is not pertinent. The size of the effect is particularly important due to the potentially significant cost involved in reshaping the built environment. Many researchers argue that the benefits accrued do not justify the extensive implementation costs, and support alternative policies to influence travel demand, such as a rise in fuel tax (e.g. Brownstone, 2008).

The US models estimated in chapter 7 support the introduction of land use policies, albeit not decidedly. In particular, population density appears to have a causal effect on transit demand. Although the size of the corresponding elasticity depends heavily on the model specification, even the lowest estimated elasticity represents a considerable effect (0.59 for IV models considering all transit modes)\textsuperscript{77}. Results are encouraging with regards to policy implications, but any benefits should be weighted against the cost of increasing density, which varies depending on the area under consideration. For instance, increasing the density in heavily built-up areas can be extremely costly, but the cost should be lower if significant brownfield sites exist. It should also be noted that even when the cost of increasing density in existing built-up areas is prohibitive, there is scope in preventing further residential sprawl, for instance by introducing planning laws that prohibit developments outside the existing city limits.

The evidence on the causal nature of the relationship between the jobs-to-housing balance and transit demand is less conclusive. The variable representing the population-employment mix becomes insignificant when instrumented. Nevertheless, the result may be due to loss in efficiency incurred due to the use of instrumental variables. The size of the effect appears to be, in general, lower than the effect of population density. However, increasing the mix of

\textsuperscript{77} The note refers to models where perceived population density was significant.
population and employment could also be less costly than increasing population density (e.g. by relaxing zoning rules).

In the London models estimated in chapters 5 and 6, no conclusion could be reached regarding the direction of the built environment-transit demand link due to weak identification in the application of instruments. The association of both population density and land use mix with transit demand appears to be small; even the combined effect is modest. Assuming the estimated effect is causal, increasing population density by 10% will result in a maximum of 1.1% increase in public transport trip making. Similarly, increasing ‘land use mix’ by 10% will increase public transport trip making by a maximum of 0.9%. Undoubtedly, the effect is small and at first glance does not provide support for the introduction of land use policies. Nevertheless, as mentioned earlier, certain measures to increase land use mix can still be pertinent as they are less costly. Examples of such policies include relaxing zoning laws to allow retail establishments in residential districts or allowing residential developments to be converted into offices. Moreover, to fully assess the benefits of changing the built environment, the effect on all aspects of travel should be examined. Although the effect of the local environment on transit use is low, the effect on other aspects of travel, particular walking, could be much larger.

As a last note, to fully understand the potential of land use policies, the associated benefits and costs should be assessed in a broader context rather than simply in terms of travel. The built environment could affect, positively or a negatively, a number of factors, such as health (Badland and Schofield, 2005; Bauman and Bull, 2007), crime (Ligett et al, 2001), neighbourhood satisfaction (Bramley and Power, 2009; Lovejoy, Handy and Mokhtarian, 2010; Yang, 2008), social interaction and community participation (Brueckner and Largey, 2008, Fan and Khattak, 2009, Lee et al, 2009; Pinjari et al, 2009). Planners should look at the full extent of the impact of built environment changes to support any policy decisions.

8.4 Limitations of the analyses
8.4.1 Land use mix measurement (Chapters 4, 5 and 6)
A key limitation of the simulation analysis of land use mix measurement is that results are not prescriptive. The simulation analysis provides an illustration of the potential consequences of using alternative measures, but cannot prescribe an optimum measure for land use mix.
The simulation analysis is complemented by the empirical investigation, from which some general advice can be drawn regarding selection of a measure for mixed uses, as outlined in the previous section. However, it should be noted that the analysis was in relation to public transport use, and based on data from the Greater London area. Researchers should be cautious in generalizing the findings to other aspects of travel behaviour or geographical areas. The work in this thesis could be extended to examine whether considering further aspects of travel behaviour, such walking trip frequency or distances travelled by car, and different geographical locations, will lead to similar conclusions.

Last, despite our effort to treat endogeneity using instrumental variables, we did not manage to construct a reliable IV model. Our conclusions regarding both the metric and spatial scale used in land use mix measurement were derived from models that treat transport supply and urban form as exogenous. Since our goal is to compare how well alternative measures of mixed uses relate to public transport use rather than to estimate the actual causal effects, the study’s conclusions are nonetheless meaningful. However, the presence of endogeneity limits the conclusions that can be drawn on the link between urban form and transit trip frequency in London, an area where the urban form-travel relationship has not been studied before. Results suggest the presence of a small association between urban form (population density and land use mix) with public transport use, but the effect might not be causal.

8.4.2 Urban structure and public transport demand (Chapter 7)

In Chapter 7, we used instrumental variables techniques to deal with endogeneity. The approach also has limitations. Although this estimator can produce consistent estimates, provided that legitimate instruments are chosen, it also entails a loss in efficiency. This can affect the statistical significance of variables, and hence the conclusions drawn. In addition, in practical applications, finding good instruments is difficult. Although we found suitable instruments for many of our models, this was not possible for all the model specifications we aimed to estimate. Specifically, we could not estimate logarithmic and Box-Cox models where both urban form and transit supply variables were treated as endogenous.

A further limitation of the work presented in chapter 7 is the use of cross-sectional data, which makes it more challenging to address some main estimation issues, namely those
related to endogeneity bias. Endogeneity bias has two main sources: unobserved heterogeneity and simultaneity. Panel data are better suited to deal with unobserved heterogeneity (for example, through estimation of fixed-effects and random-effects estimators), which can be present in the context of the study due to policy or cultural differences. We tried to have as comprehensive a model specification as possible to avoid this issue. If panel data was available, we could have also addressed simultaneity by using further instrumental variable techniques based on dynamic GMM estimators (difference- and system-GMM). These estimators use lagged values of the endogenous variables for instrument construction.

We were unable to take advantage of the NTD panel, due to the lack of suitable panel data to construct urban form variables. Even if panel data had been available, the use of fixed-effects and dynamic GMM estimators could also have been hindered by the fact that urban form is persistent over time, possibly leading to a large loss in efficiency of these estimators. On the other hand, these estimators should work well in contexts of rapid urbanization, such as the rapid urban growth experienced recently in China.

The transit demand models estimated in chapter 7 treat transit supply and urban form as endogenous. It is likely that further model covariates, such as car ownership, could also be endogenous. While car ownership can determine an individual’s need or willingness to travel by public transport, an individual’s willingness to use public transport can also influence his/her decision to purchase a car. As our effort to implement the instrumental variables approach shows, finding good instruments is difficult. Treating endogeneity becomes harder as the number of endogenous variables increases. Therefore, it made sense to simplify the model and treat as endogenous the variables for which endogeneity problems are likely to be more pronounced and which are of direct interest to the study.

Last but not least, the study does not explicitly model all interrelations between demand, supply and urban form simultaneously. It is possible that a causal relationship between urban form and transit supply exists, which could give rise to an indirect effect of urban form on transit demand. A joint model for urban form, transit demand and transit supply would be capable of modelling both the direct effect of urban form on transit demand and the indirect effect arising from its impact on supply. However, such an approach is hindered by the difficulty in defining complete structural equations for transit supply and urban form.
8.5 Directions for future research

This thesis aimed to address some of the gaps in the literature on the urban form-travel behaviour relationship. In the paragraphs that follow, we present some further directions for future research.

Despite the large literature on the link between urban form and travel behaviour, reaching general conclusions that can be applied in policy making is hard due to the often conflicting findings. Studies conducting meta-analysis (Ewing and Cervero, 2011; Ewing and Cervero, 2001; Leck, 2006) summarize existing results, but provide little insight into the factors that can explain the variable conclusions in the literature. Therefore, it would be interesting to extend existing meta-analysis studies (Ewing and Cervero, 2011) by performing meta-regressions that examine the impact of various model features on estimates of the effect of urban form on travel. Factors considered could include the type of data used (aggregate/disaggregate), the geographical area studied, whether endogeneity is treated, the approach used to treat endogeneity and the urban form measures employed. Meta-regressions have been performed to understand the findings in several research areas. For instance, Melo et al (2009) conducted a meta-regression to examine variations in estimates of the effects of urban agglomeration on productivity, Espey (1998) investigated price and income elasticities of gasoline demand and Holgrem (2007) studied elasticities of bus demand with respect to vehicle-kilometres, income, fares, fuel price and car ownership.

Certain researchers consider policies relating to urban form to be impractical. They argue that pricing policies such as increases in fuel tax could have an equal if not larger impact on travel behaviour, while being less expensive to implement (e.g. Brownstone and Fang, 2009; Brownstone, 2008). However, it can be argued that land use and pricing policies can complement each other, as urban form is likely to affect the response to price changes. For instance, the effect of increasing fuel prices on car travel could be larger in traditional/neo-traditional neighbourhoods, as there are more feasible alternatives to the car. Suburban residents are more likely to feel captive to the car and be more inelastic to price changes. Schwanen and Mokhtarian (2005) find that suburban residents become car-oriented even if they prefer not to use the car, whereas urban residents are more likely to fulfil their travel preferences. The finding supports our hypothesis. Examining whether rises in fuel prices
affect travel behaviour differently in areas with different built environment characteristics would make an interesting research question.
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Appendix I

Correspondence between land use classes considered in chapter 6 and OS Address Layer 2 use classification

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<th>OS Address Layer 2 classification</th>
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SIXTH FORM COLLEGE
SPECIAL SCHOOL
SUNDAY SCHOOL
TECHNICAL COLLEGE
TECHNOLOGY STUDIES
TRAINING
UNIVERSITY

ACTIVITY CENTRE
ADVENTURE PLAYGROUND
AMUSEMENT ARCADE
ART CENTRE
ART GALLERY
BASKETBALL
BINGO HALL
BMX RACING
BOATING
BOWLING
BOWLS
BRITISH LEGION CLUB
CASINO
CINEMA
CIRCUS
CLUB
CLUB HOUSE
COMMUNITY CENTRE
COUNTRY CLUB
CRAZY GOLF
CRICKET
CROQUET
ENTERTAINMENT CENTRE
EQUESTRIAN
EQUESTRIAN TRAINING
FITNESS CLUB
FOOTBALL
GOLF
GOLF RANGE
GUIDES MEETING PLACE
GYMNASIUM
HEALTH CLUB
HERITAGE CENTRE
HOCKEY
INTERNET CAFE
LEISURE CENTRE
LIBRARY
MARITIME MUSEUM
MILITARY YOUTH CLUB
MUSEUM
NETBALL
NIGHTCLUB
PITCH AND PUTT
PLAY AREA
PLAY CENTRE
PLAYING FIELD
POLO
READING ROOM
RECREATION GROUND
ROWING
RUGBY FOOTBALL
SAILING
SCOUTS MEETING PLACE
SKATEBOARDING
SKIING
SNOOKER
SOCIAL CLUB
SPORTS
SPORTS CLUB
SPORTS PAVILION
SPORTS VIEWING
SWIMMING
TENNIS
THEATRE
YOUTH CENTRE

retail:
CHEMIST
DEPARTMENT STORE
GENERAL COMMERCIAL
KIOSK
MARKET
RETAIL PARK
SHOPPING
SHOPPING CENTRE
SUPERMARKET
SUPERSTORE

service:
ARMY OFFICE
BANK
BUILDING SOCIETY
CENTRAL GOVERNMENT OFFICE
CHILD DAY CARE
CITIZENS ADVICE BUREAU
CIVIC HALL
CLEANING
CLINIC
DAY CARE
DENTAL SURGERY
DISABLED PERSONS SERVICE
DRY CLEANERS
EMPLOYMENT AGENCY
ESTATE AGENCY
FAMILY SERVICE
FINANCIAL AND PROFESSIONAL SERVICES
GOVERNMENT OFFICE
HAIRDRESSER
HEALTH CENTRE
HOSPITAL
INSURANCE BROKER
JOB CENTRE
LAUNDERETTE
LOCAL GOVERNMENT OFFICE
MEDICAL SERVICES
MENTAL HEALTH CENTRE
OFFICE
POST OFFICE
SURGERY
TRAVEL AGENCY
VETERINARY SURGERY
WELFARE SERVICES
Appendix II

Further model results based on sample that includes only one randomly chosen member per household (Chapter 6)

Table A.1 Coefficient estimates for a public transport trip frequency model estimated using a sample that includes only one randomly chosen member per household. Minimum distance represents land use mix.

<table>
<thead>
<tr>
<th></th>
<th>Poisson</th>
<th>NB1</th>
<th>NB2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>-0.017</td>
<td>-0.015</td>
<td>-0.018</td>
</tr>
<tr>
<td>aged 5 to 10</td>
<td>-1.5</td>
<td>-1.6</td>
<td>-1.5</td>
</tr>
<tr>
<td>aged 11 to 15</td>
<td>0.16</td>
<td>0.24</td>
<td>0.13</td>
</tr>
<tr>
<td>aged 16 to 17</td>
<td>0.43</td>
<td>0.55</td>
<td>0.42</td>
</tr>
<tr>
<td>aged 60 to 64</td>
<td>-0.1</td>
<td>-0.14</td>
<td>-0.075</td>
</tr>
<tr>
<td>aged 64 to 69</td>
<td>-0.0013</td>
<td>-0.048</td>
<td>0.027</td>
</tr>
<tr>
<td>aged 70 to 74</td>
<td>0.15</td>
<td>0.13</td>
<td>0.21</td>
</tr>
<tr>
<td>aged 75 to 79</td>
<td>-0.13</td>
<td>-0.19</td>
<td>-0.051</td>
</tr>
<tr>
<td>aged 80 and over</td>
<td>-0.13</td>
<td>-0.18</td>
<td>-0.088</td>
</tr>
<tr>
<td>income &lt; £5,000</td>
<td>0.047</td>
<td>0.024</td>
<td>0.041</td>
</tr>
<tr>
<td>income £5,000 - £9,999</td>
<td>-0.15</td>
<td>-0.19</td>
<td>-0.15</td>
</tr>
<tr>
<td>income £10,000 - £14,999</td>
<td>-0.038</td>
<td>-0.046</td>
<td>-0.042</td>
</tr>
<tr>
<td>income £15,000 - £19,999</td>
<td>-0.12</td>
<td>-0.14</td>
<td>-0.15</td>
</tr>
<tr>
<td>income £20,000 - £24,999</td>
<td>-0.2</td>
<td>-0.21</td>
<td>-0.22</td>
</tr>
<tr>
<td>income £25,000 - £34,999</td>
<td>-0.053</td>
<td>-0.072</td>
<td>-0.068</td>
</tr>
<tr>
<td>income £35,000 - £49,999</td>
<td>-0.032</td>
<td>-0.018</td>
<td>-0.055</td>
</tr>
<tr>
<td>income £50,000 - £74,999</td>
<td>-0.066</td>
<td>-0.077</td>
<td>-0.095</td>
</tr>
<tr>
<td>Employed</td>
<td>-0.015</td>
<td>0.058</td>
<td>-0.06</td>
</tr>
<tr>
<td>Student</td>
<td>0.29</td>
<td>0.34</td>
<td>0.32</td>
</tr>
<tr>
<td>homemaker</td>
<td>-0.55</td>
<td>-0.64</td>
<td>-0.58</td>
</tr>
<tr>
<td># of cars</td>
<td>-0.54</td>
<td>-0.59</td>
<td>-0.58</td>
</tr>
<tr>
<td># of motorcycles</td>
<td>-0.67</td>
<td>-0.74</td>
<td>-0.64</td>
</tr>
<tr>
<td>car license</td>
<td>-0.4</td>
<td>-0.49</td>
<td>-0.43</td>
</tr>
<tr>
<td>motocycle license</td>
<td>-0.39</td>
<td>-0.49</td>
<td>-0.42</td>
</tr>
<tr>
<td>Disability</td>
<td>-0.27</td>
<td>-0.34</td>
<td>-0.26</td>
</tr>
<tr>
<td>hhld size</td>
<td>-0.1</td>
<td>-0.12</td>
<td>-0.1</td>
</tr>
<tr>
<td># of children</td>
<td>-0.00082</td>
<td>-0.0066</td>
<td>-0.018</td>
</tr>
<tr>
<td># of elderly</td>
<td>-0.073</td>
<td>-0.069</td>
<td>-0.099</td>
</tr>
<tr>
<td># of car licenses in hhld</td>
<td>0.0043</td>
<td>0.025</td>
<td>-0.023</td>
</tr>
<tr>
<td># of motorcycle licenses in hhld</td>
<td>0.2</td>
<td>0.22</td>
<td>0.24</td>
</tr>
<tr>
<td># of employed hhld members</td>
<td>0.073</td>
<td>0.06</td>
<td>0.088</td>
</tr>
<tr>
<td># of adult students in hhld</td>
<td>-0.11</td>
<td>-0.13</td>
<td>-0.095</td>
</tr>
</tbody>
</table>
# of visitors & -0.014 & -0.033 & 0.014  
distance to station & -0.16 & *** & -0.2 & ** & -0.17 & **  
road per capita & -0.97 & -0.91 & -0.87  
Density & 9.40E-06 & ** & 0.00001 & * & 0.000014 & **  
minimum distance & -0.48 & *** & -0.47 & ** & -0.52 & **  
staff pass & 0.43 & *** & 0.48 & *** & 0.46 & ***  
New Deal pass & 1.1 & ** & 1.3 & ** & 1  
congestion charging & 0.8 & *** & 0.94 & *** & 0.83 & ***  
2005 & -0.029 & -0.045 & -0.057  
2006 & -0.11 & -0.12 & -0.12  
2007 & -0.11 & -0.11 & -0.13  
2008 & -0.042 & -0.067 & -0.052  
Weekend & -0.74 & *** & -0.86 & *** & -0.73 & ***  
bank holiday & -1.7 & *** & -1.8 & ** & -1.8 & **  
new year & -12 & -16 & -16  
Summer & 0.047 & 0.046 & 0.07

Table A.2 Observed and predicted probabilities for a public transport trip frequency model estimated using a sample that includes only one randomly chosen member per household. Minimum distance represents land use mix.
Table A.3 Model coefficients and estimated elasticities for land use mix
(Model estimated using a sample that includes only one randomly chosen member per household)

<table>
<thead>
<tr>
<th>land use mix measure</th>
<th>Poisson coefficient</th>
<th>Poisson elasticity</th>
<th>NB1 coefficient</th>
<th>NB1 elasticity</th>
<th>NB2 coefficient</th>
<th>NB2 elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>minimum distance</td>
<td>-0.48 ***</td>
<td>-0.07</td>
<td>-0.47 **</td>
<td>-0.07</td>
<td>-0.52 **</td>
<td>-0.08</td>
</tr>
<tr>
<td>retail density</td>
<td>0.00052 ***</td>
<td>0.04</td>
<td>0.0005 **</td>
<td>0.03</td>
<td>0.00067 ***</td>
<td>0.05</td>
</tr>
<tr>
<td>ratio non-residentials uses/residentials uses</td>
<td>0.57</td>
<td>0.02</td>
<td>0.53</td>
<td>0.02</td>
<td>0.74</td>
<td>0.03</td>
</tr>
<tr>
<td>share of non-residential uses</td>
<td>0.66</td>
<td>0.02</td>
<td>0.58</td>
<td>0.02</td>
<td>0.87</td>
<td>0.03</td>
</tr>
<tr>
<td>Shannon (2 uses)</td>
<td>0.22</td>
<td>0.03</td>
<td>0.18</td>
<td>0.03</td>
<td>0.3</td>
<td>0.04</td>
</tr>
<tr>
<td>Shannon (6 uses)</td>
<td>0.18</td>
<td>0.03</td>
<td>0.14</td>
<td>0.02</td>
<td>0.24</td>
<td>0.04</td>
</tr>
<tr>
<td>balance (2 uses)</td>
<td>0.33</td>
<td>0.02</td>
<td>0.29</td>
<td>0.02</td>
<td>0.44</td>
<td>0.03</td>
</tr>
<tr>
<td>balance (6 uses)</td>
<td>0.54</td>
<td>0.02</td>
<td>0.47</td>
<td>0.02</td>
<td>0.73</td>
<td>0.03</td>
</tr>
<tr>
<td>modified balance (2 uses)</td>
<td>-0.21</td>
<td>-0.20</td>
<td>-0.56</td>
<td>-0.55</td>
<td>-0.32</td>
<td>-0.31</td>
</tr>
<tr>
<td>modified balance (6 uses)</td>
<td>-0.25</td>
<td>-0.24</td>
<td>-0.65</td>
<td>-0.63</td>
<td>-0.41</td>
<td>-0.40</td>
</tr>
<tr>
<td>retail accessibility</td>
<td>0.00052 ***</td>
<td>0.04</td>
<td>0.00050 **</td>
<td>0.03</td>
<td>0.00067 ***</td>
<td>0.05</td>
</tr>
<tr>
<td>share of non-residential uses</td>
<td>0.14 ***</td>
<td>0.03</td>
<td>0.16 ***</td>
<td>0.03</td>
<td>0.17 ***</td>
<td>0.03</td>
</tr>
<tr>
<td>Shannon (2 uses)</td>
<td>0.4 ***</td>
<td>0.05</td>
<td>0.41 ***</td>
<td>0.05</td>
<td>0.48 ***</td>
<td>0.06</td>
</tr>
<tr>
<td>Shannon (6 uses)</td>
<td>0.19 **</td>
<td>0.05</td>
<td>0.17</td>
<td>0.05</td>
<td>0.24</td>
<td>0.07</td>
</tr>
<tr>
<td>modified balance (2 uses)</td>
<td>0.078</td>
<td>0.03</td>
<td>0.056</td>
<td>0.02</td>
<td>0.1</td>
<td>0.04</td>
</tr>
<tr>
<td>modified balance (6 uses)</td>
<td>-0.42 ***</td>
<td>-0.37</td>
<td>-0.47 **</td>
<td>-0.41</td>
<td>-0.48 **</td>
<td>-0.42</td>
</tr>
</tbody>
</table>
Appendix III

Definitions for modes included in the National Transit Database

Aerial Tramway Mode
A transit mode that is an electric system of aerial cables with suspended powerless passenger vehicles. The vehicles are propelled by separate cables attached to the vehicle suspension system and powered by engines or motors at a central location not on-board the vehicle.

Alaska Railroad
In recognition of the special Federal relationship with the Alaska railroad, a segment of the passenger service portion of the Alaska railroad is considered to be eligible for certain FTA funding under the Fixed Guideway Modernization program. The service encompasses only those lines operating within the Anchorage, Alaska, urbanized area (UZA) where passenger service is provided and only includes car miles for passenger cars; car miles for freight cars are specifically excluded.

Automated Guideway Transit
A transit mode that is an electric railway (single or multi-car trains) of guided transit vehicles operating without vehicle operators or other crew onboard the vehicle. Service may be on a fixed schedule or in response to a passenger activated call button. Automated Guideway transit includes personal rapid transit, group rapid transit, and people mover systems.

Bus
A transit mode comprised of rubber-tired passenger vehicles operating on fixed routes and schedules over roadways. Vehicles are powered by diesel, gasoline, battery, or alternative fuel engines contained within the vehicle.

Cable Car
A transit mode that is an electric railway with individually controlled transit vehicles attached to a moving cable located below the street surface and powered by engines or motors at a central location, not onboard the vehicle.

Commuter Rail
A transit mode that is an electric or diesel propelled railway for urban passenger train service consisting of local short distance travel operating between a central city and adjacent suburbs. Service must be operated on a regular basis by or under contract with a transit operator for the purpose of transporting passengers within urbanized areas (UZAs), or between urbanized
areas and outlying areas. Such rail service, using either locomotive hauled or self-propelled railroad passenger cars, is generally characterized by multi-trip tickets, specific station to station fares, railroad employment practices, and usually only one or two stations in the central business district.

It does not include heavy rail rapid transit, or light rail/streetcar transit service. Intercity rail service is excluded, except for that portion of such service that is operated by or under contract with a public transit agency for predominantly commuter services. Predominantly commuter service means that for any given trip segment (i.e., distance between any two stations), more than 50 percent of the average daily ridership travels on the train at least three times a week. Only the predominantly commuter service portion of an intercity route is eligible for inclusion when determining commuter rail route miles.

**Demand Response**

A transit mode comprised of passenger cars, vans or small buses operating in response to calls from passengers or their agents to the transit operator, who then dispatches a vehicle to pick up the passengers and transport them to their destinations. A demand response operation is characterized by the following a) the vehicles do not operate over a fixed route or on a fixed schedule except, perhaps, on a temporary basis to satisfy a special need, and b) typically, the vehicle may be dispatched to pick up several passengers at different pick-up points before taking them to their respective destinations and may even be interrupted en route to these destinations to pick up other passengers. The following types of operations fall under the above definitions provided they are not on a scheduled fixed route basis:

- Many origins — many destinations
- Many origins — one destination
- One origin — many destinations, and
- One origin — one destination

**Ferryboat**

A transit mode comprised of vessels carrying passengers and/or vehicles over a body of water that are generally steam or diesel powered. Intercity ferryboat service is excluded, except for that portion of such service that is operated by or under contract with a public transit agency for predominantly commuter services. Predominantly commuter service means that for any given trip segment (i.e., distance between any two piers), more than 50 percent of the average daily ridership travels on the ferryboat on the same day. Only the predominantly commuter service portion of an intercity route is eligible for inclusion when determining ferryboat route miles.
**Jitney**
A transit mode comprised of passenger cars or vans operating on fixed routes (sometimes with minor deviations) as demand warrants without fixed schedules or fixed stops.

**Heavy Rail**
A transit mode that is an electric railway with the capacity for a heavy volume of traffic. It is characterized by high speed and rapid acceleration passenger rail cars operating singly or in multi-car trains on fixed rails, separate rights-of-way from which all other vehicular and foot traffic are excluded, sophisticated signaling, and high platform loading.

**Inclined Plane**
A transit mode that is a railway operating over exclusive right-of-way on steep grades (slopes) with powerless vehicles propelled by moving cables attached to the vehicles and powered by engines or motors at a central location not onboard the vehicle. The special tramway type of vehicles have passenger seats that remain horizontal while the undercarriage (truck) is angled parallel to the slope.

**Light Rail**
A transit mode that typically is an electric railway with a light volume traffic capacity compared to heavy rail. It is characterized by passenger rail cars operating singly (or in short, usually two car, trains) on fixed rails in shared or exclusive right-of-way, low or high platform loading, and vehicle power drawn from an overhead electric line via a trolley or a pantograph.

**Monorail**
A transit mode that is an electric railway of guided transit vehicles operating singly or in multi-car trains. The vehicles are suspended from or straddle a guideway formed by a single beam, rail or tube.

**Publico**
A transit mode comprised of passenger vans or small buses operating with fixed routes but no fixed schedules. Publicos are a privately owned and operated public transit service which is market oriented and unsubsidized, but regulated through a public service commission, state or local government. Publicos are operated under franchise agreements, fares are regulated by route and there are special insurance requirements. Vehicle capacity varies from eight to 24, and the vehicles may be owned or leased by the operator.

**Trolleybus**
A transit mode comprised of electric rubber-tired passenger vehicles, manually steered and operating singly on city streets. Vehicles are propelled by a motor drawing current through overhead wires via trolleys, from a central power source not onboard the vehicle.

**Vanpool**
A transit mode comprised of vans, small buses and other vehicles operating as a ride sharing arrangement, providing transportation to a group of individuals traveling directly between their homes and a regular destination within the same geographical area. The vehicles shall
have a minimum seating capacity of seven persons, including the driver. For inclusion in the NTD, it is considered mass transit service if it is operated by a public entity, or is one in which a public entity owns, purchases, or leases the vehicle(s). Vanpool(s) must also be in compliance with mass transit rules including Americans with Disabilities Act (ADA) provisions, and be open to the public and that availability must be made known. Other forms of public participation to encourage ridesharing arrangements, such as the provision of parking spaces, use of high occupancy vehicle lanes, and coordination or clearing house service, do not qualify as public vanpools.
Appendix IV

Definitions for US geographical entities
Source: US Census Bureau (http://www.census.gov/)

*Census block*: The smallest geographical entity for which the US Census tabulates statistics. Census block boundaries are formed by visible geographical features such as streets, roads or railways, and invisible features such as the boundaries of legal geographical entities. A typical census block is a city block bounded by streets. Census blocks in urban areas tend to have small size; this is not always true in rural areas.

*Census block group*: A collection of block groups and the smallest geographical entity for which the US Census Bureau tabulates sample data (i.e. data that are collected from a sample of rather than the entire population). Census block groups are the next level up in hierarchy after blocks and a sub-division of census tracts.

*Census tract*: The next level up in hierarchy after block groups. Census tracts are defined to have a population of between 1,000 and 8,000 people, with an optimum size of 4,000 people, and to be relatively homogeneous with regard to population characteristics, economic status, and living conditions. Their boundaries largely follow permanent visible features to ensure they can remain stable over many decades.

*Urbanized area*: A densely settled area with a population of at least 50,000. In general, an urbanized area is composed of a geographic core of block groups or blocks that have a population density of at least 1,000 people per square mile, and adjoining block groups and blocks with a density of at least 500 people per square mile.

*Place*: A place is broadly defined as a concentration of population. The specific criteria generally vary by state; they commonly relate to population, population density or the distance from other places. Places can be thought of as the entities commonly recognised as cities, towns, villages or boroughs. Approximately 25,000 places were defined for the 2000 census.

*County*: The primary legal division of every state except Alaska and Louisiana. Louisiana and Alaska are divided in entities roughly equivalent to counties called parishes and boroughs respectively.

*Metropolitan Statistical Area (MSA)*: A county or group of adjoining counties that contains at least one city with a population of 50,000 or over or an urbanized area with a population of at
least 100,000. A metropolitan statistical areas is composed by the county or counties that contain all or the main part of the main city or urbanized area, and all adjoining counties that fulfil certain criteria mainly regarding commuting and population concentration. For instance, commuting to the core counties, population density and the percentage of the population that is urban must exceed some specified levels.

*Zip Code*: A postal code used by the United States Postal Service (USPS) with the purpose of sorting and delivering mail.

*Zip Code Tabulation Area*: A statistical entity created by the US Census as an approximation to the USPS 5-digit Zip Code delivery areas.

Information on the geographical entities used by the US Census can be found at the US Census website (http://www.census.gov/). Alternatively, the Missouri Census Data Centre provides a useful overview of several terms (http://mcdd.missouri.edu/maggot07.shtml).

The below figure illustrates the relationship between several geographical entities. An arrow indicates that one entity is nested in another; the arrow points in the direction of the larger entity.

**FIGURE A.1**: Relations between various US geographical entities
Appendix V

List of urbanized areas included in estimation sample (Chapter 7)

1. Abilene, TX 38. Cape Coral, FL
3. Albany, GA 40. Champaign, IL
5. Albuquerque, NM 42. Charleston-North Charleston, SC
6. Alexandria, LA 43. Charlotte, NC-SC
7. Allentown-Bethlehem, PA-NJ 44. Charlottesville, VA
8. Altoona, PA 45. Chattanooga, TN-GA
9. Amarillo, TX 46. Cheyenne, WY
10. Anchorage, AK 47. Chicago, IL-IN
11. Anderson, IN 48. Chico, CA
12. Ann Arbor, MI 49. Clarksville, TN-KY
13. Antioch, CA 50. Cleveland, OH
14. Appleton, WI 51. College Station-Bryan, TX
15. Asheville, NC 52. Colorado Springs, CO
16. Athens-Clarke County, GA 53. Columbia, MO
17. Atlanta, GA 54. Columbus, OH
18. Austin, TX 55. Corpus Christi, TX
20. Baltimore, MD 57. Dayton, OH
21. Bangor, ME 58. Daytona Beach-Port Orange, FL
22. Baton Rouge, LA 59. Decatur, IL
23. Battle Creek, MI 60. Denver-Aurora, CO
24. Bay City, MI 61. Des Moines, IA
25. Beaumont, TX 62. Detroit, MI
26. Bellingham, WA 63. Duluth, MN-WI
27. Beloit, WI-IL 64. Durham, NC
29. Billings, MT 66. Elkhart, IN-MI
30. Binghamton, NY-PA 67. Erie, PA
31. Birmingham, AL 68. Eugene, OR
32. Bloomington, IN 69. Fairfield, CA
33. Bloomington-Normal, IL 70. Fargo, ND-MN
34. Boise City, ID 71. Fayetteville, NC
35. Boston, MA-NH-RI 72. Flint, MI
36. Buffalo, NY 73. Fort Collins, CO
37. Canton, OH 74. Fort Wayne, IN
| 75. Frederick, MD     | 119. Lodi, CA                  |
| 76. Fresno, CA       | 120. Lompoc, CA                |
| 77. Gainesville, FL  | 121. Longview, WA-OR           |
| 78. Glens Falls, NY  | 122. Lorain-Elyria, OH         |
| 79. Grand Forks, ND-MN | Louisville, KY-IN             |
| 80. Grand Junction, CO | Lubbock, TX                  |
| 81. Grand Rapids, MI | 125. Lynchburg, VA             |
| 82. Great Falls, MT  | 126. Madison, WI               |
| 83. Greeley, CO      | 127. Manchester, NH            |
| 84. Green Bay, WI    | 128. Mansfield, OH             |
| 85. Greensboro, NC   | 129. McAllen, TX               |
| 86. Greenville, SC   | 130. Memphis, TN-MS-AR         |
| 87. Gulfport-Biloxi, MS | Miami, FL                  |
| 88. Hagerstown, MD-WV-PA | Middletown, OH               |
| 89. High Point, NC   | 133. Milwaukee, WI             |
| 90. Honolulu, HI     | 134. Minneapolis-St. Paul, MN  |
| 91. Houma, LA        | 135. Missoula, MT              |
| 92. Houston, TX      | 136. Mobile, AL                |
| 93. Indianapolis, IN | 137. Modesto, CA              |
| 94. Indio-Cathedral City-Palm Springs, CA | 138. Monessen, PA |
| 95. Ithaca, NY       | 139. Monroe, LA                |
| 96. Jackson, MI      | 140. Muncie, IN               |
| 97. Jackson, MS      | 141. Muskegon, MI              |
| 98. Jackson, TN      | 142. Myrtle Beach, SC         |
| 99. Janesville, WI   | 143. Napa, CA                 |
| 100. Johnson City, TN| 144. Nashua, NH-MA            |
| 102. Kalamazoo, MI   | 146. New Bedford, MA          |
| 103. Kennewick-Richland, WA | New Haven, CT |
| 104. Kenosha, WI     | 148. New York-Newark, NY-NJ-CT |
| 105. Knoxville, TN   | 149. Newark, OH               |
| 106. Lafayette, IN   | 150. Oklahoma City, OK        |
| 107. Lafayette, LA   | 151. Olympia-Lacey, WA        |
| 108. Lakeland, FL    | 152. Omaha, NE-IA             |
| 109. Lancaster, PA   | 153. Orlando, FL              |
| 110. Lancaster-Palmdale, CA | Oshkosh, WI          |
| 111. Lansing, MI     | 155. Parkersburg, WV-OH       |
| 112. Laredo, TX      | 156. Pensacola, FL-AL          |
| 113. Las Cruces, NM  | 157. Peoria, IL               |
| 114. Las Vegas, NV   | 158. Phoenix-Mesa, AZ         |
| 115. Leominster-Fitchburg, MA | Pittsburgh, PA   |
| 116. Lewiston, ME    | 160. Pocatello, ID            |
| 117. Lincoln, NE     | 161. Port Arthur, TX          |
| 118. Little Rock, AR | 162. Port Huron, MI           |
| 163. Portland, ME    | 164. Portland, OR-WA          |
165. Providence, RI-MA
166. Pueblo, CO
167. Racine, WI
168. Raleigh, NC
169. Rapid City, SD
170. Reading, PA
171. Redding, CA
172. Reno, NV
173. Richmond, VA
174. Riverside-San Bernardino, CA
175. Roanoke, VA
176. Rochester, MN
177. Rochester, NY
178. Spokane, WA-ID
179. Springfield, IL
180. Springfield, MA-CT
181. Springfield, OH
182. St. Cloud, MN
183. St. Joseph, MO-KS
184. St. Louis, MO-IL
185. State College, PA
186. Stockton, CA
187. Syracuse, NY
188. Tallahassee, FL
189. Tampa-St. Petersburg, FL
190. Terre Haute, IN
191. Toledo, OH-MI
192. Topeka, KS
193. Tucson, AZ
194. Tulsa, OK
195. Tuscaloosa, AL
196. Victorville-Hesperia-Apple Valley, CA
197. Virginia Beach, VA
198. Visalia, CA
199. Waco, TX
200. Washington, DC-VA-MD
201. Waterbury, CT
202. Waterloo, IA
203. Wausau, WI
204. Wheeling, WV-OH
205. Wichita, KS
206. Williamsport, PA
207. Wilmington, NC
208. Winston-Salem, NC
209. Worcester, MA-CT
210. Yakima, WA
211. York, PA
212. Yuba City, CA
213. Yakima, WA
214. Yakima, WA
215. Salem, OR
216. Salt Lake City, UT
217. San Angelo, TX
218. San Antonio, TX
219. San Diego, CA
220. San Francisco-Oakland, CA
221. San Jose, CA
222. San Luis Obispo, CA
223. Santa Barbara, CA
224. Santa Maria, CA
225. Santa Rosa, CA
226. Savannah, GA
227. Scranton, PA
228. Seaside-Monterey-Marina, CA
229. Seattle, WA
230. Sheboygan, WI
231. Shreveport, LA
232. Simi Valley, CA
233. Sioux Falls, SD