Network Structure and Travel

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Dedication

To my parents,
for their unconditional love and support

and

To Kailash,
for his encouragement and motivation

Abstract

Changing the design aspects of urban form is a positive approach to improving transportation. Land use and urban design strategies have been proposed to not only to bring about changes in travel behavior but as a way of providing a better quality of life to the residents. While the research on the relationship between urban form and travel behavior has been pretty extensive, there is a clear gap in the explicit consideration of the underlying transportation network, even though researchers acknowledge its importance. This dissertation aims to continue on the research interest in understanding travel behavior while explicitly accounting for the underlying transportation network structure.

Transportation networks have an underlying structure, defined by the layout, arrangement and the connectivity of the individual network elements, namely the road segments and their intersections. The differences in network structure exist among and between networks. This dissertation argues that travelers perceive and respond to these differences in underlying network structure and complexity, resulting in differences in observed travel patterns. This hypothesized relationship between network structure and travel is analyzed in this dissertation using individual and aggregate level travel and network data from metropolitan regions across the U.S. Various measures of network structure, compiled from existing sources, are used to quantify the structure of street networks. The relation between these quantitative measures and travel is then identified using econometric models.

The underlying principle of this research is that while the transportation network is not the only indicator of urban form and travel, an understanding of the transportation network structure will provide a good framework for understanding and designing cities. The importance of such an understanding is critical due to the long term and irreversible nature of transportation network decisions. The comprehensive analyses presented in this dissertation provide a clear understanding of the role of network design in influencing travel.

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List of Variables

ϕ_{tree}: Treeness (ch. 4, 5, 6, 7)

ρ_e: Completeness (ch. 7)

ρ_{la}: Street density within the activity space polygon (ch. 6)

ρ_{lb}: Street density within the trip buffer (ch. 4, 5)

ρ_{lm}: Street density in the area (ch. 7)

ρ_{pm}: Population density in the area ($persons/km^2$) (ch. 7)

ρ_{va}: Intersection density within the activity space polygon (ch. 6)

ρ_{vb}: Intersection density within the trip buffer (ch. 4, 5)

τ: Ratio of perceived (reported) travel time (min) to measured travel time (min) (ch. 4)

τ_{tti}: Time cost of highway travel, measured as the Travel Time Index (TTI) (ch. 7)

A_a: Area (km^2) of the activity space polygon (ch. 6)

A_b: Area (km^2) of the trip buffer (ch. 4, 5)

A_m: Size of the area (km^2) (ch. 7)

A_p: Area (km^2) of the polygon enclosed by the street network (ch. 4, 5, 6)

A_t: Area (km^2) covered in a defined time contour, t (ch. 7)

Acc_d: Distance based measure of accessibility (ch. 4, 5, 6)

C_m: Average circuity in an area (ch. 7)

C_t: Circuity of the trip between the origin and destination (ch. 4, 5)

D_e: Sum of the euclidean distance (km) between all OD pairs in the subsample (ch. 7)

D_n: Sum of the network distance (km) between all OD pairs in the subsample (ch. 7)

D_{te}: Euclidean distance (km) between the trip origin and destination (ch. 4, 5)

D_{tn}: Network distance (km) between the trip origin and destination (ch. 4, 5)

E: Number of links or street segments in the network (ch. 7)

E_{max}: Maximum number of links or street segments in the network (ch. 7)

$\%F$: Percentage of freeways in the area (ch. 7)

G_o: Overestimating group of travelers (ch. 4)

G_u: Underestimating group of travelers (ch. 4)

k: Hierarchy level (ch. 4, 5)

L_{fm}: Freeway kilometers in the area (ch. 7)

L_l: Length (km) of the local streets in the area (ch. 7)

L_{la}: Length (km) of the limited access roads within the activity space polygon (ch. 6)

L_{lb}: Length (km) of the limited access roads within the trip buffer (ch. 4, 5)

L_{nl}: Length (km) of the non-local streets in the area (ch. 7)

L_P: Length (km) of the trip along the shortest path (ch. 4, 5)

L_{rm}: Roadway kilometers in the area (ch. 7)

L_{sa}: Length (km) of the street network within the activity space polygon (ch. 6)

L_{sb}: Length (km) of the street network within the trip buffer (ch. 4, 5)

L_{sm}: Length (km) of the street network in the area (ch. 7)

L_{ta}: Length (km) of street segments belonging to a branch network within the activity space polygon (ch. 6)

L_{tb}: Length (km) of street segments belonging to a branch network within the trip buffer (ch. 4, 5)

L_{tm}: Length (km) of street segments belonging to a branch network in the area (ch. 7)

N_a: Measures of street network structure within the activity space polygon (ch. 6)

N_b: Measures of street network structure within the trip buffer (ch. 4, 5)

$\overline{N}_{iGo}$: Network measure, i, in the overestimating group, G_o (ch. 4)

$\overline{N}_{iGu}$: Network measure, i, in the underestimating group G_u (ch. 4)

N_m: Measures of street network structure within the area (ch. 7)

O_{30}: Cumulative measure of accessibility in an area (ch. 7)

P_p: Perimeter (km) of the polygon enclosed by the street network (ch. 4, 5, 6)

R_e: Euclidean radius (km) (ch. 7)

S_e: Euclidean speed (km/h) (ch. 7)

S_n: Average network speed (km/h) (ch. 7)

t: Time contour, defined as 30 minutes in this dissertation (ch. 7)

T_m: Measured travel time (min) (ch. 4)

T_r: Perceived (reported) travel time (min) (ch. 4)

U_m: System usage in the area, measured as daily vehicle kilometers traveled per capita (ch. 7)

V: Number of nodes or intersections in the network (ch. 7)

V_a: Number of intersection nodes within the activity space polygon (ch. 6)

V_b: Number of intersection nodes within the trip buffer (ch. 4, 5)

V_{ia}: Number of i-degree nodes within the activity space polygon (ch. 6)

V_{ib}: Number of i-degree nodes within the trip buffer (ch. 4, 5)

X_c: Exogenous control variables (ch. 7)

X_{sd}: Exogenous socio-demographic variables (ch. 4, 5, 6)

y_a: Discontinuity, measured by change in hierarchy (ch. 4, 5)

Y_P: Discontinuity of the trip along the shortest path (ch. 4, 5)

Y'_P: Relative discontinuity along the shortest path (ch. 4, 5)

Chapter 1

Introduction

The world population was at 6.1 billion at the beginning of the 21st century. Within a decade, the population has grown close to 7 billion. This trend of increasing population is expected to continue. The United Nations projects the world population to reach 10.1 billion by the end of this century. The majority of this increase is expected to come from high-fertility countries in Africa, Asia, Oceania and Latin America, where the population is expected to more than triple within this century (United Nations Population Division, 2011).

This population growth comes along with exploding urbanization and a shift in the spatial distribution of population growth. The United Nations statistics show that in 2008, for the first time in history, the percentage of people living in urban areas is higher than the percentage living in rural areas. The urbanization of population is expected to continue and by 2030, the worldwide urban population is expected to touch 5 billion. This growth is expected to be concentrated in Africa and Asia (United Nations Population Fund, 2011). Related to population growth and urbanization is the anticipated increase in vehicle ownership and vehicle stock. The total vehicle stock worldwide is projected to be over 2 billion in 2030, a 2.5 times increase over the 2002 estimates of 800 million. The vehicle ownership in developed Organization for Economic Cooperation and Development (OECD) countries is expected to reach saturation by 2030. On the other hand, in most Asian countries, the vehicle ownership will still only be at 15% to 45% saturation level (Dargay et al., 2007).

The above population, urbanization and vehicle ownership projections have far reaching implications. It is not just the actual magnitude of the growth that causes concern. Rather it is the combination of the magnitude and the small time frame within which this projected growth is expected to occur. The growth expected in the developing world pales in comparison to the growth seen in developed countries over the last half century. The urban growth seen in developing countries has already outstripped the capacity of the cities in providing basic infrastructure services (Cohen, 2006). For example, the rapid economic growth and subsequent urbanization in India has placed a huge burden on the aging transportation infrastructure. An unwanted consequence is endemic traffic congestion, pollution and a growing number of traffic related deaths and injuries (Jha et al., 2003).

From a transportation perspective, investments in transportation infrastructure are needed to mitigate the negative effects of rapid growth and to ensure an efficient and sustainable transportation system that can meet the growing travel demand. A critical component here is an understanding of the role of transportation infrastucture, specifically how the design of transportation network affects travel demand. The transport system, specifically the street system, forms the primary structural element of any city. Marshall (2005) points out that the differences in modern cities such as New York or Los Angeles can be traced back to the transportation system in influencing the growth pattern of each city. Transportation is among the longest lasting artifacts of our civilization (we still use paths first trod hundreds and thousands of years ago). Further the transportation sector is the biggest consumer of energy and one of the biggest sources of greenhouse gas (GHG) emissions. Hence it is critical that network architecture is considered in the design of urban form and sustainable environments, and that transportation network decisions, which are in many ways irreversible, be well understood.

The traditional interest in understanding transportation network structure has been limited to geographers who view the spatial nature of the transportation network as a vital input to the regional development. Transportation planners acknowledge the importance of the transport system in influencing urban form. However most studies looking at the influence of urban form typically consider a representation of the actual transportation network such as the density of the road network, the number of 3-way, 4-way or cul-de-sac intersections, lineal length of street network etc. While these descriptive measures of roadway network structure are important, they don't consider the arrangement and connectivity of nodes and links in the network and their impact on the performance of the transportation system. An in-depth analysis of the factors affecting the interaction of urban form and travel behavior must explicitly consider the transportation network in terms of its underlying structure, the actual layout of streets and routes.

This dissertation aims to continue on the research interest in understanding travel behavior (see e.g. (Krizek, 2003, Crane, 2000, Frank and Pivo, 1994, Cervero and Radisch, 1996, Kockelman, 1997, Boarnet and Crane, 2001, Kitamura et al., 1997, McNally and Kulkarni, 1997)) while explicitly accounting for the underlying transportation network structure. Network architecture is one of the slowest changing aspects of urban infrastructure and a network, once designed and implemented, cannot be easily altered. The underlying principle of this research is that while the transportation network is not the only indicator of urban form and travel, an understanding of the transportation network structure will contribute to our understanding of how cities perform, and thus how they might be designed. The results from this dissertation are expected to throw light on how a transportation network influences travel behavior and how changes in network design can be used to bring about desired changes in travel behavior.

1.1 Theoretical Framework

The simple traditional framework to analyze the relation between urban form and travel, proposed by Frank and Pivo (1994), is given below in figure 1.1. Urban form factors typically refer to the density, land use mix and other built environment attributes; non-urban factors refers to economic and demographic characteristics, individual preferences etc. The transportation network is typically considered under the umbrella of urban form factors.

Researchers have used different frameworks to analyze the importance of urban form and the built environment. For example, Pouyanne (2005) suggests modifying the traditional concept proposed by Frank and Pivo (1994) to account for the interaction between the urban form and economic and demographic variables. Boarnet and Crane (2000) used the theory of consumer demand to analyze travel behavior. In their framework, urban form influences travel by affecting the cost of travel. For example, trip distance

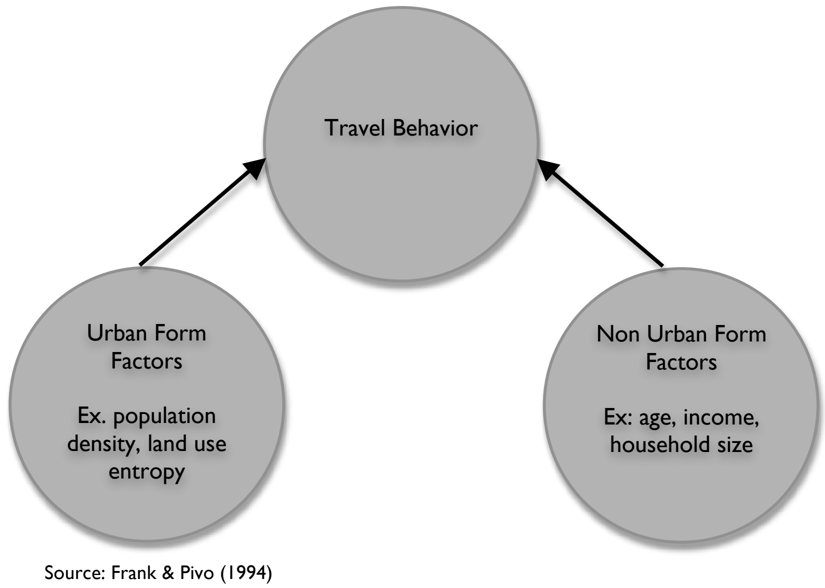


Figure 1.1: Traditional Framework: Relationship between travel behavior and the factors that affect it

which is a measure of travel cost changes with land use patterns. More compact developments bring trip origins and destinations closer, thus reducing travel distance. This relationship is non-linear. Land use patterns affect travel not only by reducing the cost of travel for a specific mode but also by affecting the relative psychological cost of travel between modes. The traditional framework has its limitations and Chapter 2 highlights some of the issues identified by researchers.

This dissertation argues for the explicit inclusion of the structure of the transportation network, as given in figure 1.2. The framework employed in this dissertation relates network structure to travel behavior, using urban and non-urban form factors as controls.

Road networks have an underlying structure. This structure is defined by the layout, arrangement and the connectivity of the individual network elements, the road segments and their intersections. The differences in network structure exist across networks: for

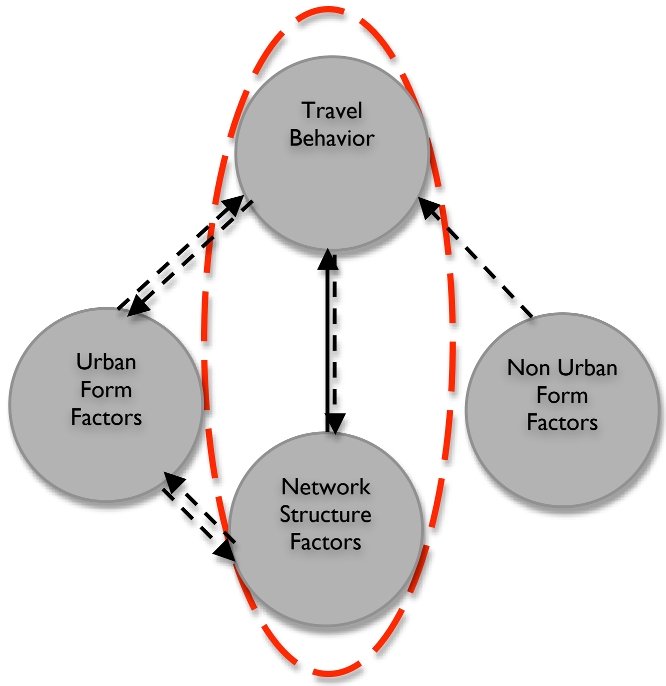
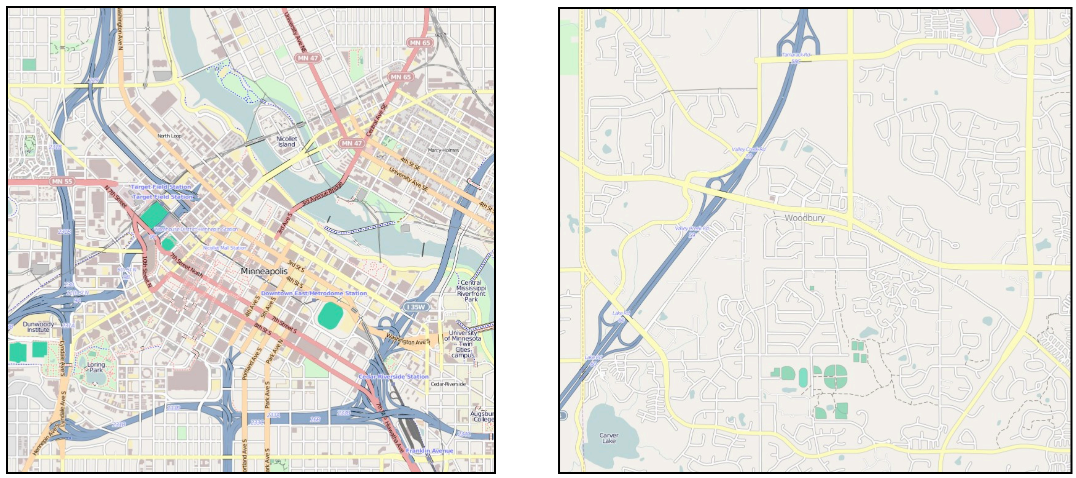


Figure 1.2: Modified Framework: Relationship between travel behavior and the factors that affect it, including the transportation network. The dotted lines indicate identified relationships that are not considered in this dissertation.

example, the street network of Chicago differs from the street network of Las Vegas. Chicago is an older city that developed around the traditional transit lines that served the city. Las Vegas on the other hand is a newer city whose spatial pattern is based on auto supported rapid urbanization. Las Vegas and Chicago both have arterial grids, but at the local street level, Las Vegas's network is much less regular, while Chicago remains more orderly. Differences in network structure exist within metropolitan networks too. For example, the downtown areas of Minneapolis and St. Paul have a typical, though imperfect grid-like structure that contrasts with the meandering tree like networks that exist in the Twin Cities suburbs such as Woodbury, as seen in figure 1.3.

Travelers perceive and respond to these differences in underlying network structure and complexity. The argument here is that network design influences traveler perceptions, more specifically the perceptions of travel distance and time. This perception of travel distance and time in turn influences the actual travel by affecting choice of



Downtown Minneapolis Woodbury

Figure 1.3: Network Comparison - Twin Cities
Source: Open Street Maps, `http://www.openstreetmap.org`

destination, mode, route, and whether to engage in activities.

Consider this theory within the framework of the travel time budget (TTB), which refers to the stability in travel time expenditures by travelers. A detailed review of the research on TTB conducted by (Mokhtarian and Chen, 2004) shows mixed results on the existence of TTB. The authors differentiate between a "budget" and an "expenditure" where *"expenditure" simply refers to the amount of quantitative resources spent on consuming a good or service or performing an activity (including travel); it does not imply stability. On the other hand, the word "budget" implies stability, referring to an allocation of time, money or generalized resources to travel which would not be influenced by policy, trends or costs.* The authors conclude that while travel time expenditures are not constant except at aggregate levels, there do exist patterns in individual travel time expenditures that can be explained by the individual and household characteristics, activity characteristics and the spatial structure of the residential locations. Levinson and Wu (2005) discuss a similar travel time tolerance rather than a budget for commuters.

The goal in this dissertation is not to argue about the existence of TTB. Rather the TTB concept is used to suggest that network design affects travelers' perception of travel time and distance. Travelers respond to this perceived travel attributes by altering actual travel to remain within their travel time tolerance. The actual travel decisions of individual travelers in turn affects the transportation system performance.

The proposed framework can also be argued using an economic perspective. The demand for a certain good is influenced by the cost. When the cost increases, the demand decreases, everything else being equal. Here the good demanded is travel and the cost is travel time or distance. Network design affects the perceived cost of travel. Hence higher the perceived cost of travel, lower the actual travel. The actual travel in turn affects system performance.

Consider figure 1.4. The figure shows the proposed modeling framework along with the hypothesized relationship between network structure and travel. Transportation networks are complex and comprise many aspects. Some aspects of the network structure affect the distance between a trip origin and destination while some aspects affect the complexity in the network. Other influences identified include efficiency, speed etc. The list goes on. The individual and combined effects of network structure are not always straightforward.

Link 1 in figure 1.4 shows that network structure factors affects perception, specifically how travelers perceive travel distance and time in the network. For example, consider the network comparisons provided in figure 1.3. A traveler who sees the grid structure in downtown Minneapolis perceives the distance to differ from the tree structure seen in Woodbury, even if the actual mileage is the same in both networks.

Link 2 hypothesizes that an individual's perception of travel affects actual travel. Existing research has shown that travel decisions are based on perceived attribute values. For example, Quentin and Hong (2005) point out that traveler's mode choice decisions are based on perceived attribute values of the available modes. A network structure that increases the perceived travel distance and time (or the onerousness of that distance and time) (in brief - weighted travel time) will lead to a reduction in actual travel. Similarly a network structure that decreases the perceived travel time and distance will lead to an increase in actual travel. In brief a network that appears more complex and thus has a higher weighted travel time will result in a lower actual travel time as travelers compensate.

Link 3 shows the hypothesized relation between network structure and actual travel. Link 4 shows that the system performance is a function of individual traveler decisions. For example, consider congestion which is a measure of system performance. An increase in actual travel will increase the congestion on the network. Link 5 shows the feedback relationship between system performance and an individual's perception of travel. Again using congestion as an example, a traveler traveling on a highly congested network (stop and go traffic conditions) will perceive the travel time to be higher compared to an uncongested network.

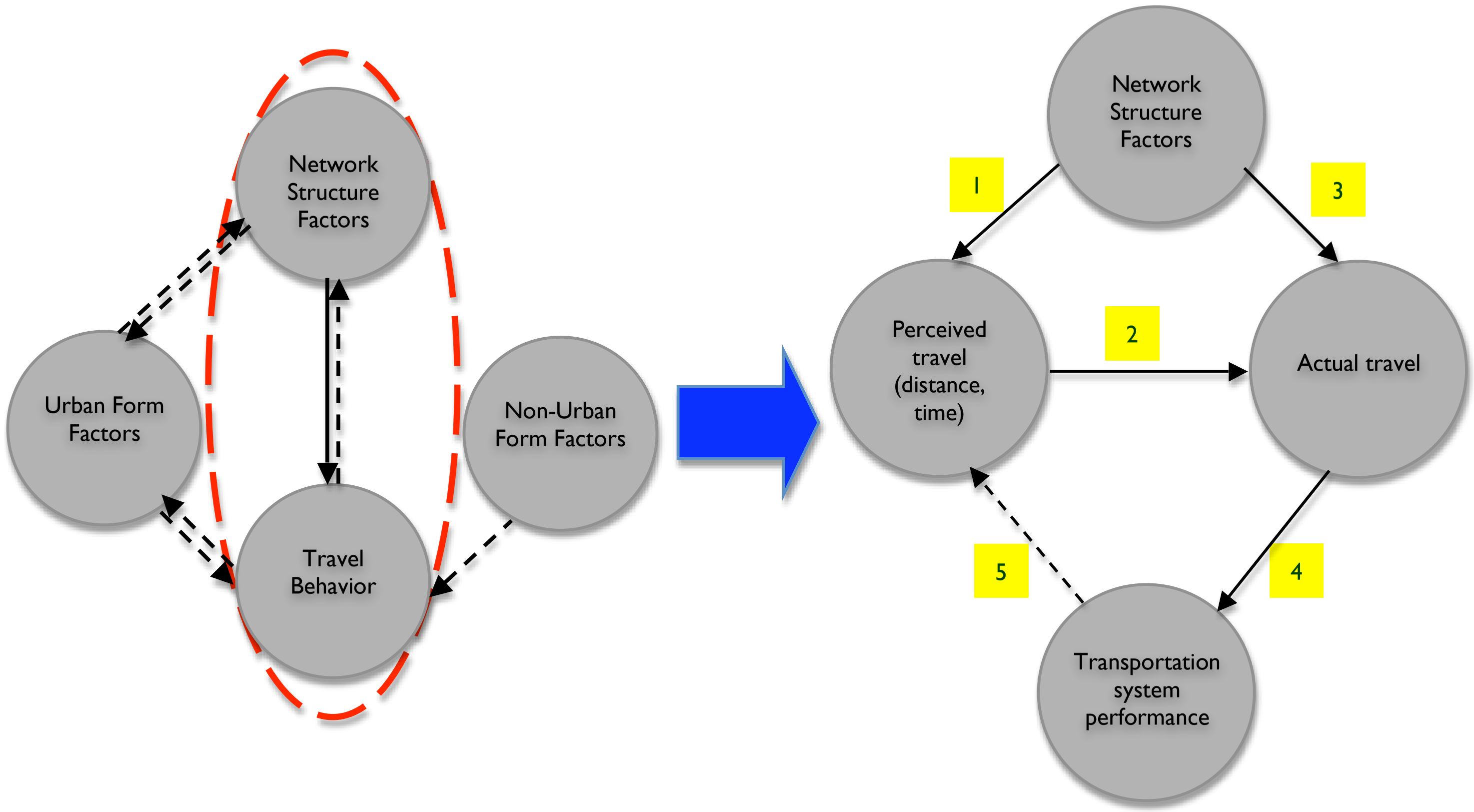


Figure 1.4: Hypothesized relationship between network structure and travel. The dotted lines indicate identified relationships that are not considered in this dissertation.

This dissertation aims to disentangle the aspects of the network design that influence distance and time perceptions. The focus is on quantifying the structure of street networks and relating it to observed travel at the individual, household and metropolitan level. As mentioned previously, the urban and non-urban factors are control variables. The chapters in this dissertation are organized to test the various hypothesized relationships shown in figure 1.4 and are organized as follows:

- Chapter 2 presents a comprehensive review of literature on urban form and travel behavior.
- Chapter 3 describes the methodology for the estimation of street network measures.
- Chapter 4 identifies the link between estimated measures of street network measure and an individual's perception of travel time. This chapter tests the relation identified by link 1 in figure 1.4.
- Chapter 5 relates street network structure to actual travel, specifically looking at trip distance and the total distance traveled by an individual on a specified travel day.
- Chapter 6 uses activity space polygons to relate street network structure to household travel.

  Chapters 5 and 6 focus on the relationship highlighted by links 1, 2 and 3 in figure 1.4.
- Chapter 7 analyzes metropolitan street network structure and transportation system performance. The analyses presented in this chapter focus on the relationship identified by links 3 and 4 in figure 1.4.
- Chapter 8 presents a final discussion of the analyses and concludes with key findings from the dissertation.

Chapter 2

Literature Review

2.1 Research Synthesis

The relationship between accessibility, urban form, built environment and travel behavior has had a rich history over the past decade and this chapter provides a brief summary of the methodologies used by various researchers to analyze these complex relationships.

2.1.1 Accessibility, urban form and travel behavior

One of earliest analyses of the relationship between accessibility and land use was conducted by Hansen (1959) as part of a study to develop a residential land use model. Horton and Reynolds (1971) provided a geographer's perspective in their evaluation of the effects of urban spatial structure and accessibility on individual travel. Though there have been substantial literature on the concept of accessibility, land use and urban form measures, there have been difficulties in developing measures that translate the concept into quantitative performance measures. (Handy and Niemeier, 1997).

An analysis of the contribution of accessibility, measuring the relative location of the home and work location, in predicting commute duration was conducted by Levinson (1998). The results indicated that the household in job-rich areas and firms in housing-rich areas have shorter commutes indicating that stability in commute duration can be maintained despite rising congestion, increasing trip lengths, suburbanization and other factors, by maintaining accessibility to jobs and housing locations.

Hanson and Schwab (1987) used the Household Travel Survey data from Uppsala in Sweden to explore the relationship between individual accessibility and travel patterns. The results indicated a weak relationship between travel and accessibility with accessibility having a greater impact on mode choice and travel distance than on trip frequency. A census tract level analysis was conducted by Frank and Pivo (1994) using household travel survey data from the longitudinal cohort Puget Sound Transportation Panel study conducted between 1989 and 1994. The results indicated a significant relationship between urban form and mode choice while controlling for the effecs of non-urban form variables.

Another analysis of the Seattle area explored the temporal relationship between accessibility and land use through an empirical analysis of changing land use patterns over a period of 30 years (Stanilov, 2003). While the results point to an interesting relation between land use and accessibility, the authors are clear to point out that the results can not be used to make inferences on the causality between accessibility and land use.

The substitution effect of walk trips was analyzed by Cervero and Radisch (1996) as a part of a study comparing two distinct neighborhoods, the transit-oriented mixed-use community of Rockridge and the auto-oriented suburban community of Lafayette, in the San Francisco Bay area using a matched-pair approach. Residents in the transit-oriented community of Rockridge showed a greater share of walking, biking and transit and a lower share of autos for non-work trips compared to Lafayette residents. The neighborhood design didn't play as strong a role in influencing mode choice for commuting trips indicating that neighborhood characteristics had more of a local effect rather than a regional effect. A previous study conducted using a matched pair analysis of transit and auto-oriented neighborhoods in San Francisco and Los Angeles indicated that differences in neighborhood design affect the commuting behavior of residents but the form of the macro-region seemed to have greater influence compared to the micro-level neighborhood design (Cervero and Gorham, 1995).

An analysis of the relationship between the three principal dimensions of the build environment, namely, density, diversity and design, and travel behavior measured by the trip rates and mode choice of residents was conducted by Cervero and Kockelman

(1997). The data from the 1990 San Francisco Bay Area travel survey were supplemented with other data sources to examine this relationship. The results confirmed the existence of a relationship between the different dimensions of the built environment and travel demand though the elasticities indicate a modest though not inconsequential relationship. The authors conclude that the results confirm the thinking of new urbanists that compact, mixed-use, pedestrian-friendly design help reduce vehicle trips and promote the usage of non-motorized travel.

Srinivasan (2001, 2002) analyzed the influence of local neighborhood characteristics on travel behavior using geographic information systems (GIS) to quantify the spatial structure of the neighborhoods and transportation corridors in metropolitan areas. The results indicate that the spatial characteristics of neighborhoods play a significant role in predicting travel behavior and can be a useful first step in linking land-use and transportation planning. Similar spatial analysis conducted by Meurs and Haaijer (2001), Naess (2006) in Europe indicated modest impacts of urban spatial structure on travel patterns in the region.

Thill and Kim (2005) revisited the debate on spatial elasticity of travel demand by analyzing the relationship between geographical accessibility and trip generation using travel demand data at the individual level, road network data and zone-level industrial and socio-economic data from Minneapolis-St.Paul. The results indicate that spatial accessibility between the trip ends play an influencing role on trip production and trip attractions at both the aggregate zonal level and disaggregate individual level. The authors concluded that travel demand responds to accessibility which in turn is influenced by trip type.

At the aggregate level, Bento et al. (2003) analyzed the influence of urban form and public transit supply on travel demand using national level travel survey data from 114 urbanized areas in the U.S. Giuliano and Narayan (2003) provide an international perspective by comparing travel diary data from the U.S and Great Britain. The results indicated that the differences in mobility patterns could be explained by the differences in both urban form and household income. Levine et al. (2009) related transportation accessibility outcomes to urban form using data from twenty four metropolitan areas in the U.S.

Muñiz and Galindo (2005) explored the role of urban form in influencing mobility and its ecological footprint, using commute data from 163 municipalities in Barcelona. Other metropolitan level comparisons include the role of monocentric and polycentric urban structures in influencing travel and its associated effects (ex. environmental costs, social costs etc) (Schwanen et al., 2001, Veneri, 2009).

Studies arguing against the influence of urban form on travel behavior

The studies listed above have typically identified either a strong or a moderate influence of urban form and associated accessibility on travel behavior. In some cases the results have been mixed and vary with travel purpose and the mode of travel. However the relation between urban form and travel has been a highly debatable topic.

An important contribution to the debate was made by Newman and Kenworthy (1989) who argued that the variation in transportation use between the U.S and other countries mainly reflects differences in land use patterns and transportation systems. This argument was countered by Gordon and Richardson (1989) and Gomez-Ibanez (1991) who criticized the theoretical and methodological foundations used in the study and the proposed policy recommendations. This debate has continued ever since (van de Coevering and Schwanen, 2006). The studies listed below argue against the existence of a relationship between urban form and travel behavior and conclude that the use of urban design to bring about changes in travel patterns isn't likely to be effective.

Boarnet and Sarmiento (1998) examined the relationship between land use and travel behavior using travel diary data from Southern California. The results indicated a pretty weak influence of land use on non-work travel but confirmed that the land use variables are endogenous to residential location decisions. Similarly the analysis conducted by Ewing et al. (1994) identified a weak relationship between neighborhood design and travel behavior.

Crane and Crepeau (1998) analyzed the influence of neighborhood design on travel using non-work trip data from the 1986 San Diego household travel survey along with GIS data on neighborhood characteristics. The results indicated that land use plays very little role in explaining travel behavior. Further the neighborhood street patterns do not play a significant role on car or pedestrian travel after controlling for the individual, household and neighborhood land use characteristics.

Boarnet and Crane (2001) expanded on the relationship between land use and travel behavior by incorporating the urban form measures into a transparent behavioral framework using travel diary data sets from Orange County/Los Angeles (conducted in 1993) and San Diego (conducted in 1986). The results indicated that urban form influenced travel behavior (if the influence exists) by altering the price of travel. The results further indicated a complex relationship between urban form and travel behavior which was sensitive to the geographical scale, data type and alternative behavioral and statistical assumptions.

An explicit consideration of the interaction between land use and the transportation system and the influence of this interaction on travel behavior was conducted by McNally and Kulkarni (1997) using cluster analysis. The results indicate that a weak link between the land use - transportation system and travel behavior with socio-economic variables playing a greater role in explaining travel behavior differences between neighborhoods compared to the neighborhood classification themes.

Kitamura et al. (2001) used accessibility indices to analyze the effect of accessibility on long-term and short-term travel behavior using data from Kyoto-Osaka-Kobe metropolitan area of Japan and the southern California coast. The study results indicate that, given automobile ownership and usage, accessibility doesn't play a causal role in influencing travel patterns. Accessibility does not affect automobile ownership or usage in a motorized metropolis and time availability rather than accessibility to opportunities affects engagement in activities. The analysis conducted by Stead (2001) using national and local travel survey data in Britain provided similar results, with socioeconomic characteristics rather than land use characteristics, influencing the travel patterns.

Residential self-selection

Research on the influence of the built environment or urban form on travel behavior have typically treated the residential location as an exogenous factor and travel behavior is assumed to be affected by the characteristics of the built environment. A recent study by Pinjari et al. (2007) attempts to account for the residential self-selection process wherein households locate in certain neighborhoods based on their attitudes, values, lifestyle and travel preferences and other unobservable factors, using a joint modeling approach. The modeling framework models the residential location choice and the commute mode choice simultaneously using individual and household data for Alameda County from the activity-based household travel survey conducted in the San Francisco Bay Area.

The results support the endogenous treatment of residential location and indicate that the household self-selection process depends on variables such as income, household size, race, auto and bicycle ownership. Similar approaches accounting for residential self-selection have been proposed by other researchers (Cervero and Duncan, 2002, Handy et al., 2005, Schwanen and Mokhtarian, 2005, Zhang, 2006, Cao et al., 2007).

A thorough review of the literature on urban form and travel patterns over twenty years has been compiled by Stead (2001). Krizek (2003) and Crane (2000) provide a similar review of the research highlighting the differences in modeling methodologies. A review of accessibility measures was conducted by Baradaran and Ramjerdi (2001).

A brief summary of the measures typically used by researchers to quantify accessibility, land use and urban form is provided in Table A.1 in Appendix A. None of the modeling methodologies used in travel behavior research however have explicitly considered the role of network design and its importance in influencing travel. The next section provides a summary of research on quantifying and characterizing transportation network structure.

2.1.2 Understanding network structure/topology

The traditional interest in understanding transportation network structure has been limited to geographers who view the spatial nature of the transportation network as a vital input to the regional development (Taaffe et al., 1996, Rodrigue et al., 2006, Haggett and Chorley, 1969). In recent years, there has been considerable interest among physicists to understand and analyze the spatial patterns of networks that connects points in geographic space, transportation networks being one of them (Gastner and Newman, 2006).

Kissling (1969) refers to network structure as a measure of the layout of the network and characteristics of individual elements in his analysis of the influence of network structure on linkage importance and nodal accessibility levels in the Nova Scotia region. Xie and Levinson (2011) provides a similar definition of network topology as the arrangement and connectivity of the network. Gauthier (1966) classified measures of network structure into two broad levels, namely, an *aggregate level*, referring to measures of overall network structure and a *disaggregate level* referring to measures of relationships between the individual elements in the network. A proper analysis of network structure thus provides an overall understanding of the entire network in addition to ascertaining the contribution of individual elements to network performance.

Garrison (1960) used measures of graph theory to measure the connectivity of the Interstate Highway system by analyzing the system as a whole and understanding the individual components that make up the system. One of the earliest studies on utilizing network measures to understand metropolitan settlement patterns was conducted by Borchert (1961). In this study, the number of road and street intersections per square mile in a 1,300 square mile (3,400 km^2) area representing Minneapolis-St. Paul were used as quantitative measures to analyze settlement patterns. The results indicated a close relationship between the road intersection density and other indices of settlement patterns such as street mileage, parcel density and residential density. The intersection count proved to be a useful index to understand current settlement patterns and to measure the changes in settlement patterns.

Kansky (1963) developed a wide range of network measures using mathematical logic and graph theory to quantify the spatial structure of transportation networks (railways and roadways) in his dissertation on the relationship between the structure of transportation networks and regional economic characteristics. The results confirmed the spatial and temporal association between the degree of transportation network structure and degree of regional economic development, after controlling for independent variables such as technological scale, size, shape and relief. Kansky's research was based on a study conducted by Garrison and Marble (1961) analyzing the relationship between the structure of transportation networks and characteristics of the area in which the networks are located.

In a study evaluating pedestrian environments, Hess (1997) used three quantitative measures of street network connectivity to explain the differences in pedestrian volumes between two neighborhoods, namely, Wallingford and Crossroads, in the Seattle area. Hess's study was part of a larger research project looking at the influence of site design in encouraging walking using pedestrian volume data from twelve neighborhoods around commercial centers in central Puget Sound region (Moudon et al., 1997, Hess et al., 1999). Dill (2004) presented results from a research project evaluating various measures of network connectivity for the purposes of increasing walking and biking.

Levinson and El-Geneidy (2009) use circuity as a tool to better understand the relationship between residential location choice relative to work. The analysis used data from twenty metropolitan regions in the US supplemented by detailed analysis of Minneapolis-St. Paul, Minnesota and Portland, Oregon. The results indicated a lower circuity for actual origins and destinations compared to random origins and destinations. This suggests that workers tend to select commutes with lower circuity applying their intelligence to locational decisions. The circuity measure has been used previously by many researchers such as Ballou et al. (2002) who estimated the circuity factor at a national level using road networks from over twenty six countries.

Recent advances in GIS capabilities and related spatial analysis software has resulted in a revival of the interest in understanding the topological properties of complex networks. Yang et al. (2009) recently developed a method to identify and classify the spatial (grid-like) patterns in road networks with complicated junctions. Other advances include the use of fractal geometry and complex network theory to understand the patterns, structure and evolution of transportation networks (Yan and Wang, 2009, Jiang and Claramunt, 2004, Kim et al., 2003, Lu and Tang, 2004). Li and Shum (2001) developed accessibility measures based on graph theory to analyze the impacts of the National Trunk Highway System (NTHS) program in China. Barabasi and Bonabeau (2003) focused on scale-free networks in an attempt to understand the underlying principle governing extremely complex systems such as the world wide web.

In other applications, Jiang et al. (2009) related human mobility patterns to the structure of the underlying street network. Marshall and Garrick (2010) used a comprehensive database of 130,000 crashes over 9 years in 24 medium-sized California cities to related road safety to street network characteristics of connectivity and density at the census block group level. Jenelius (2009) studied the structural factors that determine geographical variations in road network vulnerability. Using the Swedish road network, the authors showed that the difference in long-term vulnerability among regions can be traced to the fundamental properties of road network structure and travel patterns. Similar research conducted by Yang et al. (2009) proposed an index to assess the vulnerability of a road network from the view point of the underlying topological structure.

Xie and Levinson (2007) investigated the potential application of proposed network measures in understanding and quantifying the structural attributes of complicated road networks. Three complementary measures of network structure, namely, heterogeneity, connection patterns and continuity, were developed and tested on idealized test networks. The proposed network measures were later applied to the Swiss road networks to trace the changes in network characteristics over time (Erath et al., 2009).

In a study on transit network topology, Derrible and Kennedy (2009, 2010) use graph theory to characterize the network structure of 33 metro systems around the world. The analysis was then extended to study the relationship between network measures and transit ridership using data on a subsample of 19 subway systems. The results of the regression model show a strong relationship between the network measures and ridership indicating the importance of network design in attracting people to transit systems.

A summary of the approaches used to characterize the structure of the transportation network is provided in Table A.2 in Appendix A.

2.2 Summary

This chapter summarizes the different methodologies that have been used to understand how the urban form, built environment and associated accessibility influence travel. This dissertation continues on this research interest by explicitly considering the underlying transportation network structure. To that effect, this dissertation uses the network measures proposed by Xie and Levinson (2007), along with additional measures to quantify and characterize the underlying street network. These measures are then used to understand individual, household and metropolitan level travel. The next chapter elaborates on the methodology used to estimate various measures of street network structure.

Chapter 3

Network Measures

3.1 Introduction

This chapter summarizes the measures estimated to quantify street network structure. The measures developed to capture different aspects of network structure are broadly classified into four categories:

- Hierarchy - refers to the differentiation that exists in street networks.
- Topology - identifies the connectivity and the connection patterns that exists in street networks.
- Morphology - describes the regularity of street networks, their shape and fragmentation.
- Scale - captures the intensity of the street network within a specified area.

3.2 Street network data

The street networks used in the estimation of network measures, were extracted from the Census TIGER/line files. The Topologically Integrated Geographic Encoding and Referencing (TIGER) files, developed and maintained by the U.S Census Bureau, provide information on various features such as roads, railroads, rivers, as wells as legal and statistical geographic areas (U.S. Census Bureau, 2008). The extracted networks for the metropolitan areas were cleaned to include just the road features based on the Feature Class Codes (FCC) for the line segments provided in the Census TIGER/Line files. The FCC were also used to stratify the street segments into three main categories: interstates, arterials, and local streets.

The complete street network used in the estimation of network measures consists of all three categories. For analysis purposes, a subset network consisting of just the interstates and arterials was also used in the estimation of specific network measures. This network differentiation better captures the variations in network structure at different roadway hierarchies.

The measures of network structure were typically estimated at three levels.

- Level 1 - Individual trip level

  The measures of network structure were estimated along the route between a trip origin and destination. A buffer was created around the route to estimate measures of network structure. The size of the buffer varied based on the network considered with a 1-km buffer used with the complete street network of interstates, arterials and local streets and a 2-km buffer used with the subset network of arterials and interstates. This network differentiation better captures the variations in network structure at different roadway hierarchies. The buffer size, while admittedly arbitrary, provides a geographical definition that is required for the estimation of areal network measures. These measures are used in analysis of individual travel in two study areas, namely, Minneapolis-Saint Paul and South Florida (Fort Lauderdale and Miami). The results are presented in Chapters 4 and 5.

- Level 2 - Household level

  Here, the measures of network structure were estimated within a polygon that linked the destinations reached by the household on a given travel day. This polygon is called the activity space polygon and the measures estimated within the polygon were used to analyze household travel in Minneapolis-Saint Paul and South Florida (Fort Lauderdale and Miami). The related analyses are presented in Chapter 6.

- Level 3 - Metropolitan level

  The measures of network structure were estimated for the entire metropolitan area. The dataset includes fifty metropolitan areas across the U.S and the results are presented in Chapter 7.

  Figure 3.1 illustrates the three level of analyses conducted in this dissertation.

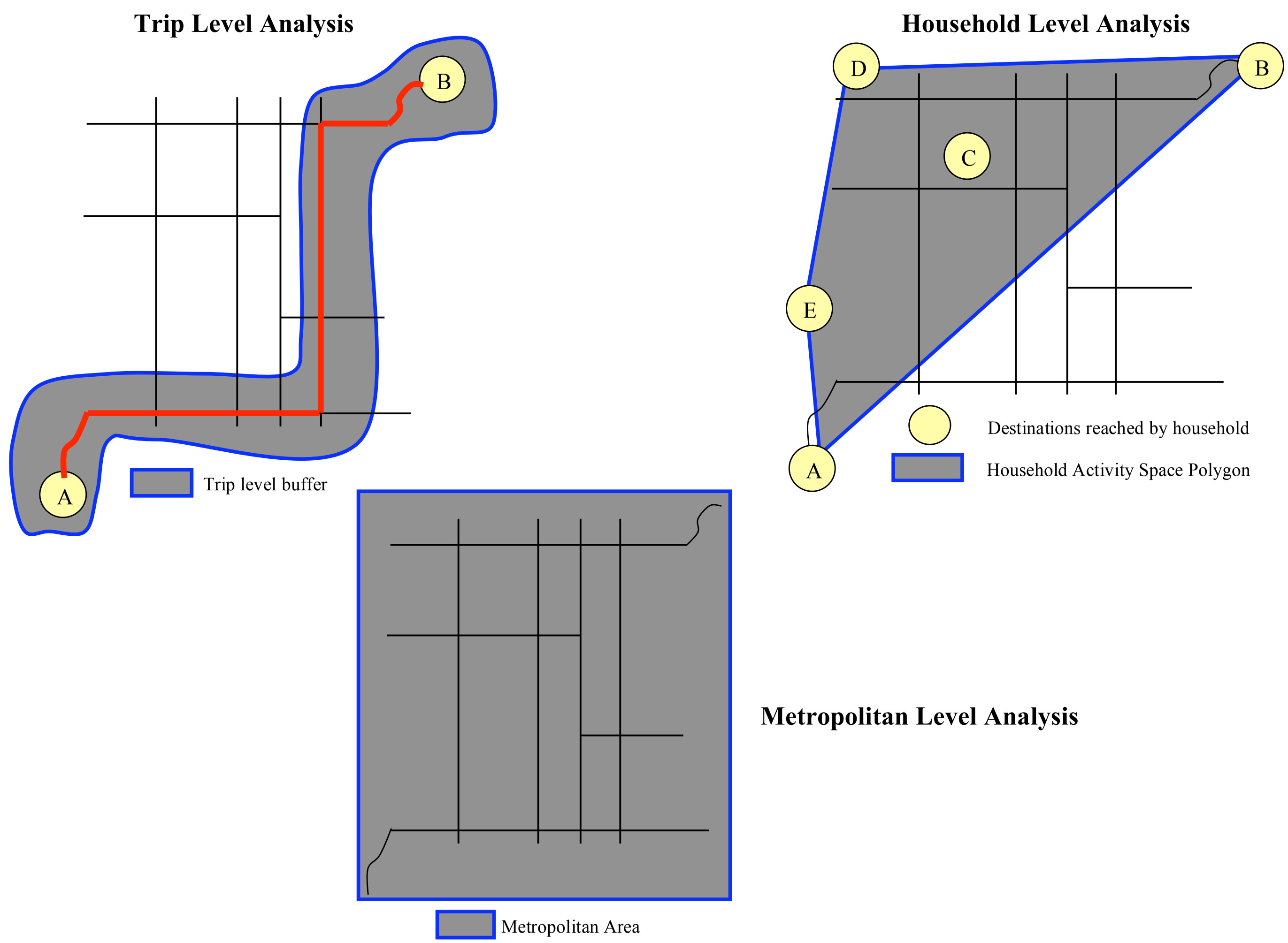


Figure 3.1: Levels of analysis

Not all measures were estimated at all three levels due to data limitations and suitability for the specific analyses. Table 3.1 summarizes the measures and the levels at which they were estimated.

Table 3.1: Estimation of Network Measures

		Level		
Measure	**Category**	**Trip**	**Household**	**Metropolitan area**
Relative discontinuity	Hierarchy	✓		
Proportion of limited access roads	Hierarchy	✓	✓	✓
Treeness	Topology	✓	✓	✓
Completeness	Topology			✓
Proportion of nodal degrees	Topology	✓	✓	
Circuity	Topology	✓		✓
Perimeter/Area (P2A)	Morphology	✓	✓	
Street density	Scale	✓	✓	✓
Intersection density	Scale	✓	✓	

3.2.1 Hierarchy

Discontinuity and relative discontinuity

The discontinuity measure quantifies the number of changes in street hierarchy experienced along the fastest path between the trip origin and destination. The relative discontinuity measure is discontinuity divided by the trip length (Xie and Levinson, 2007). This measure is estimated at the individual trip level alone. As illustrated in figure 3.2, consider a traveler moving from origin A to destination B along the highlighted shortest path, P. The shortest path consist of street segments of different hierarchies. In this example, street hierarchy is identified based on segment speed. When the traveler moves from an upstream link with hierarchy k_1 to a downstream link with hierarchy k_2, the discontinuity is measured as:

$$y_a = |k_1 - k_2| \tag{3.1}$$

The discontinuity of the trip along the shortest path, P, is estimated as:

$$Y_P = \sum_{a \epsilon P} y_a \tag{3.2}$$

The relative discontinuity is then estimated as:

$$Y'_P = Y_P / l_P \tag{3.3}$$

where

Y_P = Discontinuity of the trip along the shortest path,

l_P = Length (km) of trip along the shortest path

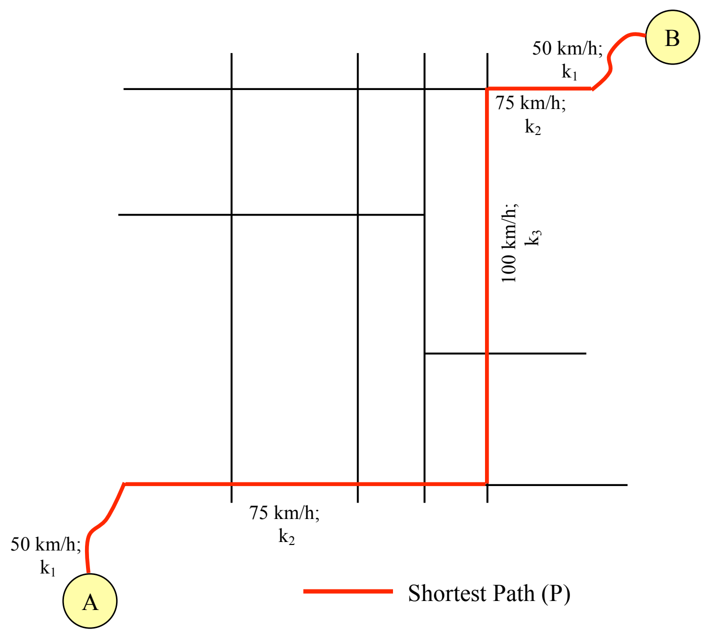


Figure 3.2: Illustration of trip discontinuity

Proportion of limited access roads

This measure captures the presence of higher hierarchy links such as interstate highways. At the individual trip level, this measure is estimated as:

$$\text{Proportion of limited access roads} = \frac{L_{lb}}{L_{sb}} \tag{3.4}$$

where,

L_{lb} = Length (km) of the limited access roads within the trip buffer,

L_{sb} = Length (km) of the street network within the trip buffer.

At the household level, this measure is estimated as:

$$\text{Proportion of limited access roads} = \frac{L_{la}}{L_{sa}} \tag{3.5}$$

where,

L_{la} = Length (km) of the limited access roads within the activity space polygon,

L_{sa} = Length (km) of the street network within the activity space polygon.

The limited access roadways in the street network were identified based on the FCC codes provided in the Census TIGER/line files. These roads are designed for higher speeds and hence facilitate longer travel.

At the metropolitan level, the measure is estimated in a slightly differently manner by focusing specifically on the freeways in the area. The percentage of freeways is estimated as:

$$\%\text{F} = \frac{L_{fm}}{L_{rm}} * 100 \tag{3.6}$$

where,

L_{fm} = Freeway kilometers in the area,

L_{rm} = Roadway kilometers in the area.

3.2.2 Topology

Treeness

This measure is based on the two basic structures of a planar transportation network: circuit and tree (Haggett and Chorley, 1969). A circuit is defined as a closed path, with no less than three links, that begins and ends at the same node. A tree is defined as a set of connected lines that do not form a complete circuit. A regional network distinguished by closed circuits is therefore called a circuit network while a network defined by a tree shaped structure is called a branching network (Xie and Levinson, 2007). Figure 3.6 illustrates the differences between a circuit and tree using sample networks. Both sample networks in figure 3.6 have the same number of nodes but the number of links and the connection patterns of the links result in a circuit or a tree network.

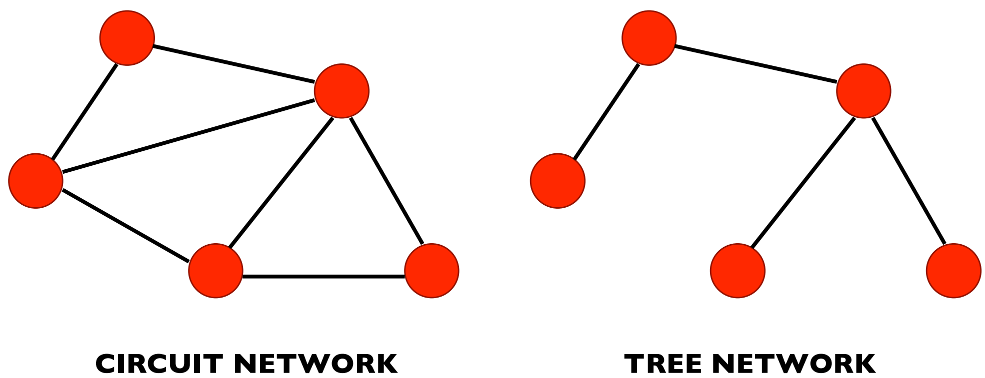


Figure 3.3: Sample circuit and tree networks

Open source software[1] was used to classify each segment in the street network as belonging to a tree network or a circuit network.

At the individual trip level, the treeness is estimated as:

$$\phi_{tree} = \frac{L_{tb}}{L_{sb}} \tag{3.7}$$

where:

L_{tb} = Length (km) of street segments belonging to a branch network within the buffer,

L_{sb} = Length (km) of the street network within the buffer.

At the household level, the treeness is estimated as:

$$\phi_{tree} = \frac{L_{ta}}{L_{sa}} \tag{3.8}$$

where:

[1] Developed by Feng Xie, Metropolitan Washington Council of Governments (MWCOG); Code can be downloaded from `http://nexus.umn.edu/Software/IdentifyingNetworkTopologies.zip`

L_{ta} = Length (km) of street segments belonging to a branch network within the activity space polygon,

L_{sa} = Length (km) of the street network within the activity space polygon

For analysis purposes, the treeness is estimated for only a subnetwork consisting of arterials and interstates at the individual and household level.

At the metropolitan level, the treeness is estimated for the complete street network as:

$$\phi_{tree} = \frac{L_{tm}}{L_{sm}} \tag{3.9}$$

where,

L_{tm} = Length (km) of street segments belonging to a branch network in the area,

L_{sm} = Length (km) of the street network in the area (km).

The treeness measures captures the differences in topology and connection patterns that exist among real-world street networks. Treeness can also be considered to be a measure of the (in)efficiency of network organization.

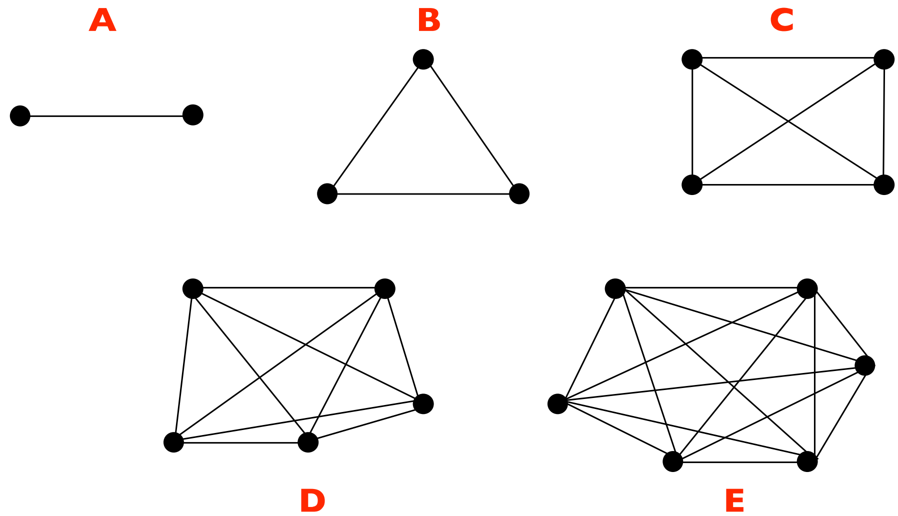
Completeness

This measure, as the name indicates, captures the level of completeness in the network using a link-node approach. This measure is similar to network connectivity measures, proposed earlier by Garrison and Marble (1961) and Kansky (1963). Road network are typically characterized by links and nodes. Links refer to the street segments while nodes refer to the intersection or junction of two or more links. Considering a road network with e links and v nodes, the network is said to be 100% complete if each node in the network is directly connected to each of the remaining nodes.

Figure 3.4 shows the relationship between the maximum number of direct connections in the network and the number of nodes in the network. Given a certain number of nodes (v) and assuming that the network is connected only by two-way links, the maximum number of links ($E_{\max}$) in a network, is given by:

$$E_{max} = V^2 - V \tag{3.10}$$

The number of links in a real world network is typically less than the maximum number of links and the completeness index used here captures this difference. This



Network	Nodes	Maximum number of 1-way links	Maximum number of 2-way Links	Completeness
A	2	1	2	100%
B	3	3	6	100%
C	4	6	12	100%
D	5	10	20	100%
E	6	15	30	100%

Figure 3.4: Maximum number of links in sample networks

measure is estimated at the metropolitan level. The completeness (ρ_e) of the street network is defined as:

$$\rho_e = \frac{E}{E_{max}} = \frac{E}{V^2 - V} \tag{3.11}$$

E refers to the number of links or street segments in the network and V refers to the number of intersections or nodes in the network.

The completeness measure is similar to the gamma (γ) index of connectivity

$$\gamma = \frac{E}{3V - 2} \tag{3.12}$$

proposed by Garrison and Marble (1961). However unlike the gamma index, it does not differentiate between planar and non-planar graphs. The completeness measure is used in the analysis of metropolitan travel presented in Chapter 7. The regression models developed to analyze metropolitan travel were tested by independently including both these measures (completeness, gamma) of connectivity. The completeness measure provided more explanatory power than the gamma index.

The street networks obtained from the Census TIGER/line files were cleaned to ensure that the network contained only the relevant links and intersection or junction nodes. Shape nodes included in the TIGER/line files to ensure spatial correctness were removed as they do not represent actual intersection or junctions.

Proportion of nodal degrees

Nodal degree is defined as the number of roadway links connected to the node. Each node in the street network represents an intersection or junction of roadway links. For example, a nodal degree of 4 represents a typical four way intersection with four roadway links connected to the node. Refer to figure 3.5. Each number in this sample network represents the nodal degree of the specific node.

The street networks obtained from the Census TIGER/line files were cleaned to ensure that the networks contained only intersection or junction nodes. Shape nodes included in the TIGER/line files to ensure spatial correctness were removed as they do not represent actual intersections or junctions.

At the individual trip level, this measure is estimated as:

$$\text{Proportion of i-degree nodes} = \frac{V_{ib}}{V_b} \tag{3.13}$$

where,

V_{ib} = Number of nodes with i-degrees within the trip buffer,

V_b = Number of intersection nodes within the trip buffer,

$i = 1, 2, \ldots$ maximum degree.

At the household level, this measure is estimated as:

$$\text{Proportion of i-degree nodes} = \frac{V_{ia}}{V_a} \tag{3.14}$$

where,

V_{ia} = Number of nodes with i-degrees within the activity space polygon,

V_a = Number of intersection nodes within the activity space polygon,

$i = 1, 2, \ldots$ maximum degree.

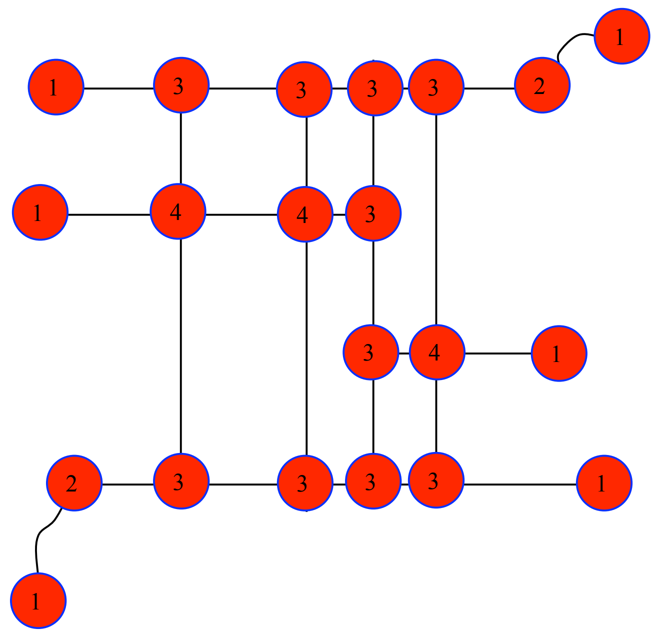


Figure 3.5: Illustration of nodal degrees in a sample network

Circuity

Circuity is defined as the ratio of the shortest path network distance to the Euclidean or straight line distance between an origin and destination. The circuity measure is unitless and is estimated using the complete street network.

Consider the sample network provided in figure 3.6. The network distance is a realistic representation of the actual transportation network distance between an origin and destination. The Euclidean distance measures the straight line distance between the origin and destination using the location coordinates (Levinson and El-Geneidy, 2009).

At the individual trip level, circuity is estimated between a given trip origin and destination as:

$$C_t = \frac{D_{tn}}{D_{te}} \tag{3.15}$$

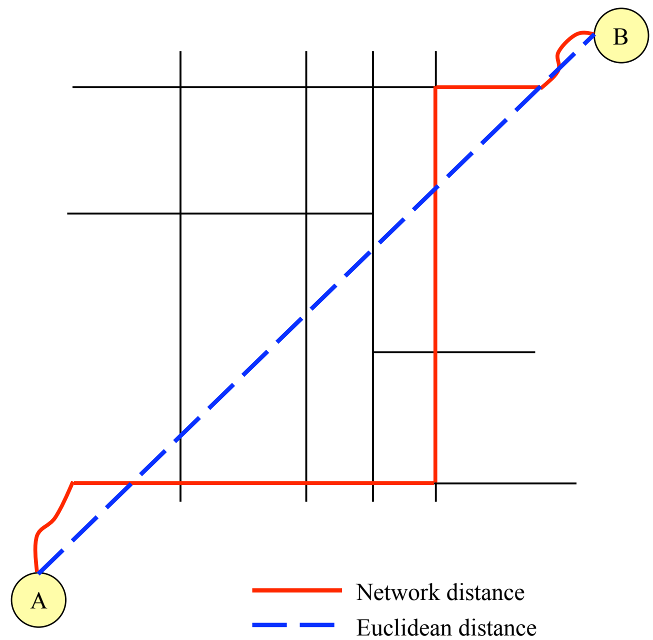


Figure 3.6: Illustration of circuity

where,

C_t = Circuity of the trip between the origin and destination,

D_{tn} = Network distance (km) between the trip origin and destination, measured along the observed path or estimated shortest path,

D_{te} = Euclidean distance (km) between the trip origin and destination.

For estimation at the metropolitan level, a slightly different approach is used. Levinson and El-Geneidy (2009) used a dataset of randomly selected, origins and destinations of actual trips to estimate circuity in their analysis of commute patterns and compared that to random OD points, finding that circuity of actual home to work trips was lower than random OD points of the same trip length. The same methodology is implemented here The circuity of random trips is constrained to match actual trip length, which is highly correlated with (but higher than) actual commute circuity.

For each metropolitan area in our dataset, two samples were generated. The first sample consists of the origins and the second sample consists of the destinations. Similar to Levinson and El-Geneidy (2009), 200 randomly distributed origins and 1000 randomly distributed destinations were generated using GIS. This provided 200*1000 OD pairs for each area resulting in a 200,000 OD matrix. The network distance and the euclidean distance were calculated for each of 200,000 OD pairs.

A subsample of OD pairs were selected out from the 200,000 random OD matrix in each study area by matching the network distance to the average commute trip length, provided in the 2001 National Household Travel Survey (NHTS) (Federal Highway Administration, 2001). The average circuity for the subsample of OD pairs in each metropolitan area is estimated as:

$$C_m = \frac{D_n}{D_e} \tag{3.16}$$

where,

C_m = Average circuity in the metropolitan area,

D_n = Sum of the network distance (km) between all OD pairs in the subsample,

D_e = Sum of the euclidean distance (km) between all OD pairs in the subsample.

The circuity measure is designed to capture the inefficiency in the network from the viewpoint of a traveler.

3.2.3 Morphology

P2A

Shape measures are commonly based on the relative amount of shape perimeter per unit area or often standardized to a simple Euclidean shape, such as circle or square (de Smith et al., 2007). In network analysis, these measures can be seen as morphological measures that capture the general impedance of the street network.

The P2A ratio is computed as explained below:

$$\text{P2A} = \frac{{P_p}^2}{A_p} \tag{3.17}$$

where:

P_p = Perimeter of the polygon enclosed by the street network, in km,

A_p = Area of the polygon enclosed by the street network, in km^2.

The P2A ratio is more practical than the simple perimeter/area ratio (P1A), because it does not change with size of the figure. That is, the P2A ratio gives the same value for a shape independent of its size. A higher P2A ratio indicates a longer perimeter relative to area and therefore more complex and elongated shape. For shapes which have a clear longest internal axis (e.g., an ellipse or rectangle) and high P2A ratio compared to circles or squares, the additional distance needed to circumnavigate such shape depends on the relative orientation of that shape with regard to the direction of travel.

If the navigator travels in a direction that is approximately normal to the longest internal axis, the impedance caused by this object will be larger than for an object with the same area but a smaller P2A ratio. If, however, the direction of travel is generally in line with the longest internal axis, the impedance caused by this object will be smaller compared to a object with a smaller P2A ratio and the same size. Despite this, the impedance averaged over the range of possible angles between travel direction and longest internal axis directions (i.e., 0-90 degrees) increases with an increasing P2A ratio. That is, for shapes that share a given area, a larger P2A ratio means longer detour on average.

In this dissertation, the estimation of the P2A measure involves identifying all polygons enclosed by the street network. For each of these identified polygons, the P2A ratio is estimated using the above equation. At the individual trip level, the polygons that intersect the trip buffer are identified.

The estimated P2A ratio of the polygons are averaged to get the trip level P2A ratio. At the household level, the polygons that fall within each household activity space polygon are identified. The estimated P2A ratio of the polygons are averaged to get the household level P2A ratio. Figure 3.7 shows a sample estimation of the P2A ratio at the trip level and household level.

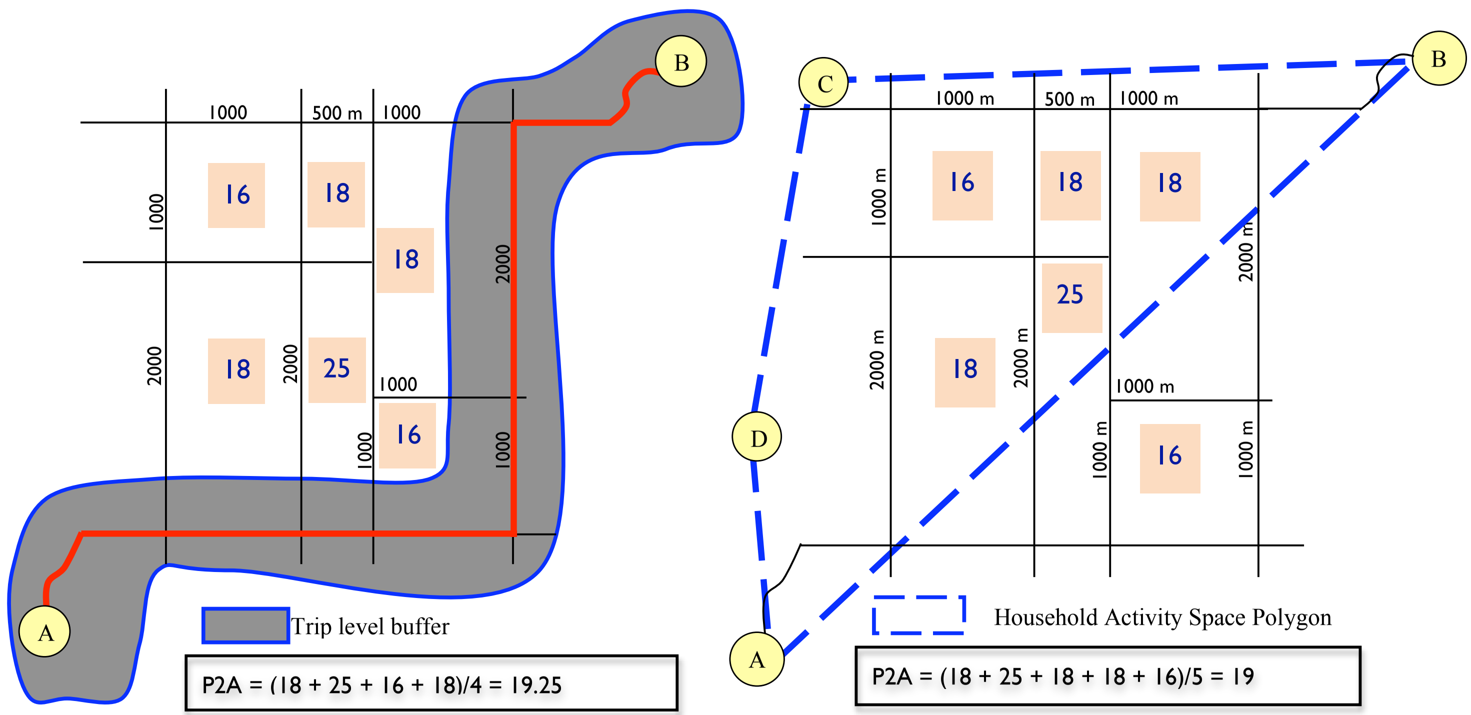


Figure 3.7: Estimation of the P2A ratio at the trip and household level

3.2.4 Scale

Street density

This measure captures the intensity of the street network in a given area. This measure is estimated using the complete street network. At the individual trip level, the street density is estimated as,

$$\rho_{lb} = \frac{L_{sb}}{A_b} \tag{3.18}$$

where,
L_{sb} = Length (km) of the street network within the trip buffer,
A_b = Area (km^2) of the trip buffer.
At the household level, this measure is estimated as,

$$\rho_{la} = \frac{L_{sa}}{A_a} \tag{3.19}$$

where,
L_{sa} = Length (km) of the street network within the activity space polygon, in km,
A_a = Area (km^2) of the activity space polygon, in km^2.
Street density for each metropolitan area is estimated as:

$$\rho_{lm} = \frac{L_{rm}}{A_m} \tag{3.20}$$

where,
L_{rm} = Roadway kilometers in the area,
A_m = Size of the area (km^2)

Intersection density

This measure is estimated for the complete street network. At the trip level, it is estimated as,

$$\rho_{vb} = \frac{V_b}{A_b} \tag{3.21}$$

where,
V_b = Number of intersections within the trip buffer,
A_b = Area (km^2) of the trip buffer.

At the household level, it is estimated as,

$$\rho_{va} = \frac{V_a}{A_a} \tag{3.22}$$

where,
V_a = Number of intersections within the activity space polygon,
A_a = Area (km^2) of the activity space polygon.

3.3 Conclusion

This chapter elaborates on the methodology used to estimate measures of street network structure. The above mentioned list of measures are by no means exhaustive but are estimated to capture important aspects of network structure and and quantify the differences between networks. The usefulness of these measures in understanding actual travel patterns is analyzed in the following chapters of this dissertation.

Chapter 4

Perception of Travel Time

4.1 Introduction

Research on travel behavior has traditionally focused on ways that infrastructure investments, namely, the urban form and built environment, can be used to influence travel. Proponents argue that overall travel can be reduced by bringing the trip origins and destination closer. This reduces overall travel distance and hence encourages other non-auto modes such as walking and biking. Horning et al. (2008) point out that the inherent assumption underlying this argument is the individual's knowledge of available destinations along with their perception of travel time and distance to various destinations. The authors administered a mail-in survey to residents living in urban, suburban and outer suburban locations in Hennepin County, Minnesota to understand the factors that influence perception of distance (travel time) to common destinations. The results showed that perception depends on the individual and environmental characteristics along with the type of destinations being analyzed.

The perception or cognition of distance and travel time has a rich history in behavioral psychology and spatial geography. Cognitive maps are one of the tools commonly used to understand distance cognition. As cited in Kitchin (1994), *"cognitive mapping" is a process composed of a series of psychological transformations by which an individual acquires, stores, recalls, and decodes information about the relative locations and attributes of the phenomena in his everyday spatial environment.* Cognitive maps are acquired through travel and interaction with the transportation system. These cognitive maps in turn influence travel (Mondschein et al., 2007).

Geographers have focused their efforts in understanding the role of spatial patterns in influencing distance or travel time cognition. Pocock (1978) argued that general layout and topography of a city provides an inherent legibility. This allows a respondent to cognize a simple structure for subsequent introspection and action. Specifically the actual physical distance, complexity, perceived linearity of the routes and the characteristics of the end points influence the judgement of distance. He argued that cities with a formal structure (e.g. London) characterized by crucial structural elements such as a river, rail network or road network have less over-estimation in distance than cities without a formal structure (e.g. Edinburgh). In a recent experiment, Crompton and Brown (2006) found that participants estimated a walk in a picturesque village to be twice as long as an equal-length journey in the city. The analysis suggested that an individual's scale of interaction with the environment influences the judgement of distance.

Burnett and Briggs (1975) categorized the factors that affect distance cognition as: *(1) stimulus-centered factors, in which cognitive distance is a function of environmental features; (2) subject-centered factors, in which cognitive distance is a function of the individual; and (3) subject/stimulus-centered factors, in which cognitive distance is a function of interactions between the individual and environmental features*, (as cited in MacEachren (1980)). Walmsley (1988) provided a similar listing of factors that influence an individual's estimate of distance within an urban context.

Focusing on stimulus-centered factors, Magel and Sadalla (1980) showed that routes where the change in direction are enforced more often, e.g. turns, are perceived to be longer. In follow-up research, Staplin and Sadalla (1981) showed that the structural attributes along a route, namely the angularity effects (right angle turns) and intersections, increased the perception of traversed distance. These findings were consistent in both laboratory and field settings. Jansen-Osmann and Berendt (2002) found similar results using virtual environmental tools.

Lee (1970) used a sample dataset of 171 student from the University of Dundee, Scotland to confirm a relation between perceived distance of urban destinations and the direction of travel (inwards or outwards) with respect to the city. Distance towards the city center was estimated to be shorter than distances away from the city center. Other attributes shown to affect perceived distance include information along the route (e.g.

number of perceived features, such as buildings), the visibility of the destination etc. (Cubukcu and Nasar, 2005).

Focusing on subject-centered factors, Stone and McBeath (2010) found differences in perception of length between males and females, while exposed to multiple routes. For men, the number of available routes had no effect on the accuracy of route length estimates. The accuracy of length estimates decreased for women with exposure to multiple routes. Matthews (1981) identified a complex relationship between the age of an individual and distance perception. Péruch et al. (1989) analyzed straight-line and travel distance estimates (in time or distance units) using an equal sample of taxi drivers and the general public from Paris. The results showed that there were no significant differences in the estimation of straight-line distance between taxi drivers and the general public. However taxi drivers consistently estimated travel distances to be shorter than the general public.

The research focus in the 1970s was mainly on the cognition of physical distance between points, typically home and other locations within the city. The focus on time perception started later with an understanding that time distance is much more important for a traveler than actual physical distance. Burnett (1978) used this argument to analyze 200 pairs of observations of cognized and actual travel time from Dallas-Fort Worth. The analysis identified a power law relationship between cognized and observed travel time similar to the power law relationship between cognized and observed physical distance. MacEachren (1980) found that travel time has a closer relationship to cognitive distance than objective distance. Säisä et al. (1986) tested the relation between travel distance, straight-line distance and travel times using data from the University of Umeä, based on the theories of cognitive maps. The authors found that the judged travel time was proportional to judged travel distance, which was longer on average than judged straight-line distances.

Time perception has deep roots in psychological research due to time being an important aspect of human experience. An individual's notion of time applies to two unique concepts, namely,

- Concept of succession
- Concept of duration

An individual's perception of duration and succession is present very early in life but the joint functioning of the two concepts is not acquired until the age of 7 or 8 when the child is capable of logical thinking (Fraisse, 1984).

Time perception is also an important factor in the field of consumer research. Graham (1981) reviewed three behavioral models to illustrate the role of time perception on consumer behavior. The author argued that time perception varies among individuals and the variation depends on the culture and the tasks being performed. Time perception is now receiving importance in travel behavior research. Li (2003) provided an alternative approach to travel behavior by formulating a time-perception model to evaluate the urban commute experience. The model placed the perceived travel time as a central factor in the evaluation of a given commute experience moderated by factors such as commute characteristics, journey episodes, travel environments and expectancy.

Levinson et al. (2004) conducted experiments comparing computer-administered stated preference (SP) surveys against virtual experience SP data to ascertain how people perceive time spent waiting at ramp meters compared with time spent driving in stop-and-go traffic. Wu et al. (2009) explored the perceived waiting time at signalized intersections by analyzing the results of an online virtual experience SP survey. The quadratic model developed using the survey data showed that the perception of waiting time is a non-linear function of actual time.

Chen and Mahmassani (2004) explored the role of travel time perception in route choice. The interdependence between trip makers' travel time perception and their learning mechanisms were modeled based on the concepts of Bayesian statistical interference. These models were embedded inside an agent-based simulation framework to study their influence on day-to-day dynamic behavior of traffic flows, particularly convergence. The results indicated that the individual's perception of travel times strongly influenced the convergence of the traffic system.

Arnold van Exel and Rietveld (2010) evaluated the accuracy of car drivers' perception of public transport travel time and the effects of these perceptions on modal choice set, using a sample of Dutch car drivers. Quentin and Hong (2005) highlighted the limitations of using observed attribute values rather than using perceived values in estimating the utility function in mode choice models. The authors investigated the effect of perceived attributes (travel time, fare) on mode choice in a transit market using simulation experiments.

This chapter extends the research interest to understand the role of network factors in influencing an individual's perception of travel time.

4.2 Modeling Methodology

The basic question addressed in this chapter is:

Do travelers perceive travel time differently and can this difference be related to network structure?

To test this theory, the ratio of perceived travel time and measured travel time of commute trips is estimated for individual travelers. The analysis focuses specifically on auto-based (drive alone or carpool) commute trips. Travelers are then stratified into two groups based on the travel time ratio:

- Overestimating group - Travelers that perceive their commute travel time to be higher than it actually is, i.e., the ratio is greater than 1.0,

- Underestimating group - Travelers that perceive their commute travel time to be lower than it actually is, i.e., the ratio is less than 1.0.

Statistical t-test comparisons are conducted to identify if there are statistically significant differences in network structure between the two traveler groups. The relation between the ratio of travel time and underlying street network structure is then analyzed using regression models.

4.3 Data

The data for the analysis come from the Twin Cities metropolitan area. The Twin Cities metropolitan area refers to the seven counties of Anoka, Carver, Dakota, Hennepin, Ramsey, Scott and Washington and includes the cities of Minneapolis and Saint Paul.

4.3.1 Dataset I - Travel Behavior Inventory

The travel data for this analysis come from two different sources. The first dataset is the year 2000 Twin Cities Travel Behavior Inventory (TBI). The TBI is a comprehensive one-day household travel survey conducted by the Metropolitan Council and the Minnesota Department of Transportation (Mn/DOT). Travel surveys are conducted by planning agencies to understand the travel patterns of the residents in the region and to provide a factual basis to guide highway and transit investment decisions. Survey respondents maintain a complete record of all trips undertaken on the specified travel day. Each recorded trip contains relevant information such as trip origin and destination, travel mode used, the purpose of the trip, the trip arrival and departure time etc. Socio-demographic information regarding the individual such as age, gender, employment status, occupation type; and household information such as household size, household income, vehicle ownership and type, residence type are also collected (Metropolitan Council of the Twin Cities Area., 2003).

The surveyed sample includes households in the the seven counties within the metropolitan area and twelve adjacent counties. The final sample consists of 6,219 households comprising of 14,671 individuals, totaling 58,345 trips. The data are extracted to include only those trips that originated and were destined for the Twin Cities metropolitan area resulting in 38,432 trips.

The data on commute trips and reported trip arrival and departure times are most relevant to this analysis.

4.3.2 Dataset II - Surveys from the I-35W Bridge Collapse and Reopening

The second dataset comes from a compilation of surveys conducted during the collapse and subsequent rebuilding of the Interstate 35W Highway Bridge over the Mississippi River in Minneapolis. The I-35W bridge collapsed on August 1, 2007 and the newly reconstructed bridge was open to traffic on September 17, 2008. The surveys were conducted as part of a research effort at the University of Minnesota to understand the impacts of the bridge collapse on traveler behavior (Zhu, 2010). The collected surveys are listed below:

W-2007

A computer-based internet survey was conducted in September 2007, administered in eight zip codes in the Twin Cities area. Consistent with prior research, this survey is denoted W-2007.

A detailed description of the data collection efforts is provided in Tilahun (2009). A recruitment postcard for the online survey was sent out to a pool of 5,000 individuals. The completed dataset consisted of 215 surveys, of which 167 surveys were usable. The final dataset of auto based trips, used in this analysis, consisted of 136 records. The survey explicitly asked respondents to provide their home and work locations along with an estimate of their travel time for the commute trip.

A copy of the internet (W-2007) survey questionnaire relevant to this analysis is provided in Appendix B.

P-2008

A mail-in paper survey was conducted in October 2008, immediately after the opening of the I-35W replacement bridge. Consistent with prior research, this survey is denoted P-2008.

This survey focused mainly on two communities closest to the I-35W bridge and thus significantly affected by the bridge collapse: the downtown area of the City of Minneapolis and the Minneapolis campus of the University of Minnesota. A total of 840 surveys were handed out and 137 completed surveys were received. Respondents were asked to provide relevant information on home and work locations, commute trip arrival and departure time, travel mode and socio-demographics. In addition, respondents were asked to draw their actual commute routes on street maps provided for this purpose. This information was collected for five phases:

- Phase 1 - Before the bridge collapse (e.g., in July 2007),
- Phase 2 - Before the bridge reopening (e.g., September 17, 2008),
- Phase 3 - After the bridge reopening (September 18, 2008),
- Phase 4 - The following weeks (Sept. 19 to Oct. 23, 2008),

- Phase 5 - Current status (at the time of the survey).

A copy of the survey (P-2008) questionnaire relevant to this analysis is provided in Appendix B. The analysis uses data from Phase 4 of the survey.

Global positioning systems (GPS) installed in subject vehicles

GPS data were collected as part of several other projects for a time period of thirteen weeks, three weeks before the reopening of the I-35 W replacement bridge on September 17, 2008 and between eight to ten weeks after that. Logging GPS units were installed in subject vehicles and accurately monitored the travel trajectories of the vehicle at a frequency of one point every 25 meters (Zhu, 2010).

The data downloaded from the GPS units provide information on the trip origin and destination along with the actual routes and trip travel times. The information on home and work locations and reported commute travel time had been previously obtained as part of the recruitment questionnaire. This information on home and work locations was used to extract the commute trips from the GPS dataset. The GPS units were installed in 127 vehicles and the final dataset used here consisted of 72 usable units with complete information. To ensure consistency with the mail-in paper survey (P-2008) conducted during the same time period, the analysis uses only GPS trips recorded in October.

Combining the different I-35W travel surveys into one dataset helps overcome the limitation of small sample size, especially while separating the travelers into groups. While each of the above surveys differed in terms of their focus and the exact wording of the survey questionnaire, all of them contained information on the travelers' reported travel time for the commute trip. Also the use of two different datasets provided us a larger sample of travelers in the region. The TBI, while older, has a larger sample size and covers all the seven counties in the Twin Cities metropolitan area. On the other hand, the I-35W surveys, while newer, are smaller and are more specific to communities near the I-35W bridge.

4.3.3 Street Network

The street network data for the Twin Cities were extracted from the year 2000 Census TIGER/Line files. The free flow speeds of the road segments provided in the street network were updated with actual speeds to better account for congestion. The average congested speeds in the Twin Cities network were obtained from a GPS study (Zhu, 2010), conducted at the University of Minnesota before and after the reopening of the new I-35W bridge. The GPS data come from two parallel independent studies.

- Real-time tracking GPS data collection:

  This was a thirteen week study overseen by Professor Randall Guensler at the Georgia Institute of Technology and a subcontractor, Vehicle Monitoring Technologies (VMTINC). The whole study lasted thirteen weeks and GPS units were first installed in the vehicles of subjects two weeks prior to the reopening of the new I-35W bridge in September 2008.

- Logging GPS data collection:

  This study is elaborated above in the data section.

GPS units installed in the subject vehicles were used as probes to accurately measure the travel speeds (morning peak, evening peak and off-peak) on the Twin Cities roadway segments during different time periods, namely,

- Period 1 - From the start of the GPS based studies in August, 2008 to September 17th 2008, when the new I-35W bridge reopened.

- Period 2 - Between September 18th, 2008 to October 11th, 2008, when the shoulder lane on Interstate I-94 reverted back to a bus-only shoulder lane. The bus only shoulder lane on I-94 had been converted to a general purpose travel lane immediately after the collapse of the I-35W bridge.

- Period 3 - Between Oct 12th, 2008 to the end of the GPS based studies in November, 2008.

To clarify, the data from the real-time tracking GPS study are used only for estimating the congested speeds on the Twin Cities network while the data from the logging GPS study are used to provide actual commuter route information in addition to estimating the congested speeds on the network.

4.4 Analysis

4.4.1 Identification of actual commute route:

The first step in the analysis is to identify the route between commute trip origin and destination for respondents in both datasets, with the exception of the GPS respondents and P-2008 respondents. For GPS respondents, the raw data obtained from the GPS units provide a complete recording of vehicle trajectories. Each vehicle trajectory recording provides information on the latitude and longitude coordinates, date and time, and the instant speed of the vehicle. The data are used to identify the actual route between the commute trip origin and destination. In order to account for multiple recordings of the same vehicle trajectories, the most frequently used commute route is identified for each traveler, using a previously developed algorithm (Zhu and Levinson, 2010). The P-2008 respondents provided a rendering of their actual routes on street maps provided for this purpose.

On the other hand, the TBI provides information on the trip origin and destination but does not necessarily identify the actual route chosen by the traveler. Similarly the respondents in the W-2007 survey provided only their home and work locations and did not provide any information on their actual commute routes. Hence the fastest path (computed over roadway segments weighted with average congested speeds derived from the GPS data) between the given trip origin and destination is identified for each trip in these two datasets.

Although travelers will not always follow the fastest route, it is a common route choice criterion for car drivers. The use of the fastest route or shortest travel time route from origin to destination is based on existing research on route choice. As Zhu and Levinson (2010) point out, the trip-based modeling paradigm is based on Wardrop's first principle, in which "the journey times in all routes actually used are equal and less than those which would be experienced by a single vehicle on any unused route" (Wardrop, 1952). This assumption has been countered by research on route choice that argue that travel time is not the only criterion that travelers use.

The TBI and W-2007 travel surveys contain information on the trip origin and destination but no information on the actual routes. Considering the data available, the shortest travel time path is the best assumption that could be used. Even if the route geometry deviates from the actually chosen route of a survey respondent, it is not expected that the network characteristics in the buffers around these two route alternatives would vary significantly or have a noticeable impact on the role of the network characteristics.

4.4.2 Estimation of measures of network structure along actual commute route:

The next step is to estimate the trip level measures of network structure along the identified commute route, for respondents in both datasets. As mentioned above, the actual route is either obtained directly from the surveys (GPS surveys, P-2008 surveys) or estimated using shortest path algorithms (TBI, W-2007 surveys). A 1-km buffer is created around this actual route and various measures of network structure are estimated within the buffer using the complete street network (including interstates, arterials, and local streets). A similar analysis is carried out using a subset network consisting of just the interstates and arterials. A 2-km buffer around the actual route is used in the arterial network to estimate select measures of network structure. A VBA based code developed in ArcGIS, is used to calculate the trip level measures of network structure along the commute route. As mentioned in Chapter 3, the buffer size, while admittedly arbitrary, provides a geographical definition that is required for the estimation of areal network measures. Various buffer sizes (1-km, 2-km, 5-km, 10-km, 20-km etc.) were tested but the final buffer size (1-km/2-km) selection was based on the ability to capture the various network measures and the subsequent performance of these measures in related regression models.

The following measures of network structure are estimated along the actual route for respondents in both datasets.

- Hierarchy

  Relative discontinuity

  Proportion of limited access roads

- Topology

  Arterial treeness

Trip circuity

- Morphology

  P2A

- Scale

  Street density

  Intersection density

The estimation of the above measures are elaborated in Chapter 3.

4.4.3 Estimation of perceived (reported) commute travel time and measured commute travel time:

The measured travel time is then calculated along the identified commute route using the congested speeds in the street network for all respondents (TBI, W-2007 and P-2008) in both datasets, with the exception of GPS respondents. For GPS respondents, the time data are directly obtained from the GPS units. As explained above, the most frequently used commute route is identified for each GPS traveler. The actual commute time is then obtained by averaging the travel times on the most frequently used commute routes.

The reported travel time is obtained directly from the surveys for GPS survey respondents and W-2007 respondents. The reported travel time is estimated for TBI respondents and P-2008 respondents using the reported trip arrival and departure times. In this analysis, the reported travel time in the surveys is used as a proxy for perceived travel time. A summary of the reported and measured travel time for the two datasets is provided in Table 4.1.

Figures 4.1 and 4.2 present a histogram plot of reported and measured travel times from TBI and the I-35 W surveys. The histograms show a change in trend at the 26 to 30 minute time category. For time categories under 25 minutes, the proportion of travelers is higher for measured commute time than reported commute time. For time periods greater than 25 minutes, the proportion of travelers is higher for reported commute time than measured commute time. On first glance, it seem that for longer trips, travelers report the travel time to be higher than for shorter trips. But closer investigation

Table 4.1: Summary of reported and measured travel times

	TBI, Commute trips				I-35W Travel Surveys, Commute trips			
Variable (Unit)	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Reported time (min)	25.10	15.46	1.00	157.00	25.08	12.63	2.000	90.000
Measured time (min)	15.86	10.15	0.04	71.51	18.17	10.47	0.02	47.72
Total observations	4,105				258			

using histogram plots of the ratio of reported time to measured time, stratified by measured time, presented in Figures 4.3 and 4.4 show that the proportion of travelers that overestimate their travel time (reported time is greater than measured time) is highest for shorter trips and reduces as the trip duration increases. The trend is clearer for travelers in the TBI compared to the I-35W surveys but the pattern is consistent between the two datasets. This is consistent with Vierordt's Law which states that within a series of stimulus intervals, longer intervals tend to be underestimated while shorter intervals tend to be overestimated (Brown, 1995).

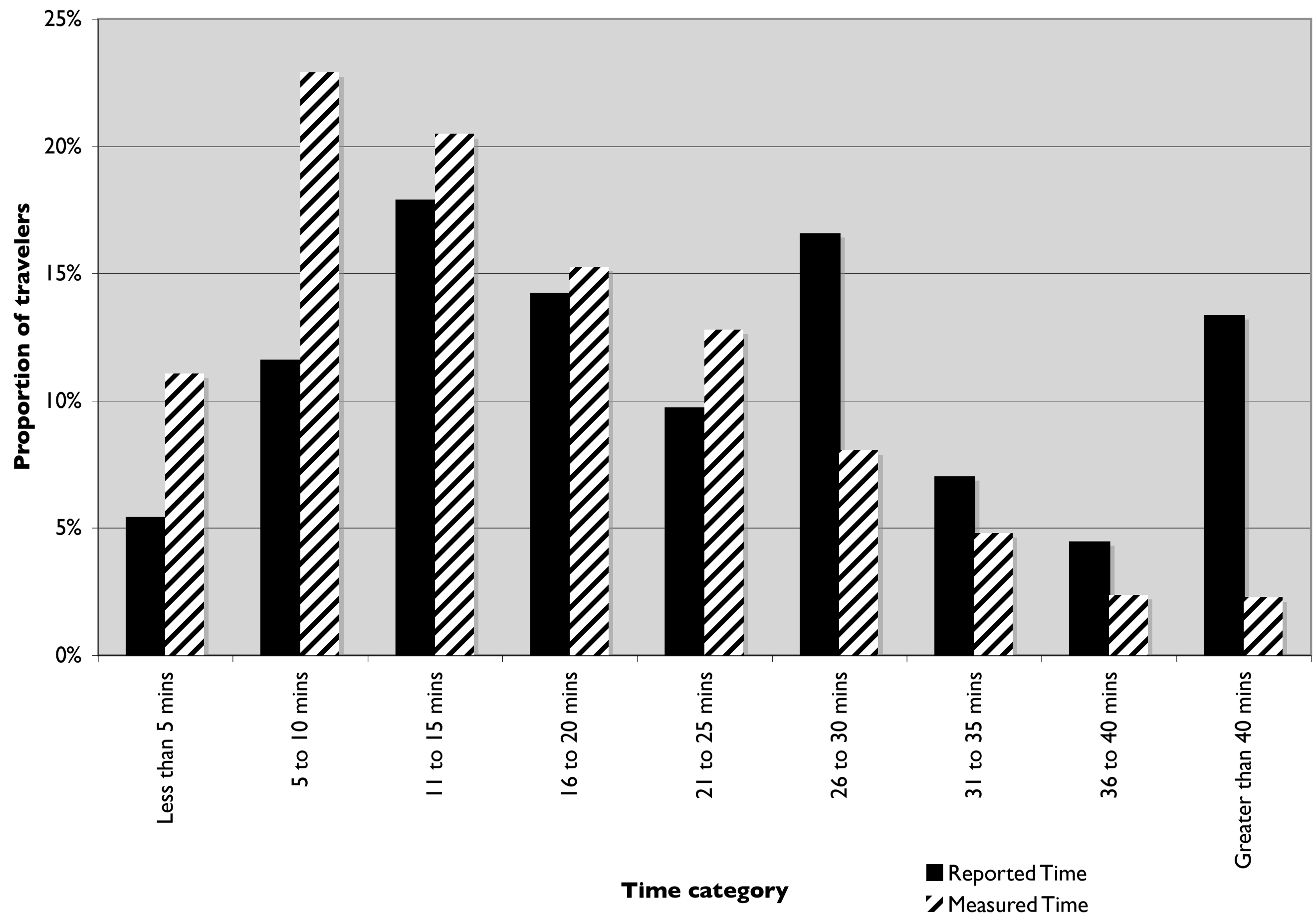


Figure 4.1: Frequency plot of reported and measured commute time - TBI

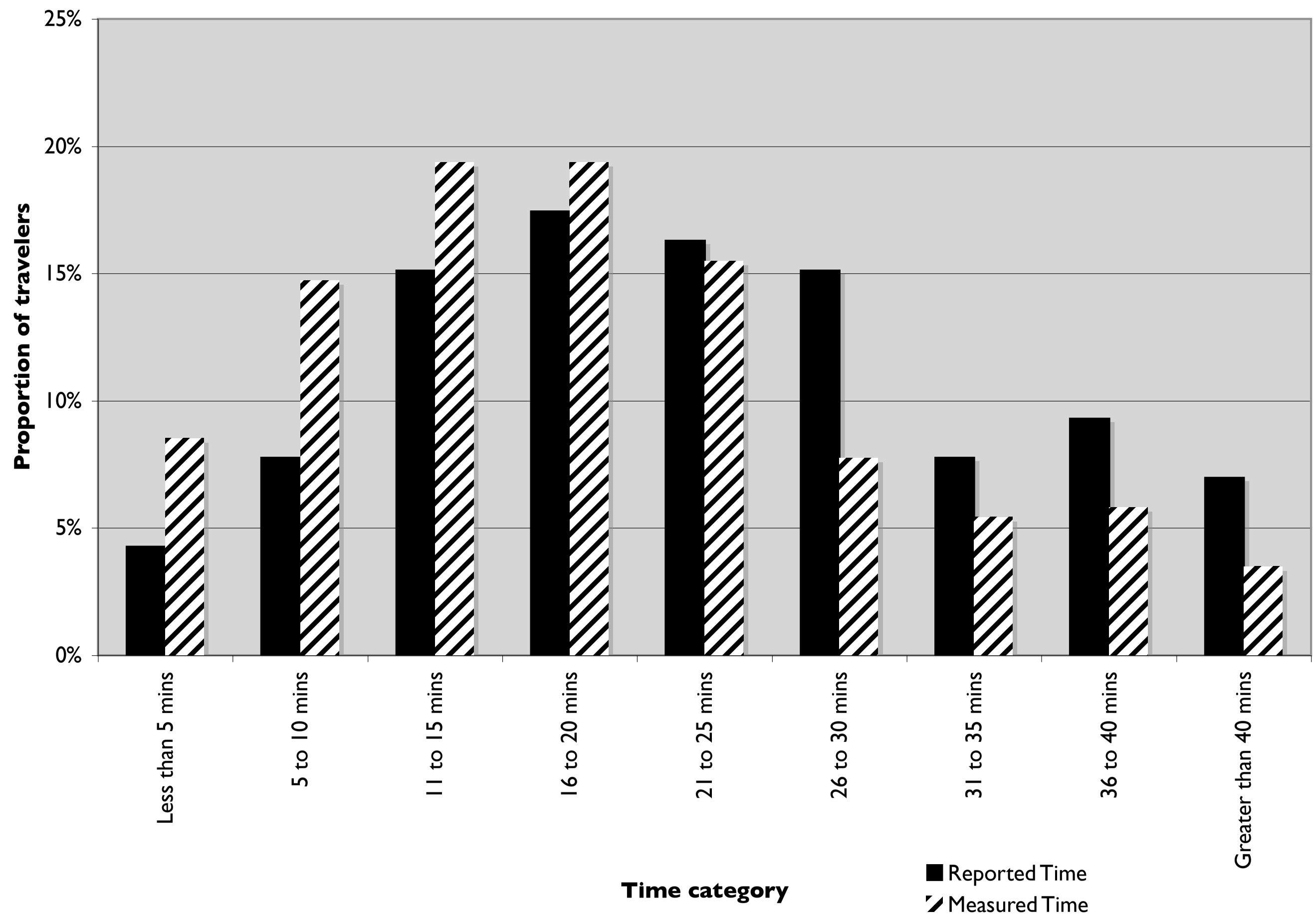


Figure 4.2: Frequency plot of reported and measured commute time - I-35 W surveys

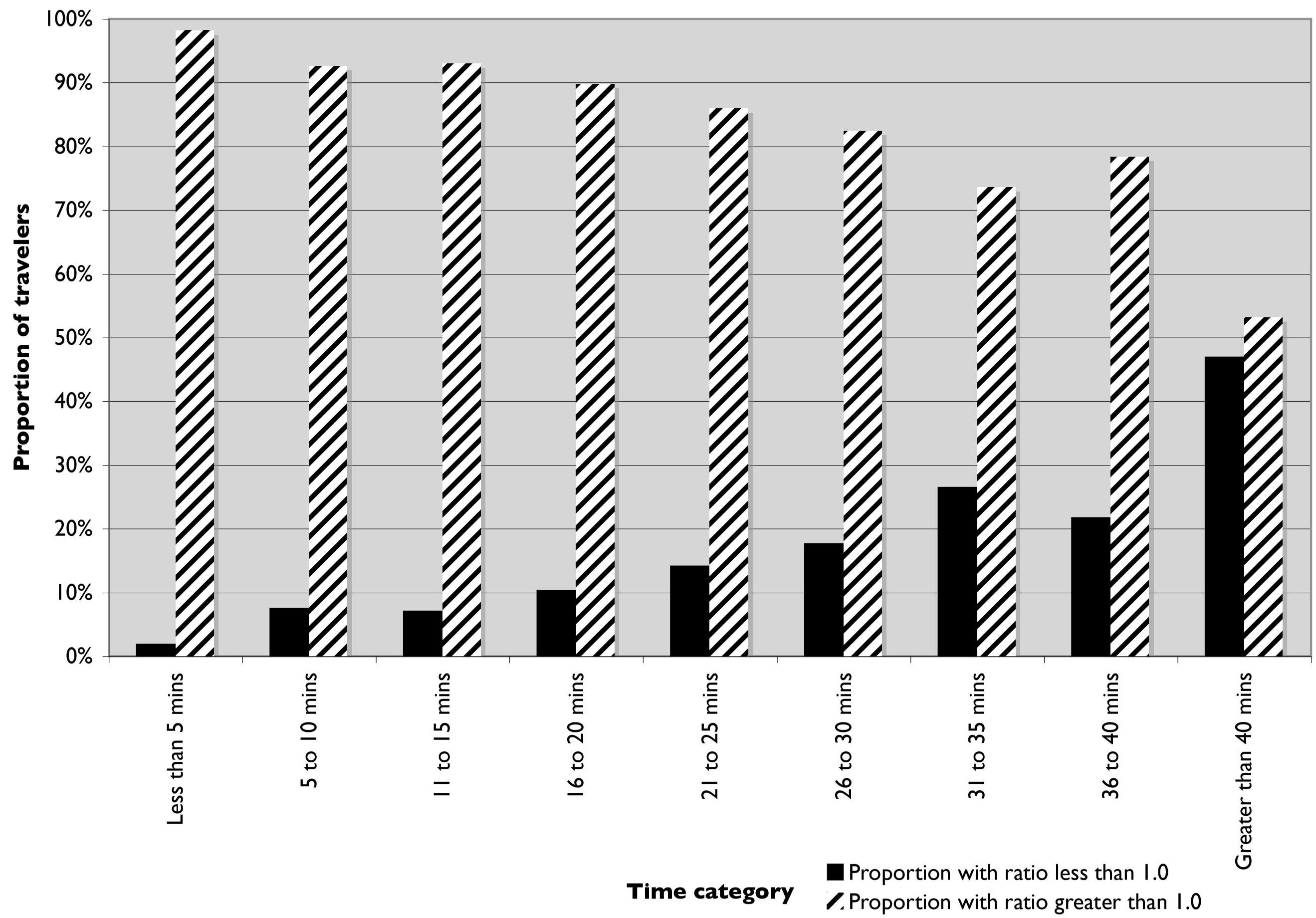


Figure 4.3: Frequency plot of the ratio of reported to measured commute time, stratified by measured time - TBI

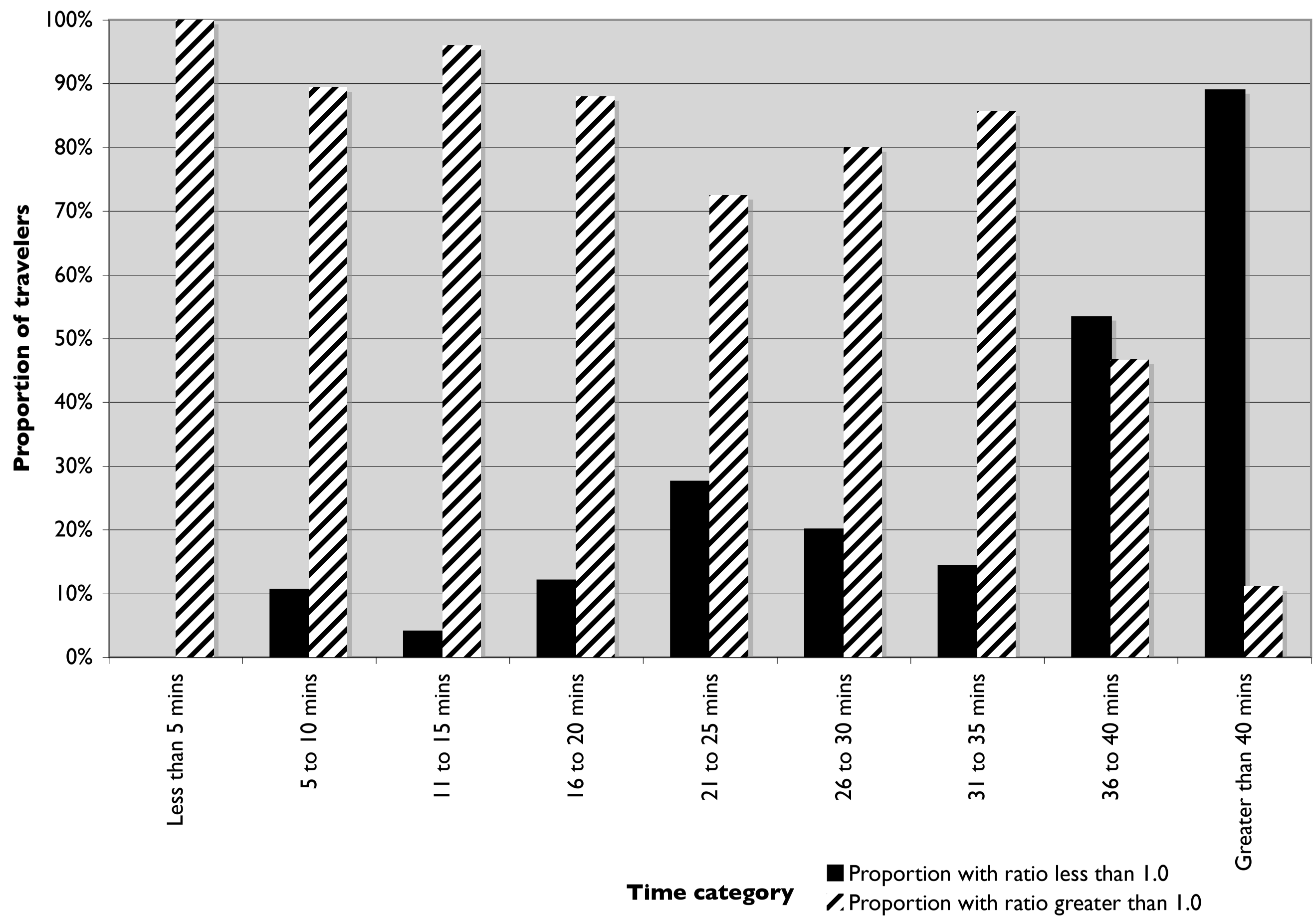


Figure 4.4: Frequency plot of the ratio of reported to measured commute time, stratified by measured time - I-35 W surveys

4.4.4 Classify travelers into groups based on ratio of perceived (reported) travel time to measured travel time:

The ratio of perceived travel time and measured travel time is calculated for each respondent in both datasets.

$$\tau = \frac{T_r}{T_m} \tag{4.1}$$

where,

τ = Ratio of perceived (reported) travel time to measured travel time

T_r = Perceived (reported) commute travel time, in minutes,

T_m = Measured commute travel time, in minutes

Travelers are classified into two groups based on this ratio.

- Overestimating Group, G_o : Travelers perceive their commute travel time to be higher than it actually is,

$$\begin{aligned} G_o &: T_r > T_m \\ G_o &: \tau > 1.0 \end{aligned} \tag{4.2}$$

- Underestimating Group, G_u: Travelers perceive their commute travel time to be lower than it actually is.

$$\begin{aligned} G_u &: T_r < T_m \\ G_u &: \tau < 1.0 \end{aligned} \tag{4.3}$$

4.4.5 T-test comparisons of network structure between the two traveler groups:

This step in the analysis compares the trip-level measures of network structure between the two traveler groups, using the statistical t-test. The t-test checks if the mean value of a specific network measure is statistically different between the two traveler groups. The t-test comparison is conducted separately for each network measure in both datasets.

$$\overline{N}_{iGo} = \overline{N}_{iGu} \tag{4.4}$$

where,
$\overline{N}_{iGo}$ = Network measure, i, in the overestimating group, G_o,
$\overline{N}_{iGu}$ = Network measure, i, in the underestimating group G_u.

Hypotheses

The hypotheses formulated for the t-test analysis are presented below:

Aspects of network structure (*operational variables: relative discontinuity*) that increase travel complexity will increase perceived travel time (T_r). Hence,

- Hypothesis 1 - The mean of relative discontinuity is higher for travelers in the overestimating group (G_o) compared to travelers in the underestimating group (G_u).

Aspects of network structure that increase network speed (*operational variables: proportion of limited access roads*) will decrease perceived travel time (T_r). Hence,

- Hypothesis 2 - The mean of the proportion of limited access roads is lower for travelers in the overestimating group (G_o) compared to travelers in the underestimating group (G_u).

Aspects of network structure that decrease network speed (*operational variables: street density, intersection density*) will increase perceived travel time (T_r). Hence,

- Hypothesis 3 - The mean of the street density is higher for travelers in the overestimating group (G_o) compared to travelers in the underestimating group (G_u).
- Hypothesis 4 - The mean of the intersection density is higher for travelers in the overestimating group (G_o) compared to travelers in the underestimating group (G_u).

Aspects of network structure that increase network travel distance between fixed origins and destinations(*operational variables: arterial treeness, P2A, trip circuity*) will increase perceived travel time (T_r). Hence,

- Hypothesis 5 - The mean of arterial treeness is higher for travelers in the overestimating group (G_o) compared to travelers in the underestimating group (G_u).

- Hypothesis 6 - The mean of trip circuity is higher for travelers in the overestimating group (G_o) compared to travelers in the underestimating group (G_u).
- Hypothesis 7 - The mean of P2A ratio is higher for travelers in the overestimating group (G_o) compared to travelers in the underestimating group (G_u).

4.4.6 Results of t-test comparisons

The results of the t-test analysis for both datasets is presented in Table 4.2. The results show that most measures of network structure are statistically different between the two traveler groups. The measures of relative discontinuity, street density and intersection density perform as hypothesized. These measures have a higher mean for travelers in the overestimating group (G_o) and are statistically different compared to travelers in the underestimating group (G_u). The proportion of limited access roads has a lower mean for travelers in the overestimating group (G_o) and is statistically different compared to travelers in the underestimating group (G_u). This is also in line with the hypothesis but is however seen only in the I-35W travel surveys. The mean of the arterial treeness measure is statistically different and is lower for travelers in the overestimating group (G_o) compared to the underestimating group (G_u) in the TBI dataset, contradicting the hypothesis. It however does not vary between the two traveler groups in the I-35W surveys. The mean of the P2A ratio variable is lower for travelers in the overestimating group (G_o) compared to travelers in the underestimating group (G_u) but is statistically significant only in the TBI dataset. The measure of trip circuity does not differ statistically between the two traveler groups in both datasets.

The two datasets show slight differences in the influence of network measures. The differences could be attributed to the differences in the data collection, time period of the travel surveys and the methodology used to obtain actual commute route and travel time information. However the results are mostly in line with the hypotheses and show that network measures do vary between traveler groups. The next section details the results of regression models estimated using the above mentioned network measures.

Table 4.2: T-test comparisons of estimated measures of network structure

Ho: Difference between means is not zero								
	TBI, Commute trips				I-35W Travel Surveys, Commute Trips			
Network Variables	Mean(G_o)	Mean(G_u)	t	Sig	Mean(G_o)	Mean(G_u)	t	Sig
Relative discontinuity, Y'_P	0.304	0.199	5.493	***	0.331	0.251	1.917	*
Proportion of limited access roads	0.055	0.054	0.732		0.082	0.105	-2.767	***
Arterial Treeness, ϕ_{tree}	0.009	0.011	-1.672	*	0.012	0.012	0.054	
Trip Circuity, C_t	1.344	1.365	-0.751		1.333	1.362	-0.856	
P2A	24.505	24.906	-2.657	***	23.292	22.925	1.007	
Street density, ρ_{lb}	18.296	15.164	12.643	***	18.936	15.373	4.137	***
Intersection density, ρ_{vb}	28.936	22.374	11.853	***	37.926	34.989	1.679	*
Number of of observations	3,655	450			213	45		
Total observations	4,105				258			
G_o: Travelers perceive their commute travel time to be higher than measured travel time								
G_u: Travelers perceive their commute travel time to be lower than measured travel time								
* p<.10, ** p<0.05, *** p<.01								

4.5 Predicting the ratio of travel time, τ:

The above section presented individual t-test comparisons of network measures between the two traveler groups. In this section, the independent network measures are combined in regression models that predict the ratio (τ) of perceived travel time (T_r) to measured travel time (T_m). Network structure is complex and the measures estimated here capture certain aspects of the structure. How these measures interact with each other is not easily understood. The t-test comparisons identify how the measures perform individually while the regression model looks at the combined effects of these measures.

The TBI dataset is used to estimate the regression model due to the sample size. A correlation table is presented in Table 4.3 to ensure that only independent network measures are included in the regression model. Based on the correlation table, the intersection density variable is dropped from the analysis due to its high correlation with the street density variable.

The functional form of the regression model is as given below:

$$\tau = \frac{T_r}{T_m} = f(N_b, X_{sd}, Acc_d) \tag{4.5}$$

where,

τ = Ratio of perceived(reported) travel time to measured travel time,

N_b = Measures of street network structure within the trip buffer,

X_{sd} = Socio-demographic characteristics (e.g. age, household size, household income),

Acc_d = Distance based measure of accessibility, estimated as the straight line distance between the traveler's residence and the downtowns of Minneapolis and St. Paul.

The results of the two linear regression models are presented in Table 4.4 and the associated elasticity estimates are presented in Table 4.5. The first model includes all commuters in the TBI while the second model is a sub-model that includes only travelers that over perceive (G_o) their commute travel time. The models include non-network variables as control variables to see if the influence of network measures exist even in the presence of these variables.

The results in both models show that the network variables influence the ratio of reported travel time to measured travel time. The street density is positive and significant in both models. This corroborates the hypothesis that the higher street density in the network leads travelers to perceive their travel time to be higher resulting in an increase in the ratio (τ). Similarly the trip circuity variable is also positive and significant in both models, confirming that higher circuity in the street network between an origin and destination causes travelers to perceive their travel time to be higher. The arterial treeness variable is also positive as hypothesized but is significant only in the sub-model of travelers that over perceive (G_o) their travel time. The proportion of limited access roads is negative and significant in both models as expected. The P2A variable contradicts the hypothesis. This variable measures the impedance in the network and had been expected to increase the perceived travel time. The relative discontinuity variable shows a negative influence but is however insignificant in both models.

It is important to note that some variables (e.g. trip circuity) perform differently in the regression models compared to the t-test analysis. This shows that the combined effects of the network variables can differ from the individual effects of the network variables. While the use of a correlation test ensures that the variables are independent from each other, the exact influence of the measures is not always straight forward. The sub-model consisting only of travelers that overestimate the travel time (G_o) shows the same influence as the complete model but has a better fit in terms of the R^2. The socio-demographic variables act as control variables in this model. The results show a relation between the street network structure and individual perception of travel time, after controlling for non-network variables. For additional reference, scatterplots of the predicted ratio of travel time versus actual ratio of travel time are presented in Figures C.1 and C.2 in Appendix C.

Table 4.3: Correlation of network measures - TBI, commute trips

	Relative discontinuity, Y'_P	Proportion of limited access roads	Arterial Treeness, ϕ_{tree}	Trip Circuity, C_t	P2A	Street density, ρ_{lb}	Intersection density, ρ_{vb}
Relative discontinuity, Y'_P	1						
Propotion of limited access roads	0.0275	1					
Arterial Treeness, ϕ_{tree}	-0.0087	-0.0108	1				
Trip Circuity, C_t	**0.0646**	**0.0375**	-0.0158	1			
P2A	**-0.0776**	**0.1202**	**-0.2369**	**0.0725**	1		
Street density, ρ_{lb}	**0.2295**	**0.1357**	**-0.0796**	**-0.0392**	**-0.4454**	1	
Intersection density, ρ_{vb}	**0.2219**	**0.1264**	-0.0214	**-0.0601**	**-0.5395**	**0.9579**	1
bold - indicates significance at 95% confidence level							

4.5.1 Standardized coefficients

The above regression models measure the average change in the dependent variable (τ in this analysis), due to a unit change in the independent variable, assuming that all other independent variables remain constant. The coefficients in the regression model are hence referred to as partial regression coefficients. The issue with interpreting the results of the regression model is in understanding the relative importance of each independent variable, especially when the independent variables are measured in different units. Standardized regression coefficients are typically used to overcome this limitation in a regression model. The coefficients in a standardized regression model (commonly referred to as β coefficients) are all measured in standard deviations rather than the units of the independent variables. This allows direct comparison of the relative contribution of each independent variable. The variable with the highest β coefficient has the highest influence on the dependent variable (Bring, 1994).

Table 4.6 presents the results of the standardized regression model, predicting the ratio (τ) of perceived travel time (T_r) to measured travel time (T_m). The β coefficients presented here have a slightly different interpretation than the traditional regression coefficients. For example, the standardized beta coefficient for the proportion of limited access roads is 0.027 in the first model, which can be interpreted as: A one standard deviation in the proportion of limited access roads results in a 0.027 standard deviation decrease in the dependent variable, τ. Similarly a one standard deviation in trip circuity results in a 0.756 standard deviation increase in the dependent variable, τ. The standardization of the variables shows that trip circuity has the highest influence on τ, based on the magnitude of the β coefficient.

4.6 Discussion

The objective in this chapter is to identify differences in how travelers perceive their commute travel time. Further the goal is to relate these differences in perception to the underlying measures of network structure along the commute route. To that effect, travelers are categorized into two groups, based on the ratio of their reported travel time and measured travel time. A t-test comparison is conducted to identify differences in individual network measures between the two groups followed by regression models estimated to analyze the combined effect of these measures. The analysis presented in this chapter identified statistically significant differences between traveler groups and the regression models confirmed the same.

The analysis presented here does have some limitations. The data analyzed here are compiled from different sources. The compilation helped overcome limitations in sample size. However the actual wording and format of the survey questionnaire differed between the various surveys. This resulted in minor differences in how the perceived and actual route/travel time information was obtained from travelers. The reported travel time is either obtained directly (GPS survey, W-2007) or estimated from reported arrival and departure times (TBI, P-2008). Similarly the actual route information is either obtained directly (GPS, P-2008) or identified using shortest path algorithms (TBI, W-2007). Future extensions would be to collect relevant survey data on commute routes and travel time.

An understanding of how travelers perceive their travel time is important due to its effect on actual travel. The analysis presented forms the base for the remainder of this dissertation. The following chapters look at the influence of street network structure on actual individual travel (Chapter 5), actual household travel (Chapter 6 and metropolitan system performance (Chapter 7).

Table 4.4: Predicting the ratio of reported travel time to measured travel time - TBI, commute trips

Dependent variable, τ = Reported travel time (T_r)/ Measured travel time (T_m)								
			All commuters			Using only commuters that over estimate travel time		
Independent Variables	Unit	Hypothesis	Coef.	Sig	t-stats	Coef.	Sig	t-stats
Distance to downtown Minneapolis	km		0.010		0.892	0.012		0.984
Distance to downtown St. Paul	km		-0.006		-0.687	0.000		-0.001
Relative discontinuity, Y'_P	1/km	+S	-0.259		-0.469	-0.323		-0.555
Proportion of limited access roads		-S	-4.039	*	-1.827	-4.731	*	-1.893
Arterial Treeness, ϕ_{tree}		+S	4.582		1.222	8.137	**	2.356
Trip Circuity, C_t		+S	8.112	***	5.010	8.801	***	6.509
P2A			-0.073		-1.481	-0.101	**	-2.031
Street density, ρ_{lb}	1/km	+S	0.100	***	4.118	0.086	***	3.130
Age of Traveler			0.001		0.189	-0.002		-0.336
Number of workers in household			0.018		0.234	0.007		0.092
Total vehicles in household			-0.086		-1.568	-0.082		-1.322
Medium income			-0.111		-0.721	-0.087		-0.534
High Income			-0.025		-0.150	-0.095		-0.565
Part time employee			0.142		0.971	0.135		0.843
Non Telecommuter			0.099		0.925	0.163		1.492
Constant			-8.464	***	-3.663	-8.342	***	-3.489
Number of observations			4,105			3,655		
R-squared			0.572			0.623		
Adj. R-squared			0.570			0.622		
* p<.10, ** p<0.05, *** p<.01								

Table 4.5: Predicting the ratio of reported travel time to measured travel time - TBI, commute trips; Elasticity estimates

Dependent variable, τ = Reported travel time (T_r)/ Measured travel time (T_m)				
			All commuters, using dummy for travelers that over perceive their travel time	Using only commuters that over estimate travel time
Network Variables	Unit	Hypothesis	Elasticity	Elasticity
Distance to downtown Minneapolis	km		0.077	0.012
Distance to downtown St. Paul	km		-0.059	0.000
Relative discontinuity, Y'_P	1/km	+S	-0.035	-0.323
Proportion of limited access roads		-S	-0.102	-4.731
Arterial Treeness, ϕ_{tree}		+S	0.020	8.137
Trip Circuity, C_t		+S	5.054	8.801
P2A			-0.829	-0.101
Street density, ρ_{lb}	1/km	+S	0.831	0.086

Table 4.6: Predicting the ratio of reported travel time to measured travel time, Standardized β coefficients - TBI, commute trips

Dependent variable, τ = Reported travel time (T_r)/ Measured travel time (T_m)				
Network Variables	Unit	Hypothesis	All commuters, using dummy for travelers that over perceive their travel time	Using only commuters that over estimate travel time
Distance to downtown Minneapolis	km		0.016	0.019
Distance to downtown St. Paul	km		-0.011	0.000
Relative discontinuity, Y'_P	1/km	+S	-0.017	-0.021
Proportion of limited access roads		-S	-0.027	-0.029
Arterial Treeness, ϕ_{tree}		+S	0.019	0.030
Trip Circuity, C_t		+S	0.756	0.792
P2A			-0.037	-0.049
Street density, ρ_{lb}	1/km	+S	0.085	0.067
Age of Traveler			0.002	-0.003
Number of workers in household			0.002	0.001
Total vehicles in household			-0.014	-0.013
Medium income			-0.009	-0.007
High Income			-0.002	-0.006
Part time employee			0.009	0.008
Non Telecommuter			0.007	0.010
N. of cases			4,105	3,655
* p<.10, ** p<0.05, *** p<.01				

Chapter 5

Spatial Separation

5.1 Introduction

The previous chapter showed that network structure influences the perception of travel time. The analysis showed that certain aspects of network structure increase the travel time, as perceived by the individual traveler while certain aspects decrease the perceived travel time. This chapter aims to expand understanding of the affect on travel behavior, specifically distance, of the underlying highway network structure. The objective here is to see if travelers respond to the perceived travel time by either increasing or decreasing their actual travel.

The hypothesis is that key measurable characteristics of transportation network architecture affect the trip length, after controlling for attributes that are not explicitly network based, such as land use, urban scale and socio-demographic factors. Previous research has implicitly assumed that network structure could be reduced to network travel time or network distance. This research aims to unpack that assumption for several reasons.

First, while actual distance and time are likely to be important variables affecting the perception of travel distance and travel time, as much research has shown in the transit mode choice literature (van Exel and Rietveld, 2010) and in route choice (Levinson et al., 2004, 2006, Zhu, 2010, Zhang et al., 2009), not all travel time is weighted the same, much less perceived accurately.

Second, if travel time or network or aerial distance is the dependent variable, the use of travel time directly on the right hand side of the equation begs the question of the affect of the network on that travel time. Third, things which increase actual travel time, given a fixed origin and destination, decrease the willingness to choose that fixed origin and destination in the first place. Increasing a route's cost decreases demand for that route. Identifying the effects of network structure on actual travel behavior will produce different effects than identifying the effects of network structure on travel time. Fourth, policy makers and development regulators can establish rules which affect the architecture of networks (Southworth and Ben-Joseph, 2003), but cannot easily establish rules which affect network travel time.

5.2 Methodology

The model used to test the relationship between network structure and travel is given below:

$$T = f(N_b, X_{sd}, Acc_d) \tag{5.1}$$

where:
T = travel behavioral decision, i.e., trip length,
N_b = Measures of street network structure with the trip buffer,
X_{sd} = Socio-demographic characteristics (e.g. age, household size, residence type),
Acc_d = Distance based measures of accessibility.

5.2.1 Data

The data for this current analysis come from Minneapolis-Saint Paul and South Florida (Fort Lauderdale and Miami). The data compilation process for the dependent and independent variables is detailed below.

Travel Behavior

The travel behavioral data for the two study areas come from the respective household travel surveys. The data for South Florida (Fort Lauderdale and Miami) come from the

1999 Southeast Florida Travel Survey, maintained by the Florida Department of Transportation (Florida Department of Transportation, 1999). The travel survey provides information on the one-day travel patterns of randomly selected residents in southeast Florida, comprising the counties of Palm Beach, Miami-Dade and Broward. The Southeast Florida travel survey consists of 33,082 trips undertaken by 4,603 households comprised of 8,873 individuals. For the purpose of our analysis, trips originating and destined for Fort Lauderdale (Broward County) and Miami (Miami-Dade County) alone were extracted from the complete travel survey dataset, which provided 9,402 trips for the Fort Lauderdale area and 9,334 trips for the Miami area. The 9,402 trips in the Fort Lauderdale area comprise 1,900 commute trips (home to work/work to home) while the 9,334 trips in the Miami area comprise 2,279 commute trips.

The data for Minneapolis-Saint Paul are from the Twin Cities Travel Behavior Inventory (TBI), a similar comprehensive one-day travel survey conducted by the Metropolitan Council and the Minnesota Department of Transportation (Mn/DOT). The TBI data have already been elaborated in Chapter 4. The extracted dataset for use in this analysis consists of 38,432 trips within the Twin Cities metropolitan area, of which there are 5,341 commute trips.

Typical variables obtained from the travel surveys for analysis purposes include travel distance, trip mode choice and socioeconomic variables.

Street Network

The street network data for the study areas (Twin Cities, South Florida) were extracted from the year 2000 Census TIGER/Line files (U.S. Census Bureau, 2008). The free flow speeds of the road segments provided in the street network were updated with actual speeds to better account for congestion. The average congested speeds in the Twin Cities network were obtained from a GPS study (Zhu, 2010), as explained in Chapters 4. The actual speed data for South Florida come from the Navteq Traffic Patterns speed data (Navmart, 2010), which provides 15-minute raster traffic flow times derived from GPS observations of service subscribers.

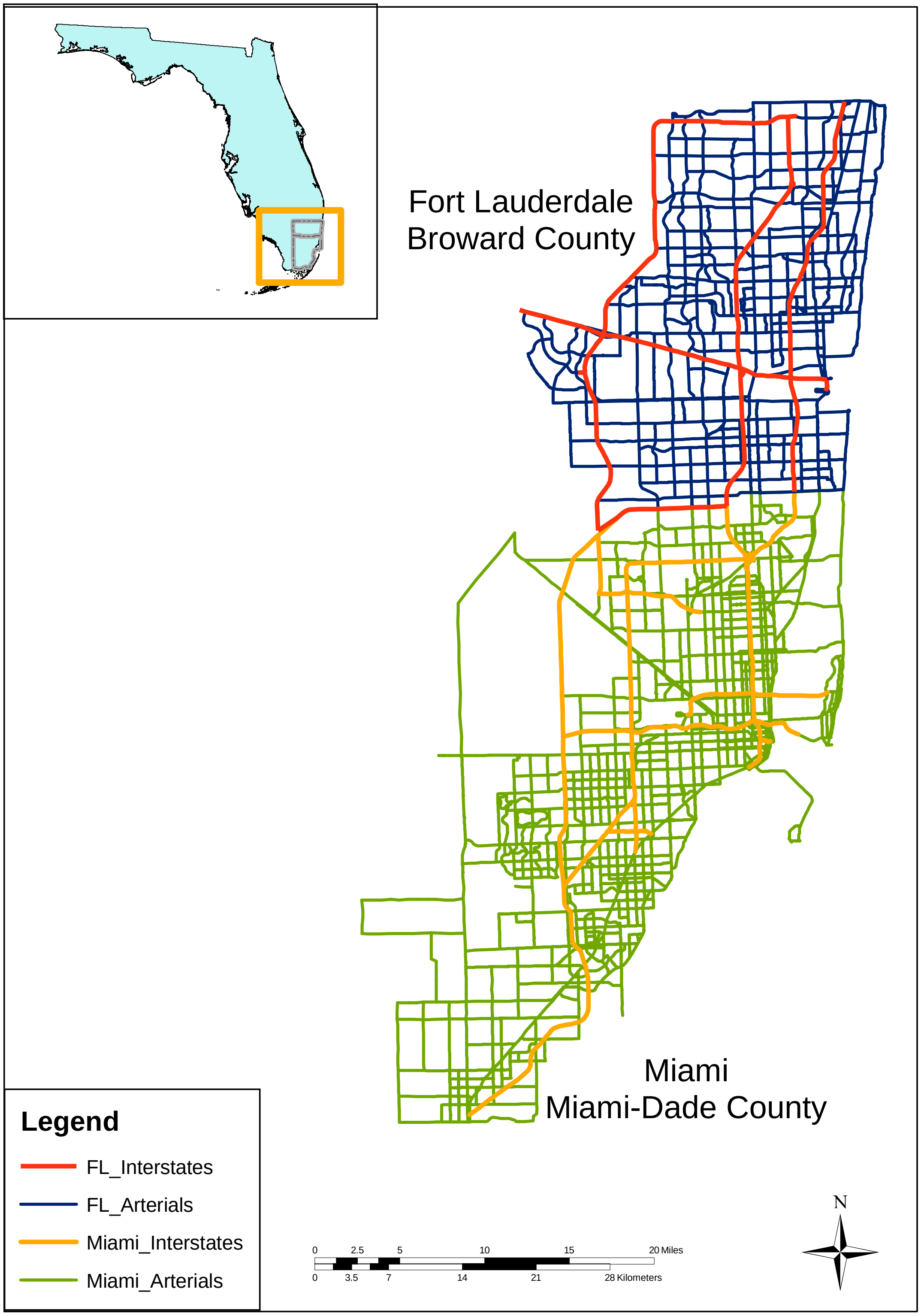


Figure 5.1: Fort. Lauderdale and Miami - Study Area

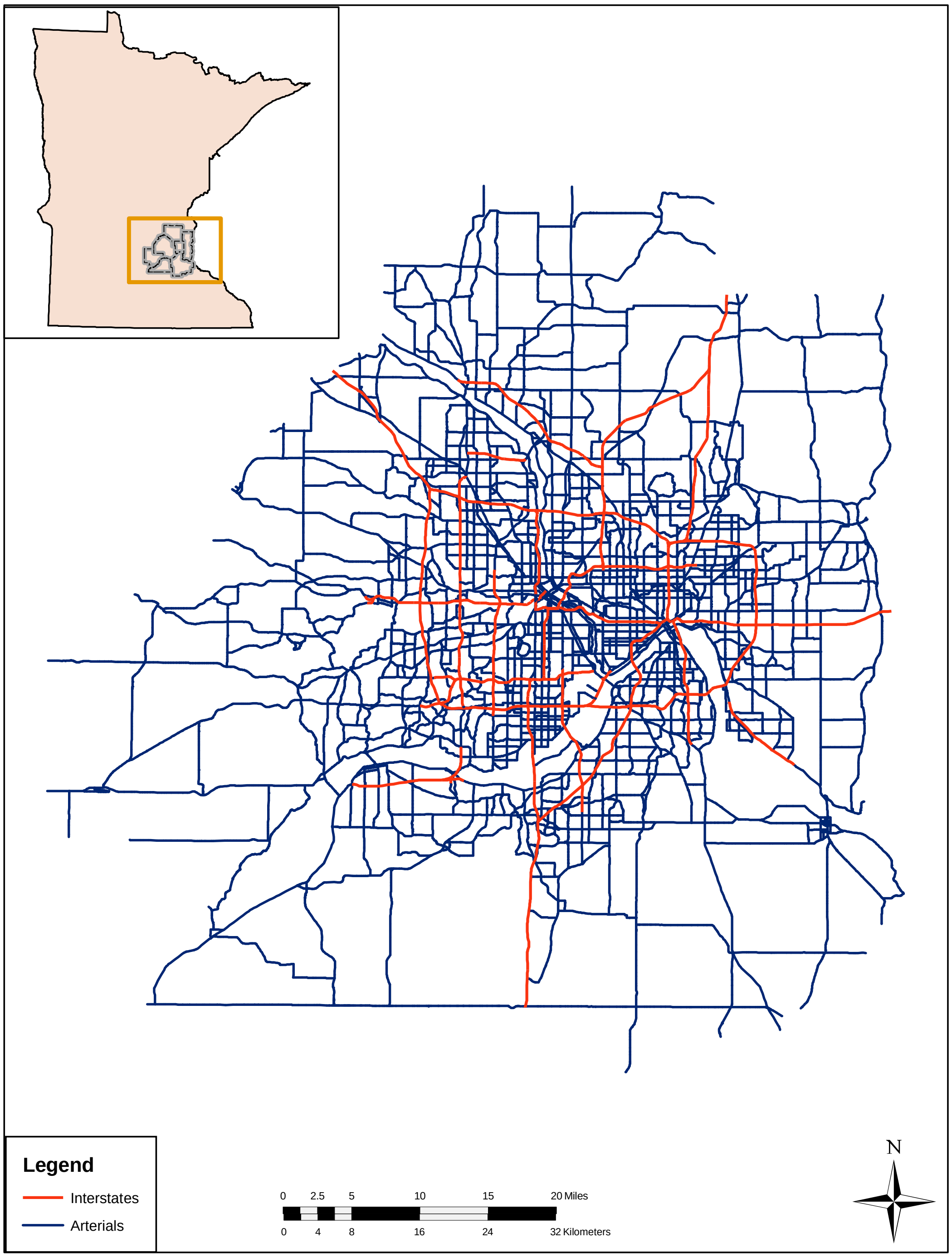


Figure 5.2: Twin Cities - Study Area

5.2.2 Estimation of network measures

The travel survey data provide information on the origin and destination of each trip. The first step in the estimation of network measures is to identify the fastest route between each reported origin destination (OD) pair in the travel survey. The fastest path (computed over roadway segments weighted with average congested speeds) between the given trip origin and destination is identified for each trip in the survey dataset. The focus is on auto-based trips (drive alone, carpool) using the street network.

The next step is to create buffers around the identified fastest path within which the measures of network structure are estimated. The buffer size around the fastest path varies by the network with a 1-km buffer used for the complete network and a 2-km buffer used for the arterial network. The complete street network consists of the interstates, arterial and local streets in the area while the arterial network is a subset of the complete network and consists of just the interstates and arterials.

The following measures of network structure are estimated within each trip buffer from the two travel surveys. The actual methodology for the estimation of the above measures is already explained in Chapter 3. All measures of network structure, with the exception of arterial treeness, are estimated for the complete street network.

- Hierarchy

  Relative discontinuity

  Proportion of limited access roads

- Topology

  Arterial treeness

  Trip circuity

  Proportion of nodal degrees

- Morphology

  P2A

- Scale

  Street density

Intersection density

Some of the above network measures, for example, street density are estimated based upon the entire buffer area. It could be argued that these measures should be estimated along the chosen route, rather than in relation to the buffer area. This argument is correct. However the travel survey data do not contain information on the actual route between the trip origin and destination. Given the uncertainty about the actual route chosen, the estimation of network measures based on the buffer seems to be a reasonable definition. If data on actual routes were to be available, the data on the exact route rather than the buffer should be used.

A correlation test is conducted to ensure that the estimated measures captures various aspects of underlying street network structure along the trip. The correlation statistics for the two study areas are presented in Tables 5.1 and 5.2. The correlation tables shows that certain measures of network structure such as, intersection density, proportion of nodal degree are highly correlated with other variables such as street density and P2A ratio. Hence in order to ensure the effectiveness of the independent network variables, the measures of nodal degrees and intersection density are removed from the regression models presented later in this chapter.

Table 5.1: Correlation of network measures - TwinCities

	Relative discontinuity, Y'_P	Proportion of limited access roads	Arterial Tree-ness, ϕ_{tree}	Proportion of nodal degree - 1 degree nodes	Proportion of nodal degree - 3 degree nodes	Proportion of nodal degree - 3+ degree nodes	Trip circuity, C_t	P2A	Street density, ρ_{lb}	Intersection density, ρ_{vb}
Relative discontinuity, Y'_P	1									
Proportion of limited access roads	-0.005	1								
Arterial Tree-ness, ϕ_{tree}	**0.017**	0.010	1							
Proportion of nodal degree - 1 degree nodes	**-0.060**	**-0.060**	**-0.053**	1						
Proportion of nodal degree - 3 degree nodes	**-0.042**	**-0.059**	**-0.145**	**0.575**	1					
Proportion of nodal degree - 3+ degree nodes	**0.056**	**0.067**	**0.118**	**-0.855**	**-0.916**	1				
Trip circuity, C_t	**0.036**	**0.022**	0.002	**0.033**	**0.027**	**-0.033**	1			
P2A	**-0.045**	**0.239**	**-0.173**	**0.481**	**0.639**	**-0.641**	**0.048**	1		
Street density, ρ_{lb}	**0.097**	**0.073**	**-0.077**	**-0.793**	**-0.641**	**0.795**	**-0.019**	**-0.417**	1	
Intersection density, ρ_{vb}	**0.091**	**0.034**	**-0.025**	**-0.796**	**-0.667**	**0.813**	**-0.026**	**-0.536**	**0.934**	1

bold - indicates significance at 95% confidence level

Table 5.2: Correlation of network measures - South Florida

	Relative discontinuity, Y'_P	Proportion of limited access roads	Arterial Treeness, ϕ_{tree}	Proportion of nodal degree - 1 degree nodes	Proportion of nodal degree - 3 degree nodes	Proportion of nodal degree - 3+ degree nodes	Trip circuity, C_t	P2A	Street density, ρ_{lb}	Intersection density, ρ_{vb}
Relative discontinuity, Y'_P	1									
Proportion of limited access roads	**-0.119**	1								
Arterial Treeness, ϕ_{tree}	-0.008	**0.0566**	1							
Proportion of nodal degree - 1 degree nodes	**-0.046**	**0.189**	**-0.203**	1						
Proportion of nodal degree - 3 degree nodes	**-0.041**	-0.024	**-0.308**	**0.339**	1					
Proportion of nodal degree - 3+ degree nodes	**0.053**	**-0.088**	**0.318**	**-0.777**	**-0.856**	1				
Trip circuity, C_t	**0.165**	**0.065**	-0.025	**0.053**	**0.070**	**-0.076**	1			
P2A	-0.016	**0.059**	**-0.220**	**0.668**	**0.659**	**-0.808**	**0.101**	1		
Street density, ρ_{lb}	**0.104**	**-0.032**	**0.162**	**-0.506**	**-0.318**	**0.491**	**-0.053**	**-0.406**	1	
Intersection density, ρ_{vb}	**0.126**	**-0.276**	**0.161**	**-0.534**	**-0.365**	**0.537**	**-0.075**	**-0.520**	**0.886**	1

bold - indicates significance at 95% confidence level

5.2.3 Control Variables

Distance measure

A distance measure is introduced to account for the accessibility and relative location of households with respect to the downtown or city center in both study areas. The downtown district in each study area is identified using Google maps (Google, 2009) and a working knowledge of the area. The transportation analysis zones (TAZ) corresponding to the downtowns in both study areas are identified using a GIS.

The Euclidean or straight line distance from the household location to the respective downtowns is then estimated using the X, Y coordinates of the household and the X, Y coordinates of the TAZ centroid. The following distances are obtained:

- Twin Cities

  Distance to downtown Minneapolis

  Distance to downtown St. Paul

- South Florida

  Distance to downtown Fort Lauderdale

  Distance to downtown Miami

Socio-demographic variables

The socio-demographic variables are obtained from the travel survey data for the respective study areas and are used as control variables in our analyses. Typical variables include age, gender, employment type, income level, household size, and auto ownership.

A summary statistics of the estimated network measures for the two study areas is provided in Table 5.3.

Table 5.3: Summary statistics of estimated network measures

		Twin Cities				South Florida			
Independent Variables	Unit	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Relative discontinuity, Y'_P	1/km	0.441	1.137	0.000	58.395	0.455	0.808	0.000	30.923
Proportion of limited access roads		0.049	0.045	0.000	0.268	0.062	0.058	0.000	0.456
Arterial Treeness, ϕ_{tree}		0.009	0.029	0.000	0.625	0.004	0.012	0.000	0.167
Proportion of nodal degree - 1 degree nodes		0.166	0.085	0.000	0.438	0.152	0.058	0.000	0.372
Proportion of nodal degree - 3 degree nodes		0.537	0.110	0.107	0.842	0.620	0.070	0.255	0.818
Proportion of nodal degree - 3+ degree nodes		0.297	0.173	0.026	0.893	0.228	0.105	0.053	0.707
Trip circuity, C_t		1.426	1.905	0.000	161.826	1.402	0.775	0.050	33.436
P2A		24.523	3.363	17.196	56.505	24.388	3.185	17.771	37.782
Street density, ρ_{lb}	1/km	18.439	5.281	2.671	34.465	14.002	2.126	5.773	23.001
Intersection density, ρ_{vb}		29.191	11.641	0.642	67.575	50.260	13.084	13.793	105.723
Distance to downtown Minneapolis	km	16.287	9.732	0.050	63.783				
Distance to downtown St. Paul	km	21.177	10.713	0.042	74.268				
Distance to downtown Fort Lauderdale	km					28.114	18.913	0.472	81.815
Distance to downtown Miami	km					30.556	14.976	0.965	61.293
No of observations		19,379				4,720			

5.3 Hypotheses

The model identified above is operationalized with a set of specific hypotheses.

- The first broad hypothesis is that aspects of network structure which increase network travel distance between fixed origins and destinations (operational variables: network circuity, P2A, treeness) will reduce actual travel distance undertaken by travelers at those origins. Travelers will respond to higher point-to-point travel times by reducing trip length (changing the point of destination vis-a-vis the point of origin).

- Second, aspects of network structure which decrease network speed (operational variables: street density) also reduce actual trip length. Similarly aspects of network structure that increase network speed (operational variables: proportion of limited access roads) will increase trip length.

- Third, aspects of network structure which increase perceived travel complexity or decrease network efficiency (operational variables: discontinuity) will decrease actual trip length.

5.4 Analysis

Two types of analyses are conducted here using the network and travel data for the two study areas. The first analysis uses the trip distance between the origin and destination, measured along the network, as the dependent variable. This analysis is further separated by trip purpose into analysis of work and non-work trips. The second analysis uses the estimated vehicle kilometers traveled (VKT) per individual commuter as the dependent variable. The analysis is limited to auto based (drive-alone, carpool) trips in both study areas. The objective in these analyses is to understand the influence of network measures on the dependent variable, after accounting for non-network control variables.

5.4.1 Predicting trip (network) distance

To obtain the dependent variable for the first analysis, the length of the street segments along the identified fastest path between each origin-destination pair is summed up to obtain the trip (network) distance. Separate regression models are estimated for the two study areas, Twin Cities and South Florida (Fort Lauderdale and Miami). The two regression models of trip distance are:

- Regression of trip distance of work trips,
- Regression of trip distance of non-work trips

The stratification by trip purpose (work/non-work) across the two study areas is to capture any variations in the influence of the independent network measures. Table 5.4 presents the results of the regression models of trip distance for work trips, while Table 5.5 presents the results for non-work trips, for both study areas.

Looking at the results of the regression model of trip distance for work trips, it is clear that most measures of network structure are significant and influence trip (network) distance as hypothesized, even after controlling for other independent variables. The measures of relative discontinuity, P2A ratio and street density have the expected negative influence on trip distance in both study areas. The proportion of limited access roads has a significant positive influence in both study areas, corroborating our hypothesis. The measures of arterial treeness and trip circuity have the expected negative coefficient in both areas. However both measures are significant in the Twin Cities area alone.

The distance measures, accounting for the relative location of the individuals' residence with respect to the downtown or city center, are positive and significant in both study areas. This is expected since individuals that live further away from the downtown or city center, typically have lower accessibility and hence need to travel longer to access opportunities. The results of the regression model of trip distance for non-work trips show similar patterns of influence but minor differences in the magnitude of influence of the independent variables, in both study areas. The socio-demographic variables are used as control variables in this analysis and perform as expected.

The regression models for work trips and non-work trips were tested for varying trip lengths, for example, trip lengths less than 20 km, trip lengths between 20 km and 60 km and trip lengths greater than 60 km. This stratification by trip distance is to check our hypotheses and see if the influence of the independent network measures varies with distance. The results are presented in Tables D.1 and D.2 in Appendix D. The results show the same patterns of influence of network variables on trip distance in all the models.

The next analysis presented below examines how network measures along a recurring trip (e.g., morning commute) affect the total travel undertaken by an individual in an urban area.

5.4.2 Predicting Vehicle Kilometers Traveled (VKT)

The second analysis conducted in this paper regresses VKT per individual commuter on measures of network structure estimated along the home to work trip. The travel survey data are used to identify the commuters in the two study areas along with the trips undertaken by each commuter on the given travel day. The dependent variable, VKT per individual commuter, is obtained by summing up the trip (network) distance between the origin and destination for all the identified trips. The VKT per individual commuter is then estimated as a function of the network measures along the home to work trip using a simple linear regression model (with robust standard errors).

The reasons for using the network measures along the home to work trip to predict VKT are: Firstly the home to work trip is a recurring trip and definitely contributes to an individual's total travel on a typical day. Secondly, preliminary analysis of the travel survey data confirms that the home to work trip distance comprises a high percentage of the total daily VKT. For example, in the Twin Cities, for over 55% of the commuters, the home to work trip comprises more than 50% of the total daily VKT.

The regression is conducted for both study areas and the results are tabulated in Table 5.6. The socio-economic variables are used as control variables in this analysis. The results indicate that while the influence of network structure on VKT per individual commuter is not as pronounced as the results for travel distance, there is influence of network structure measures on total travel.

The relative discontinuity variable is negative and significant in both study areas, confirming our hypothesis. Similarly the proportion of limited access roads is positive and significant in both study areas, in line with our hypothesis. The differences in the patterns of influence of the network measures between the two study areas arise in the following variables: The treeness variable is negative as hypothesized but is siginificant only in the Twin Cities area. The difference could be attributed to the higher number of roadway segments characterized as belonging to a tree network in the Twin Cities area compared to the South Florida area. The trip circuity also shows a negative influence in both study areas but is also significant only in the Twin Cities. On the other hand, the P2A ratio and street density variables corroborate the hypothesis of negative influence in the South Florida area but shows no significant influence in the Twin Cities.

The distance measures to the downtowns in both study areas are also positive and significant, similar to the above models of trip distance. This suggests that individuals who reside farther away from the city center typically have more daily travel, in line with existing literature on travel behavior. In summary, the regression models corroborate the formulated hypotheses and show the same patterns of influence except for some minor differences beween the two study areas.

5.4.3 Standardized coefficients

The elasticity estimates from each of the above three regression models are presented in Table 5.7. A summary of the formulated hypotheses and the results of the analyses are provided in Table 5.8. Additionally scatterplots of the predicted distance versus actual distance obtained from the above three regression models are presented in Figures D.1 through D.6 in Appendix D.

The elasticity estimates measure the change in the dependent variable (distance in these analyses) due to an unit change in the independent variable. For example, consider the elasticity estimates for work trips presented in Table 5.7. An unit change in the relative discontinuity results in a 0.15 decrease in the network distance between an origin and destination in the Twin Cities and a 0.16 decrease in South Florida. Similarly an unit increase in the proportion of limited access roads results in 0.29 to 0.44 increase in the network distance between an origin and destination in both study areas. An unit increase in the P2A variable results in a 0.64 to 1.10 decrease in the network distance for work trips in both areas.

The elasticities presented in Table 5.7 provide an estimate of the influence of the independent variables on the network distance. However as explained in Chapter 4, it is difficult to understand the relative contribution of each independent variable, since these variables are measured in different units and have different scales. Standardized regression models are used to overcome this limitation and Table 5.9 summarizes the standardized regression estimates for the above three regression models.

The β coefficients can be directly compared due to the standardization of the independent variables. So using the β coefficients for work trips presented in Table 5.9 we can see that the proportion of limited access roads has the highest influence on distance and can be interpreted as follows: a one standard deviation in the proportion of limited access roads results in a 0.29-0.47 standard deviation increase in the network distance between the work trip origin and destination. Similarly one standard deviation increase in the relative discontinuity variable results in a 0.27 standard deviation decrease in the network distance for work trips. The other network variables can be interpreted in a similar manner.

5.5 Discussion

The previous chapter looked at the influence of network structure on travel time perception. This chapter extends this idea by testing the relation between underlying street network structure and actual travel. The hypothesis here is that travelers respond to their perceived travel time by increasing or decreasing actual travel. The analyses presented confirms the same and quantifies the impact of network measures on travel.

Based on survey and street network data, the empirical analysis identified several significant relationships between network structure and travel (trip distance, VKT). The inclusion of network structure as a factor in influencing travel differentiates this research from prior research in this field. Whereas some of the analyzed network variables have so far been used in the context of urban form, network connectivity and micro neighborhood design, the role of other, so far relatively unobserved and more complex attributes are also determined.

The stratification of the data by trip purpose and across two study areas has shown similarities in the patterns of influence but minor differences in the magnitude of influence of the independent network variables. What can be concluded is that network structure does influence individual travel, even after controlling for the effect of other independent socio-demographic variables. It is important to clarify that the analyses presented here confirm the relation rather than causality between network structure and travel. Confirming causality would require the use of temporal network and travel data, to see how changes in the street network brings about corresponding changes in travel or vice-versa.

The following chapters extend this analysis to understand the relation between network structure and household and regional travel.

Table 5.4: Predicting network distance (km): origin to destination, work trips

			Twin Cities			South Florida		
Independent variables	Unit	Hypothesis	Coef.	Sig	t	Coef.	Sig	t
Distance to downtown Minneapolis	km		0.22	***	7.42	NA	NA	NA
Distance to downtown St. Paul	km		0.10	***	4.10	NA	NA	NA
Distance to downtown Fort Lauderdale	km		NA	NA	NA	0.19	***	7.18
Distance to downtown Miami	km		NA	NA	NA	0.15	***	5.31
Relative discontinuity, Y'_P	1/km	-S	-8.80	***	-2.73	-7.25	***	-7.88
Proportion of limited access roads		+S	94.41	***	18.52	80.77	***	20.18
Arterial Treeness, ϕ_{tree}		-S	-35.90	***	-3.85	-7.06		-0.38
Trip circuity, C_t		-S	-1.98	***	-4.47	-0.24		-0.14
P2A		-S	-0.46	***	-6.01	-0.63	***	-6.81
Street density, ρ_{lb}	1/km	-S	-0.41	***	-5.91	-0.55	***	-4.42
Age of Traveler			0.00		-0.26	0.01		0.40
Number of workers in household			-1.16	***	-4.03	-0.36		-1.58
Number of non-workers in household			0.11		0.72	-0.03		-0.20
Total vehicles in household			1.05	***	4.15	0.43	*	1.67
Medium income			1.69	***	3.63	0.27		0.47
High Income			1.58	***	2.69	1.04		1.53
Part time employee			-3.68	***	-8.55	-0.66		-1.03
Non Telecommuter			-2.31	***	-4.96	-1.37	*	-1.73
Urban area dummy - Miami			NA	NA	NA	-1.55		-1.23
Constant			32.13	***	11.17	24.76	***	6.19
No. of observations			4,105			1,492		
R-squared			0.301			0.429		
Adj R-squared			0.298			0.423		
* p<.10, ** p<0.05, *** p<.01								

Table 5.5: Predicting network distance (km): origin to destination, non-work trips

			Twin Cities			South Florida		
Independent variables	Unit	Hypothesis	Coef.	Sig	t	Coef.	Sig	t
Distance to downtown Minneapolis	km		0.03	*	1.74			
Distance to downtown St. Paul	km		0.03	***	2.72			
Distance to downtown Fort Lauderdale	km					0.07	***	4.35
Distance to downtown Miami	km					0.11	***	6.52
Relative discontinuity, Y'_P	1/km	-S	-1.22	***	-4.25	-2.10	***	-3.19
Proportion of limited access roads		+S	63.24	***	28.60	64.38	***	19.64
Arterial Treeness, ϕ_{tree}		-S	-11.69	***	-5.12	11.99		0.74
Trip circuity, C_t		-S	-0.14	**	-2.57	-0.70	***	-3.29
P2A		-S	-0.45	***	-18.91	-0.42	***	-9.09
Street density, ρ_{lb}	1/km	-S	-0.52	***	-20.46	-0.40	***	-5.66
Age of Traveler			-0.01		-1.28	-0.04	***	-2.94
Number of workers in household			-0.73	***	-5.43	-0.28		-1.51
Number of non-workers in household			-0.28	***	-3.90	0.21	*	1.82
Total vehicles in household			0.60	***	5.84	0.00		0.02
Medium income			0.52	**	2.45	-1.32	***	-2.93
High Income			0.21		0.78	-0.55		-1.11
Part time employee			-0.74	***	-4.56	-0.06		-0.19
Non Telecommuter			-0.22		-1.28	0.20		0.50
Urban area dummy - Miami			NA	NA	NA	0.71		0.98
Constant			28.06	***	26.34	19.88	***	11.12
No. of observations			15,274			3,228		
R-squared			0.157			0.286		
Adj R-squared			0.156			0.282		
* p<.10, ** p<0.05, *** p<.01								

Table 5.6: Predicting VKT per individual commuter

			Twin Cities			South Florida		
Independent variables	Unit	Hypothesis	Coef.	Sig	t	Coef.	Sig	t
Distance to downtown Minneapolis	km		1.08	***	8.77			
Distance to downtown St. Paul	km		0.13		1.47			
Distance to downtown Fort Lauderdale	km					0.34	***	3.24
Distance to downtown Miami	km					0.29	***	2.87
Relative discontinuity, Y'_P	1/km	-S	-13.22	**	-2.31	-9.41	***	-3.68
Proportion of limited access roads		+S	182.88	***	10.52	131.51	***	8.81
Arterial Treeness, ϕ_{tree}		-S	-104.96	***	-4.34	-8.52		-0.13
Trip circuity, C_t		-S	-4.01	***	-4.47	-2.63		-0.88
P2A		-S	-0.06		-0.22	-0.67	*	-1.74
Street density, ρ_{lb}	1/km	-S	0.36		1.56	-1.75	***	-3.55
Age of Traveler			0.05		0.93	-0.04		-0.59
Number of workers in household			-3.81	***	-3.40	0.19		0.19
Number of non-workers in household			1.64	**	2.51	1.82	***	2.63
Total vehicles in household			2.46	**	2.36	0.54		0.50
Medium income			4.75	**	2.44	2.93		1.25
High Income			5.79	**	2.44	5.45	*	1.94
Part time employee			-5.90	***	-3.45	3.19		1.16
Non Telecommuter			-4.29	***	-2.60	-4.62		-1.31
Urban area dummy - Miami			NA	NA	NA	-0.38		-0.08
Constant			20.67	*	1.88	52.71	***	3.47
No. of observations			2,296			1,122		
R-squared			0.200			0.161		
Adj R-squared			0.195			0.148		
* p<.10, ** p<0.05, *** p<.01								

Table 5.7: Elasticity estimates

			Work Trips		Non-work Trips		VKT per individual commuter	
Independent variables	Unit	Hypothesis	Twin Cities	South Florida	Twin Cities	South Florida	Twin Cities	South Florida
Distance to downtown Minneapolis	km		0.21		0.05		0.40	
Distance to downtown St. Paul	km		0.12		0.06		0.06	
Distance to downtown Fort Lauderdale	km			0.39		0.22		0.27
Distance to downtown Miami	km			0.32		0.38		0.25
Relative discontinuity, Y'_P	1/km	-S	-0.15	-0.16	-0.06	-0.12	-0.08	-0.08
Proportion of limited access roads		+S	0.29	0.44	0.30	0.41	0.20	0.28
Arterial Treeness, ϕ_{tree}		-S	-0.02	0.00	-0.01	0.00	-0.02	0.00
Trip circuity, C_t		-S	-0.15	-0.02	-0.02	-0.11	-0.11	-0.10
P2A		-S	-0.64	-1.10	-1.12	-1.15	-0.03	-0.47
Street density, ρ_{lb}	1/km	-S	-0.42	-0.55	-0.98	-0.63	0.13	-0.69

Table 5.8: Summary of regression results

			Trip distance between origin and destination				VKT per individual commuter	
			Work Trips		Non-work Trips			
Independent network variables	Unit	Hypothesis	Twin Cities	South Florida	Twin Cities	South Florida	Twin Cities	South Florida
Relative discontinuity, Y'_P	1/km	-S	-S	-S	-S	-S	-S	-S
Proportion of limited access roads		+S	+S	+S	+S	+S	+S	+S
Arterial Treeness, ϕ_{tree}		-S	-S	NS	-S	NS	-S	NS
Trip circuity, C_t		-S	-S	NS	-S	-S	-S	NS
P2A		-S	-S	-S	-S	-S	NS	-S
Street density, ρ_{lb}	1/km	-S	-S	-S	-S	-S	NS	-S
No. of observations			4,105	1,492	15,274	3,228	2,296	1,122

Table 5.9: Standardized β coefficients

			Work Trips		Non-work Trips		VKT per individual commuter	
Independent variables	Unit	Hypothesis	Twin Cities	South Florida	Twin Cities	South Florida	Twin Cities	South Florida
Distance to downtown Minneapolis	km		0.18		0.02		0.33	
Distance to downtown St. Paul	km		0.09		0.03		0.04	
Distance to downtown Fort Lauderdale	km			0.36		0.15		0.22
Distance to downtown Miami	km			0.23		0.18		0.15
Relative discontinuity, Y_P'	1/km	-S	-0.27	-0.27	-0.15	-0.22	-0.16	-0.12
Proportion of limited access roads		+S	0.29	0.47	0.28	0.41	0.21	0.26
Arterial Treeness, ϕ_{tree}		-S	-0.07	-0.01	-0.03	0.02	-0.08	0.00
Trip circuity, C_t		-S	-0.09	-0.01	-0.03	-0.07	-0.06	-0.04
P2A		-S	-0.11	-0.19	-0.15	-0.15	-0.01	-0.07
Street density, ρ_{lb}	1/km	-S	-0.16	-0.11	-0.27	-0.10	0.05	-0.12
Age of Traveler			0.00	0.01	-0.01	-0.05	0.02	-0.02
Number of workers in household			-0.07	-0.04	-0.05	-0.03	-0.08	0.01
Number of non-workers in household			0.01	0.00	-0.03	0.03	0.05	0.08
Total vehicles in household			0.08	0.04	0.06	0.00	0.07	0.02
Medium income			0.06	0.01	0.02	-0.07	0.07	0.05
High Income			0.05	0.05	0.01	-0.03	0.07	0.08
Part time employee			-0.11	-0.02	-0.03	0.00	-0.06	0.03
Non Telecommuter			-0.07	-0.04	-0.01	0.01	-0.05	-0.04
Urban area dummy - Miami				-0.08		0.04		-0.01
No. of observations			4,105	1,492	15,274	3,228	2,296	1,122

Chapter 6

Household Activity Spaces

6.1 Introduction

The analyses of individual travel presented in Chapters 4 and Chapters 5 confirmed the relationship between street network structure and individual travel. Chapter 4 identified a relationship between street network structure and an individual's perception of travel time while Chapter 5 identified a relationship between street network structure and actual travel (trip length). The goal in this chapter is to extend the analysis to the household level using network and travel data from the same two study areas, namely Minneapolis-Saint Paul and South Florida (Fort Lauderdale and Miami). Existing quantitative measures as well as new measures are developed to account for the underlying structure of the street network. The influence of these measures on household travel are then tested using statistical models.

Household travel is analyzed here using the concept of activity spaces. The concept of activity space is based on the space-time framework, proposed by (Hägerstrand, 1970), which accounts for the spatial and temporal dimensions of activity participation. Individuals are modeled as paths or trajectories in time-space, subjected to various constraints such as coupling constraints, capacity constraints and authority constraints. The transportation system determines the area of the time-space prism since the travel speeds and network constraints affect the time needed for travelers to get to their numerous destinations and hence the time remaining to participate in activities (Fan and Khattak, 2008).

Newsome et al. (1998) refer to activity space as the *"graphical representation of the space within which a group of activities are carried out by the individual or the household, subject to time constraints imposed by or on the traveler"*. The observed activity space represents the typical area over which the individual or household is likely to regularly engage in activities on a given travel day. The potential activity space, on the other hand, represents the maximal area over which the traveler could engage in activities.

This chapter extends a recent paper by Cerda and El-Geneidy (2009) looking at the relationship between regional accessibility measures on housing prices and travel activity patterns by including measures of network structure into the model, in addition to the other measures of accessibility, land use and socio-demographic variables.

6.2 Methodology

The proposed model to test the relationship between measures of street network structure and household travel is provided below. Household travel is measured as the size of the household activity space. The activity space measured here represents observed activity space, due to the use of reported travel survey data.

$$A_a = f(N_a, X_{sd}, Acc_d) \tag{6.1}$$

where:

A_a = Area (km^2) of the household activity space,

N_a = Measures of street network structure within the activity space polygon,

X_{sd} = Household socio-demographic characteristics (e.g. household size, household income),

Acc_d = Distance based measure of household accessibility.

The following sections details the steps in obtaining the above variables.

6.2.1 Data

As elaborated in Chapters 4 and Chapters 5, the travel data and street network data for the analysis are from two study areas, namely, Minneapolis-Saint Paul and South Florida (Fort Lauderdale and Miami). A snapshot of the street networks in the two study areas is already provided in Figures 5.1 and 5.2 in Chapter 5.

6.2.2 Identification of household activity space

The first step in the analysis is to obtain the household activity space using the observed travel survey data. The travel survey data provide information on all trips undertaken by an individual on the specified travel day. Here, the individual level travel data are aggregated to the household level. For each household in the travel survey, the household location and the destinations reached by all household members on the travel day are identified. These are then mapped in a Geographic Information System (GIS) using geocoded X and Y coordinates. The convex hull application in ESRI's ArcGIS 9.3 is used to link the origin and all destinations creating the household activity space polygon. This process is implemented on the travel survey data for both study areas.

Since the focus of this research is on the quantification of street networks, only those destinations that were reached using the automobile mode (drive alone, carpool) are considered. Destinations reached by household members using non-auto modes are not considered in the identification of the household activity spaces in both study areas. Non-auto mode share is small in each area. Census Journey-to-Work indicates a 88.4% auto mode share in the Twin Cities and a 90.1% auto mode share in South Florida (McGuckin and Srinivasan, 2003).

A minimum of three points (an origin and two destinations) are needed to generate the activity space for each household. Hence households with no trips on the travel day and households with just one destination on the travel day are removed from our analysis. The final dataset consists of 1,021 households in South Florida and 2,740 households in the Twin Cities. The area (in km^2) is calculated for each identified activity space polygon in the two study areas.

Figure 6.1 provides a sample of the activity space identified for a household in the Twin Cities travel survey.

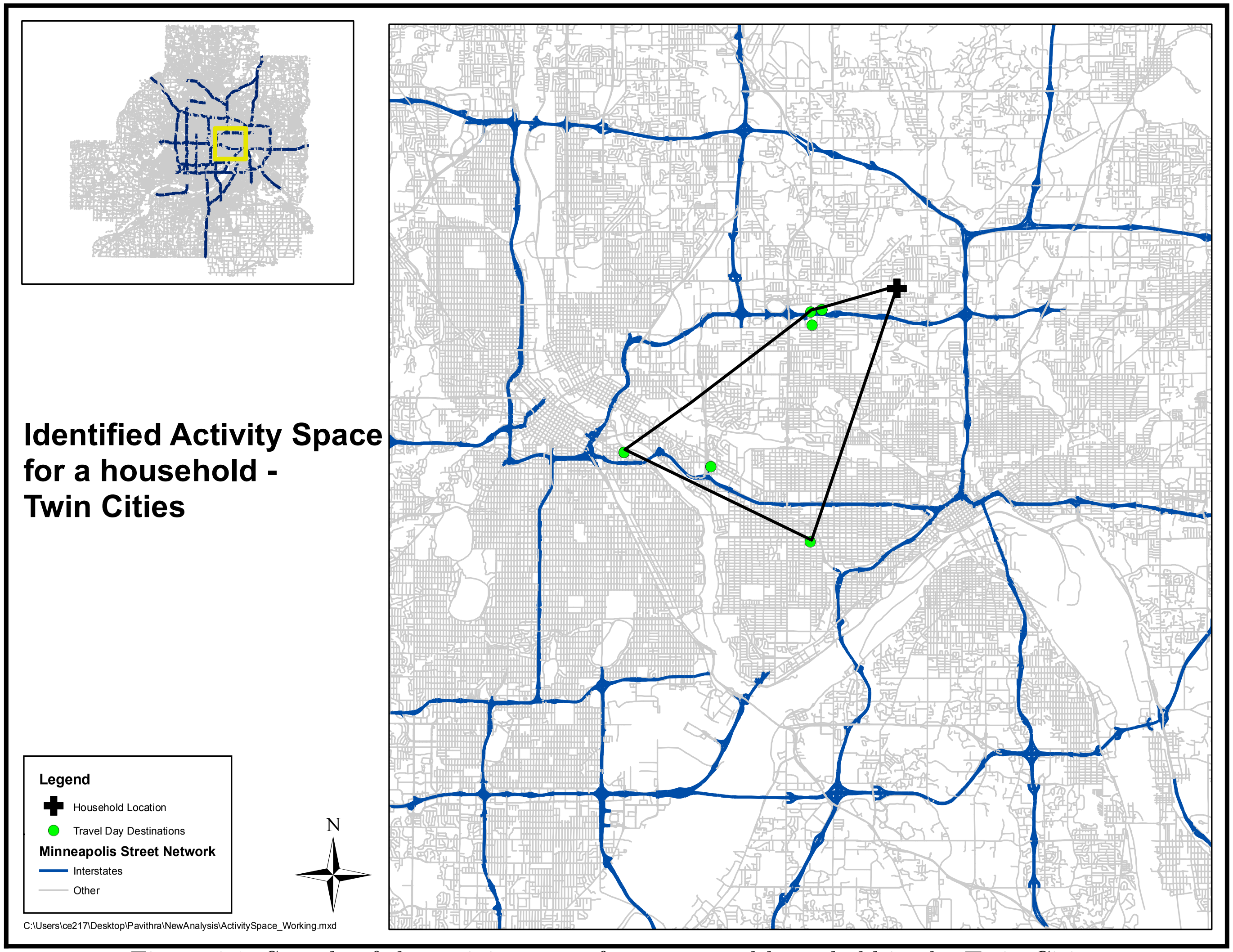


Figure 6.1: Sample of the activity space for a surveyed household in the Twin Cities
Source: Census TIGER/line files, `http://www.census.gov/geo/www/tiger/`

6.2.3 Estimation of Network Measures

The next step in the analysis is to estimate measures of street network structure within the identified activity space polygon for each household in the two travel surveys. As explained in Chapter 3, the measures used to quantify the street network structure within each household activity space polygon are listed below.

- Hierarchy

  Proportion of limited access roads

- Topology

  Arterial treeness

  Proportion of nodal degrees (1,3)

- Morphology

  P2A

- Scale

  Street density

  Intersection density

The measures of street network structure estimated within the activity space polygon for the households in both study areas are summarized in Table 6.1.

The estimated measures are designed to capture different aspects of street network structure. A correlation test is conducted to ensure that the measures capture different aspects of structure and are hence effective predictors in the model of household activity space. A correlation matrix of the estimated network measures is provided in Tables 6.3 and 6.2. The correlation table shows that intersection density within the activity space polygon is highly correlated with the measures of street density and the Proportion of nodal degrees. Hence this variable is dropped from the actual model of household activity space polygon.

Table 6.1: Summary statistics of network measures within the activity space polygon

			Twin Cities				South Florida			
Network variables	Unit	Category	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Proportion of limited access roads		Hierarchy	0.094	0.055	0.000	0.565	0.053	0.042	0.000	0.306
Arterial Treeness, ϕ_{tree}		Topology	0.006	0.015	0.000	0.496	0.003	0.022	0.000	0.464
Nodal degree - Proportion of 1-degree nodes		Topology	0.160	0.078	0.000	0.435	0.146	0.054	0.000	0.371
Nodal degree - Proportion of 3-degree nodes		Topology	0.527	0.104	0.024	0.814	0.617	0.066	0.194	0.816
P2A		Morphology	23.990	3.143	18.365	55.145	24.417	3.697	18.311	49.440
Street density, ρ_{la}	1/km	Scale	10.913	4.546	1.741	75.544	15.050	10.533	1.993	228.377
Intersection density, ρ_{va}		Scale	28.779	10.848	1.977	106.978	49.877	13.275	3.628	133.648
No of observations			2,258				631			

Table 6.2: Correlation of estimated measures of network structure within the activity space polygon - Twin Cities

	Proportion of limited access roads	Arterial Treeness, ϕ_{tree}	Nodal degree - Proportion of 1-degree nodes	Nodal degree - Proportion of 3-degree nodes	P2A	Street density, ρ_{la}	Intersection density, ρ_{va}
Proportion of limited access roads	1						
Arterial Treeness, ϕ_{tree}	-0.0104	1					
Nodal degree - Proportion of 1-degree nodes	0.0299	**-0.1955**	1				
Nodal degree - Proportion of 3-degree nodes	**0.0913**	**-0.2505**	**0.6688**	1			
P2A	**0.3821**	**-0.2042**	**0.5069**	**0.6156**	1		
Street density, ρ_{la}	**0.1005**	**0.0679**	**-0.5919**	**-0.4996**	**-0.0954**	1	
Intersection density, ρ_{va}	**-0.0735**	**0.13**	**-0.814**	**-0.6981**	**-0.4709**	**0.7364**	1

bold - indicates significance at 95% confidence level

Table 6.3: Correlation of estimated measures of network structure within the activity space polygon - South Florida

	Proportion of limited access roads	Arterial Tree-ness, ϕ_{tree}	Nodal degree - Proportion of 1-degree nodes	Nodal degree - Proportion of 3-degree nodes	P2A	Street density, ρ_{la}	Intersection density, ρ_{va}
Proportion of limited access roads	1						
Arterial Treeness, ϕ_{tree}	-0.0632	1					
Nodal degree - Proportion of 1-degree nodes	**0.1838**	-0.0175	1				
Nodal degree - Proportion of 3-degree nodes	0.0372	-0.0439	**0.3874**	1			
P2A	**0.1070**	**-0.0763**	**0.5818**	**0.5841**	1		
Street density, ρ_{la}	0.0097	-0.0595	**-0.276**	-0.0669	-0.0078	1	
Intersection density, ρ_{va}	**-0.2380**	**-0.1472**	**-0.6002**	**-0.4013**	**-0.5011**	**0.3182**	1

bold - Indicates significant at 95% confidence level

6.2.4 Control Variables

Distance measure

Similar to the analysis of individual travel presented in Chapters 4 and 5, a distance measure is introduced to account for the accessibility and relative location of households with respect to the downtown or city center in both study areas.

The following distances are obtained:

- Twin Cities

  Distance to downtown Minneapolis

  Distance to downtown St. Paul

- South Florida

  Distance to downtown Fort Lauderdale

  Distance to downtown Miami

Socio-demographic variables

The socio-demographic variables are obtained from the travel survey data for the respective study areas and are used as control variables in our analyses. Typical variables included in our analysis are household income, household auto ownership, the number of workers and non-workers in the household. The inclusion of these socio-demographic variables is based on existing literature on travel behavior.

6.3 Hypotheses

The model identified above is operationalized with a set of specific hypotheses.

An increase in the proportion of limited access roads will increase activity space. Aspects of network structure that increase network speed will increase the activity space due to the increase in ability to cover larger distances.

An increase in the proportion of lower degree nodes (1,3) compared to the typical 4-degree nodes will reduce activity space. Aspects of the network that increase network complexity or decrease network efficiency will decrease activity space.

An increase in street density will decrease the activity space. Aspects of network structure which decrease network speed also reduce actual trip length and hence the associated activity space

An increase in the P2A ratio and treeness will decrease the activity space. Aspects of network structure which increase network travel distance between fixed origins and destinations (operationalized as P2A and treeness) will reduce actual travel distance undertaken by travelers at those origins. Travelers will respond to higher point-to-point travel times by reducing trip length (changing the point of destination vis-a-vis the point of origin).

6.4 Analysis

The relationship between network structure and household spatial patterns is analyzed here using travel survey data from the Twin Cities and South Florida. The use of two study areas allows the comparison of the influence of network measures across regions. Separate regression models are developed for the two study areas. As mentioned previously, the household spatial patterns are measured by the identified activity spaces. The measures of network structure within the identified activity spaces are then estimated.

The models for the two study areas predict the area of the activity space as a function of independent network and non-network control variables. The model with the best fit uses the natural log of the dependent variable, i.e., the area of the activity space. The independent variables remain in their linear form. The results of the regression models (robust standard errors) are presented in Table 6.4. Scatterplots of the predicted activity space area versus the actual activity space area for the two study areas are presented in Figures E.1 and E.2 in Appendix E.

The model results corroborate the hypothesis that measures of network structure influence household spatial patterns, as measured by the activity space, after accounting for the non-network control variables. The measures of P2A ratio and street density have the expected significant negative influence on the activity space in both study areas. The proportion of limited access roads has a significant positive coefficient in both the models as expected. The measure of arterial network treeness has a negative coefficient but is statistically significant only in the Twin Cities model.

The proportion of 1-degree nodes show differences in its influence across the two models. The Twin Cities model shows a significant negative influence on the activity space while the South Florida model shows a highly positive influence. The proportion of 3-degree nodes is positive and significant in both models. The positive coefficient for the nodal degree variables could mean that these measures do not necessarily increase network complexity or inefficiency, as we hypothesized. Further research is needed to understand the aspects of network structure that are captured by these measures and the reasons for the differences in influence across the two study areas.

The distance measures in both models have a positive and significant coefficient, except for the distance to downtown Fort Lauderdale, which is insignificant. The distance measure can be considered to be a proxy for accessibility available to households. Households located away from downtown have less accessibility or access to opportunities. This results in a larger activity space as travelers need to travel longer to reach the desired opportunities.

Other independent variables in the model perform as expected. The use of two study areas in the analysis is to identify any differences in the influence of roadway network measures on spatial patterns. The model results show similarity in the influence of network measures across the two study areas. However the magnitude of influence varies across the two regions. The key differences between the models arise in the nodal degree variables. The household level socio-demographic variables perform as expected. The number of workers in the household increases the household activity space which is expected due to households deciding their residential location balancing the travel requirements of multiple workers, compared to single-worker households. The income variables show that medium and high income households have a larger activity space compared to low income households, which corroborates the existing literature on travel behavior.

6.5 Discussion

The objective in this chapter is to understand the relationship between the measures of network structure and the household spatial patterns, using travel survey data from two study areas, namely the Twin Cities and South Florida. The measures of network

Table 6.4: Prediction of household spatial patterns

ln(Area of Activity Space)								
			Twin Cities			South Florida		
	Unit	Hypothesis	Coef.	t	Sig.	Coef.	t	Sig.
Distance to downtown Minneapolis	km		9.82E-06	2.35	**	NA	NA	NA
Distance to downtown St. Paul	km		1.84E-05	6.13	***	NA	NA	NA
Distance to downtown Fort Lauderdale	km		NA	NA	NA	8.65E-06	1.50	
Distance to downtown Miami	km		NA	NA	NA	1.21E-05	1.99	**
Proportion of limited access roads		+S	7.48E+00	9.98	***	3.22E+00	1.99	**
Arterial Treeness[1], ϕ_{tree}		-S	-4.41E+00	-2.16	**	-1.46E+00	-1.05	
Proportion of 1-degree nodes$^+$		-S	-4.22E+00	-5.05	***	5.31E+00	3.52	***
Proportion of 3-degree nodes$^+$		-S	8.85E-01	1.81	*	4.53E+00	3.40	***
P2A		-S	-1.76E-01	-10.33	***	-2.01E-01	-10.36	***
Street density, ρ_{la}	1/km	-S	-1.94E-01	-7.16	***	-4.33E-02	-2.92	***
Number of non-workers in household			9.87E-03	0.43		6.15E-02	1.58	
Number of workers in household			2.21E-01	6.55	***	1.16E-01	2.22	**
Total vehicles in household			1.32E-01	4.33	***	7.09E-02	1.34	
Medium income			1.62E-01	2.61	***	3.48E-01	3.02	***
High Income			2.44E-01	3.10	***	4.30E-01	2.79	***
Urban area dummy - Miami			NA	NA	NA	9.07E-02	0.35	
Constant			8.10E+00	16.21	***	3.67E+00	5.21	***
Number of observations			2,258			631		
R-squared			0.507			0.357		
* p<0.10, ** p<0.05, *** p<0.01								
$^+$ Proportion of 4+degree nodes is the base category								
[1] - Treeness estimated for a subnetwork consisting of interstates and arterials								

structure were developed to capture the broad aspects of networks such as hierarchy, topology, morphology and scale. The focus was on developing measures that can provide a quantitative value for the structure of the underlying street network. The analysis is restricted to automobile trips in the two areas.

The final model predicting the size of the activity space shows the influence of network measures, after accounting for non-network measures. The quantification of the network and the use of these measures in explaining travel patterns differentiates this research from other research in this area. Whereas some of the analyzed network variables have so far been used in the context of urban form, network connectivity and micro neighborhood design, the analysis presented here goes a step further and looks at how network structure impacts travel decisions.

The model elasticities can be read directly from Table 6.4 and illustrate the actual influence of network variables. For example, a unit increase in the P2A ratio of the network within the activity space decreases the household activity space by approximately 17% to 20% in both the study areas. A unit increase in street density decreases the activity space in the Twin Cities by 19.4% and 4.3% in South Florida. The difference in the influence of variables such as street density highlights the importance of separating out the two study areas.

Consistent with the analyses presented in Chapter 4 and 5, standardized regression estimates are provided in Table 6.5. As explained previously, the interpretation of the β coefficients is slightly different than the elasticity estimates. So an one standard deviation in the proportion of limited access roads results in a 0.265 standard deviation increase in the area of the activity space in the Twin Cities and 0.096 standard deviation increase in South Florida. The estimates also provide a direct comparison of the independent network variables. For example, we can see that among all the independent variables, street density has the largest magnitude of influence on the household activity space in the Twin Cities while the P2A variable has the largest influence in South Florida.

This chapter extends the analysis of network structure and individual travel to a more aggregate level by considering the total travel of a household, using data from two urban areas. The next chapter analyzes the influence of network structure on transportation system performance, using data from the top fifty metropolitan areas across the U.S.

Table 6.5: Prediction of household spatial patterns - Standardized β coefficients

ln(Area of Activity Space)				
	Unit	Hypothesis	Twin Cities	South Florida
Distance to downtown Minneapolis	km		6.41E-02	
Distance to downtown St. Paul	km		1.34E-01	
Distance to downtown Fort Lauderdale	km			1.16E-01
Distance to downtown Miami	km			1.26E-01
Proportion of limited access roads		+S	2.65E-01	9.58E-02
Arterial Treeness[1], ϕ_{tree}		-S	-4.43E-02	-2.27E-02
Proportion of 1-degree nodes[+]		-S	-2.14E-01	2.04E-01
Proportion of 3-degree nodes[+]		-S	5.95E-02	2.11E-01
P2A		-S	-3.59E-01	-5.26E-01
Street density, ρ_{la}	1/km	-S	-5.70E-01	-3.23E-01
Number of nonworkers in household			7.13E-03	5.18E-02
Number of workers in household			1.25E-01	7.66E-02
Total vehicles in household			8.01E-02	4.52E-02
Medium income			5.18E-02	1.23E-01
High Income			6.09E-02	1.12E-01
Urban area dummy - Miami			NA	3.19E-02
Number of observations			2,258	631
[+] Proportion of 4+degree nodes is the base category				
[1] - Treeness estimated for a subnetwork consisting of interstates and arterials				

Chapter 7

Metropolitan Mobility

7.1 Introduction

The previous chapters in the dissertation looked at the relationship between street network structure and travel at a micro-level. Chapter 4 identified a relationship between street network structure and an individual's perception of travel time. Chapter 5 confirmed a relation between network structure and individual travel, specifically trip distance. Chapter 6 extended this analysis to confirm a relation between street network structure and household travel.

This chapter continues the research interest in understanding travel behavior while explicitly accounting for the underlying street network structure, using aggregate level travel data from metropolitan areas across the U.S. In a recent study on network topology, Derrible and Kennedy (2009, 2010) use graph theory to characterize the network structure of 33 metro systems around the world. The analysis was then extended to study the relationship between network measures and transit ridership using data on a subsample of 19 subway systems. The results of the regression model show a strong relationship between the network measures and ridership indicating the importance of network design in attracting people to transit systems.

This chapter aims to extend this interest in complex network analysis to road networks across the U.S and relate it the system performance and usage. The goal is to quantify the street networks of fifty metropolitan areas and to understand the influence of these quantitative measures on two aspects of transportation (street) network performance, namely congestion and highway system usage.

7.2 Methodology

The objective of this research is to understand the systematic variation in transportation system performance with measures of network structure, using data from the top fifty metropolitan areas across the U.S. The metropolitan areas were selected based on the year 2000 population data obtained from the U.S Census Bureau.

7.2.1 Data

The first step in this analysis is to obtain the relevant network and non-network data for the metropolitan areas considered in the analysis. The primary data for this empirical analysis come from the following sources:

Street Networks

The street networks for the fifty metropolitan areas, used in this analysis, were extracted from the Census TIGER/line files. As mentioned previously, the Topologically Integrated Geographic Encoding and Referencing (TIGER) files, developed and maintained by the U.S Census Bureau, provide information on various features such as roads, railroads, rivers, as wells as legal and statistical geographic areas (U.S. Census Bureau, 2008). The extracted networks for the metropolitan areas were cleaned to include just the road features based on the Feature Class Codes (FCC) for the line segments provided in the Census TIGER/Line files.

Travel Data

The travel data are from the Texas Transportation Institute's Urban Mobility Report and provide information on the long-term congestion trends and the most recent congestion comparisons for 90 urban areas across the U.S (Schrank and Lomax, 2009). The data typically include information on the:

- System usage - Vehicle miles traveled (VMT), annual passenger miles, unlinked transit passenger trips

- System supply - Highway lane miles by functional category
- Congestion measures - Annual hours of delay on the system, annual cost of congestion, congestion indexes like the Travel Time Index (TTI) and the Roadway Congestion Index (RCI).

The data on highway system usage were also supplemented by data from the Federal Highway Administration (FHWA)'s Highway Performance Monitoring System (HPMS) which is a national level continuing database that summarizes important statistics on the condition and performance of the highway system (Federal Highway Administration, 2000). The travel data for the year 2000 were extracted for the purpose of this analysis.

Socio-Demographic Data

The socio-demographic data were obtained for the year 2000 from the U.S Census Bureau for the fifty metropolitan areas considered in the analysis. The socio-demographic variables are used as control variables in our analysis. Typical variables used in this analysis include population density, median household income and auto mode share of the of the metropolitan area.

7.2.2 Estimation of Network Measures

The next step in the analysis is to estimate relevant network measures that capture the variations in network structure across the different metropolitan areas. The estimated network measures are used to quantify and characterize the street network structure for the metropolitan areas in our analysis.

The following measures of street network structure are estimated for each of the fifty metropolitan areas:

- Hierarchy

  Percentage of freeways

- Topology

  Treeness

  Completeness

Average circuity

- Scale

Street density

The estimation of street network measures have already been elaborated in Chapter 3.

7.2.3 Control Variables

Accessibility

In addition to the network variables, a comparable measure of accessibility O_{30} is estimated for each study area using a combination of the estimated circuity and the population density of the urbanized area, along with network speed. The estimation is as follows:

$$O_{30} = A_t * \rho_{pm} \tag{7.1}$$

where,
A_t = Area (km^2) that is covered in t minutes,
t = any time contour, defined as 30 minutes (or 0.5 hour) in this analysis,
ρ_{pm} = Population density in the area (persons/km^2).

$$A_t = \pi * {R_e}^2 \tag{7.2}$$

where,
R_e = Euclidean radius in km, estimated as:

$$R_e = S_e * t \tag{7.3}$$

where,
S_e = Euclidean speed in km/h,
t = 30 minutes as defined previously.

$$S_e = S_n/C_m \tag{7.4}$$

where,

S_n = Average network speed in km/h, provided by the Urban Mobility Report,

C_m = Estimated average circuity

The accessibility measure in this analysis measures the average number of people that can be reached in 30 minutes by automobile at uniform average metropolitan density. A review of accessibility shows many methods to estimating accessibility in the region (El-Geneidy and Levinson, 2006). The approach presented here is a simple measure estimated using the data available for all study areas and incorporates both the density aspect of urban areas and the structure of the street network. The accessibility measure is estimated for 48 of the 50 study areas due to the lack of appropriate circuity measures for two study areas.

A summary statistics of the estimated network and control variables is provided in Table 7.1.

Table 7.1: Summary statistic of estimated measures

Independent variables	Obs	Mean	Std. Dev.	Min	Max
Percentage of freeways, %F	50	3.12E+00	8.17E-01	1.59E+00	4.96E+00
Treeness, ϕ_{tree}	50	2.49E-01	7.28E-02	1.23E-01	4.50E-01
Completeness, ρ_e	50	1.35E-05	7.30E-06	3.60E-06	4.30E-05
Average circuity, C_m	48	1.31E+00	6.91E-02	1.20E+00	1.46E+00
Street density, ρ_{lm}	50	4.71E+00	1.29E+00	2.10E+00	7.51E+00
Accessibility, O_{30}	48	1.27E+06	3.92E+05	5.77E+05	2.19E+06

A correlation matrix of the above estimated network measures is provided in Table 7.2. The lack of high correlation between any of the estimated measures of network structure in Table 7.2 confirms that the variables are measuring different aspects of network structure.

Table 7.2: Correlation of estimated measures

	Percentage of freeways, %F	Treeness, ϕ_{tree}	Completeness, ρ_e	Average circuity, C_m	Street density, ρ_{lm}	Accessibility, O_{30}
Percentage of freeways, %F	1					
Treeness, ϕ_{tree}	0.208	1				
Completeness, ρ_e	0.176	-0.134	1			
Average circuity, C_m	0.158	**0.504**	-0.037	1		
Street density, ρ_{lm}	-0.276	-0.180	-0.019	0.260	1	
Accessibility, O_{30}	-0.206	**-0.385**	0.115	-0.140	**0.481**	1
bold - indicates significance at 95% confidence level						

7.3 Model

The basic research question addressed in this chapter is: *Does network structure affect transportation system performance?*

$$P = f(N_m, X_c) \tag{7.5}$$

where,

P = Performance of the system, measured here as congestion (τ_{tti}) and usage (U_m),

N_m = Measures of street network structure within the area,

X_c = Exogenous control variables.

The influence of network structure on travel performance is analyzed here using two models. The first model predicts the congestion in an urban area. The second model analyzes the relationship between the highway usage in an urban area and network structure. The model specifications and hypotheses are detailed below:

7.3.1 Model 1: Dependent variable: Congestion (τ_{tti})

Congestion refers to capacity utilization and is directly related to the cost of travel. Congestion occurs when the demand on the road system exceeds the capacity of the system over a period of time. Therefore,

$$\tau_{tti} = \frac{Demand}{Supply} \tag{7.6}$$

$$Demand = f(p) \tag{7.7}$$

where,
p = Population of the area,

$$Supply = f(L_{rm}, N_m) \tag{7.8}$$

where,
L_{rm} = Total roadway kilometers in the area and is represented as,

$$L_{rm} = L_l + L_{nl} \tag{7.9}$$

where,
L_l = Length of the local streets in the area (km),
L_{nl} = Length of the non-local streets in the area (km),
N_m = Measures of street network structure within the area.
The core hypotheses are:

- An increase in the demand, measured as population of the area, increases congestion, *ceteris paribus.*

- An increase in the supply of the system decreases congestion.

  An increase in roadway kilometers in the area decreases congestion

  An increase in the circuitness of the network decreases congestion. Circuitness is a measure of network organizational efficiency.

7.3.2 Model 2 : Dependent variable: System Usage - DVKT per capita (U_m)

$$U_m = f(\tau_{tti}, N_m, O_{30}) \tag{7.10}$$

where,

U_m = Daily vehicle kilometers traveled (DVKT) per capita on all the roadways in the urban area, obtained from HPMS data,

τ_{tti} = Time cost of highway travel, measured by congestion,

N_m = Measures of street network structure within the area,

O_{30} = Cumulative measure of accessibility in the metropolitan area.

The actual measures of network structure (N_S) that influence the network quantity and quality are identified based on an understanding of the transportation system.

The core hypotheses are described below.

Price (τ_{tti}) of highway travel measured in congestion, using the Travel Time Index (ratio of congested to freeflow time) decreases the DVKT per capita. We posit that travelers respond to an increase in price by reducing travel.

Network structure (N_m) comprises several measures, and how they operate is not always straight-forward. On the one-hand improving efficiency lowers the network distance or travel time required to reach destinations, and thus for a given set of activities, reduces the required travel. On the other hand, reducing distance required for a given set of destinations may lead to *induced demand*, whereby lowering net cost of traveling on the network point-to-point leads people to making longer trips. It is anticipated that the efficiency for given trips will outweigh induced demand effects, but this is in the end an empirical question that cannot be resolved by theory. The hypotheses are listed below.

- An increase in the percentage of freeways, measuring the speed on the network, will increase DVKT. Higher hierarchy links such as freeways are usually faster and are more suited for longer travel.

- An increase in the street density, representing the quantity or supply of the network increases the DVKT per capita. This is in line with the induced demand hypothesis, where increases to roadway capacity or supply encourages people to drive more by reducing the cost of travel.

- An increase in the completeness of the network, measuring the efficiency in network connectivity between the origins and destinations, decreases DVKT per capita.

- An increase in the circuity, measuring the network inefficiency at the OD trip level, will increase the DVKT per capita. Higher circuity indicates greater inefficiency between OD pairs as travelers need to use more circuitous route (greater network distance) to reach their destination.

Finally, accessibility to population measures the number of opportunities (in this case other people, which is highly correlated with access to employment and retail activities) that can be reached in a given time. The more opportunities available, the less need for longer distance travel, and thus the lower the system usage.

7.4 Analysis

The objective of this research is to develop quantitative measures of network structure and understand the influence of these measures on two aspects of system performance in an urban area. The first model analyzes the relationship between congestion in an area and the estimated measures of network structure. The second model analyzes the relationship between the system usage and the identified network measures. This section presents the two models estimated and elaborates on the the results from the respective models.

7.4.1 Model 1

Model 1 uses the basic model of congestion defined previously to understand the relationship between network structure and congestion. The congestion in the urban area is given by the Travel Time Index (TTI), provided as part of the the Urban Mobility Report. The TTI is a ratio that measures the travel time in the peak period to the travel time under free-flow conditions (Schrank and Lomax, 2009). A higher value of TTI indicates higher congestion. As explained in the Urban Mobility Report, *"a TTI of 1.35 indicates that a trip that takes 20 minutes under free flow conditions takes 27 minutes in the peak period."*

The TTI in an urban area is used as a dependent variable in this model. The results of the log-log regression model (robust standard errors) that provided the best fit are presented in Table 7.3. Various formulations of the independent and dependent variables were tested. The log-log regression model was selected based on the model fit and the performance of the independent network variables. The standardized β coefficients are also included in this table. A scatterplot of actual versus predicted congestion in presented in Figure F.1 in Appendix F.

The results presented in Table 7.3 identify the factors that influence congestion. All independent variables perform as expected. The hypothesis argued for an increase in congestion due to an increase in demand. This is confirmed by the positive and significant coefficient for the population variable. Both the supply variables, namely, the total length of local roads and the total length of non-local roads have a negative influence on congestion as hypothesized. However the total length of local roads is not significant.

The result from this model, relevant to the current analysis, is that the treeness in the roadway network has a positive and significant influence on congestion. This is in line with the hypothesis that a minimally connected tree network leads to congestion on the existing system due to the lack of travel options. The results show that network (in)efficiency, as captured by the treeness variable, affects system performance, after accounting for other non-network control variables such as population.

Table 7.3: Model 1 - Predicting Congestion (TTI)

Independent variables (ln)	Unit	Hypothesis	Coef.	Standardized β Coef.	t	Sig.
Population, p		+S	0.13	1.44	6.19	***
Total length of local roads, L_l	km	-S	-0.02	-0.17	-0.57	
Total length of non-local roads, L_{nl}	km	-S	-0.06	-0.55	-1.99	*
Network treeness, ϕ_{tree}		+S	0.05	0.22	2.10	**
Constant			-1.04		-6.13	***
Number of observations	50					
Adj. R-squared	0.5891					
Natural log of all variables considered in the analysis						
* p<0.10, ** p<0.05, *** p<0.01						

7.4.2 Model 2

This model tests the relationship between system usage in an area and the measures of network structure, after controlling for non-network measures. The simple model presented here in Table 7.4 predicts the system usage as a function of the population. The system usage is measured as the total DVKT in the area. This model has an extremely good fit with an R^2 of 0.9036. The model shows that the usage of the system is largely a function of the population. However the use of population to predict DVKT does not tell us anything about the other system variables that influence usage. In order to get a better understanding of the system, we replace the absolute measure of DVKT by the relative measure of DVKT per capita.

Table 7.4: Model 2 - Predicting System Usage (DVKT)

Dependent variable (ln): System usage (DVKT)			
Independent variables (ln)	Coef.	t	Sig.
Population, p	0.89	18.70	***
Constant	4.41	12.60	***
Number of observations	50		
Adj. R-squared	0.9036		
Natural log of all variables considered in the analysis			
* p<0.10, ** p<0.05, *** p<0.01			

7.4.3 Model 3

Table 7.5 presents two models of system usage using DVKT per capita as the dependent variable. Additionally scatterplots of the actual versus predicted DVKT per capita from the two models of system usage are presented in Figures F.2 and F.2 in Appendix F.

Both models predict DVKT per capita as a function of network and non-network variables. The difference between the two models lies in the non-network variables considered in the analysis. The first model, Model 3A, uses population density and the predicted congestion from Model 1 as explanatory variables in predicting system usage. Model 3B, on the other hand, replaces these variables with the measure of accessibility. Both models use the same measures of network structure: street density, percentage of freeways, completeness and circuity. Other common explanatory variables between the two models include auto mode share and median household income in the area.

The use of predicted congestion in Model 3A, rather than actual congestion is to account for the causality between network congestion and usage. The congestion in a region is a function of the system usage and the system usage in turn is a function of the congestion. The existence of this causality was confirmed by separate analyses including actual congestion measures (TTI, weighted average speed) in the models of system usage.

The results from both the models of system usage, presented in Table 7.5, confirms the influence of network structure on system usage. Focusing on the measures of network structure, the street density has a significant positive influence on DVKT per capita in both models, confirming the hypothesis that a larger supply of the street network of an urban area encourages more travel. The percentage of freeways in the area is also significant and positive, as hypothesized. Higher hierarchy links such as freeways are faster and are suited for longer travel. Hence an increase in the percentage of freeways in the area increases DVKT per capita. The coefficient for the completeness in the network, measuring the efficiency in network connectivity, is negative in both models but is significant only in Model 3A. An efficiently connected network reduces the DVKT by providing good connectivity between the origins and destinations in the region and bringing them closer, reducing the need for travel. The average trip circuity is significant and negative in Model 3B and while positive Model 3A. As noted previously, the effects of network structure are complex, and proper interpretation, given the sensitivity of this variable to model specification, require further investigation. The results from both models confirm the theory that aspects of network structure influence the performance of the transportation system.

The socio-demographic measures of population density, auto mode share, median household income and accessibility in the urban area show the expected influence on DVKT per capita. On a side note, Model 3B with the inclusion of accessibility shows a much better model fit, confirmed by the higher R^2. The better model fit with the inclusion of accessibility shows that the estimated accessibility is a better combination of congestion and density than using these variables independently and linearly in the regression models. As El-Geneidy and Levinson (2006) point out, using measures of mobility or congestion to understand the land-use and transportation interaction is insufficient. Cities with the highest congestion might not be desirable places to live from a mobility (congestion) viewpoint but are still attractive to residents because of the opportunities that they provide.

Table 7.5: Model 3 - Predicting System Usage (DVKT) per capita

Dependent variable (ln): System usage (DVKT) per capita										
	Unit	Hypothesis	Model 3A				Model 3B			
Independent variables (ln)			Coef.	Standarized β Coef.	t	Sig.	Coef.	Standarized β Coef.	t	Sig.
Predicted congestion			-1.93	-0.46	-2.44	**	NA	NA	NA	NA
Population density, ρ_{pm}	persons/km2		-0.19	-0.29	-1.36		NA	NA	NA	NA
Accessibility to population, O_{30}		-S	NA	NA	NA	NA	-0.52	-0.73	-8.34	***
Street density, ρ_{lm}	1/km	+S	0.36	0.48	3.35	***	0.56	0.75	9.63	***
Percentage of freeways, %F		+S	0.22	0.27	2.12	**	0.35	0.43	7.36	***
Completeness, ρ_e		-S	-0.20	-0.44	-4.04	***	-0.05	-0.10	-1.22	
Average circuity, C_m		+S	0.76	0.18	1.97	*	-0.65	-0.15	-1.94	*
Median household income			0.41	0.26	2.26	**	0.29	0.18	2.32	**
Auto mode share			0.86	0.31	2.12	**	0.84	0.30	3.21	***
Constant			-2.26		-0.95		6.28		3.83	***
Number of observations			48				48			
Adj. R-squared			0.6835				0.8285			
Natural log of all variables considered in the analysis										
* p<0.10, ** p<0.05, *** p<0.01										

7.5 Conclusions

The objective in this chapter is to develop quantitative measures that capture various aspects of network structure, such as topology, connectivity, and heterogeneity that exist in road networks, using aggregate level travel data from fifty metropolitan areas across the U.S. The influence of these measures on system performance is then tested using two linear regression models. The first model analyzes the relationship between congestion and the estimated network measures. The second model analyzes relationship between the DVKT per capita and estimated network measures.

The results from both the models confirm that the quantitative measures of network structure affect the system performance, after accounting for independent control variables that are non-network based. However the influence of network design varies based on the aspect of travel that is being measured. The model predicting congestion shows the influence of network treeness while the model predicting DVKT per capita shows the influence of street density, completeness and the percentage of freeways in the urban area.

Both the models of system performance are log-log models and the elasticity estimates can therefore be directly obtained from the respective model coefficients. Looking at the model results, a 1% increase in treeness of the roadway network increases the congestion in the area by 0.05%. Similarly a 1% increase in the completeness of a street network decreases the DVKT per capita by 0.20%. A 1% increase in street density increases the DVKT per capita by a range of 0.36% - 0.56% while a 1% increase in the percentage of freeways increases the DVKT per capita by a range of 0.22% - 0.35%.

Similar to the elasticity estimates, the standardized β coefficients presented in Table 7.5 also identify the relative contribution of the independent network variables. The street density variable shows the largest influence on the DVKT per capita in both models. The network completeness has the second highest influence in Model 3A while the percentage of freeways has the second highest influence in Model 3B.

The take-away here is that the design of a roadway network is correlated with the performance of the transportation system. This correlation is posited to be causal, though that waits further tests to corroborate. If so, a combination of network design measures can be used to bring about desired changes in travel patterns. The measures of network structure need to be considered along with other urban form measures to manage travel. For example, consider a scenario with two areas with the same urban form in terms of population and employment density. Considering everything else to be the same, a small change in efficiency of network connectivity, i.e., a 1% increase in completeness, can have additional benefits of 0.20% reduction in DVKT per capita. While the analysis presented here is a simple representation of the relationship between network structure and travel, it does point to the importance of analyzing the influence of the network layout on the travel patterns in a region.

Chapter 8

Conclusions

The objective of this dissertation is to identify a relationship between street network structure and observed travel patterns. The theory underlying this research is that network design affects travel by influencing travelers' perception of distance and time, which in turn affects actual or observed travel. The theoretical framework is explained in Chapter 1. The underlying theory of network structure and travel time perception is tested in Chapter 4. This is followed by independent but interrelated analyses of network structure and observed individual travel (chapter 5), household travel (chapter 6) and metropolitan travel (chapter 7). The analyses presented in these chapters provide a comprehensive understanding of the underlying relationship.

There are many factors that affect travel in a region and the models developed in this dissertation are but simple representations. The results imply that network design should be one of the tools to be considered in analyzing travel. The results in the dissertation complement the role of conventional measures of urban form and the built environment. The individual effect of the proposed measures of network structure in the models may be small, but a combination of network measures can be used to affect travel demand. This understanding and application of network structure measures to network design is critical in the design of new networks, especially in developing countries, and enhancements to existing systems.

8.1 Limitations & Extensions

As with any research, there are some limitations in this dissertation. The measures of network structure used in this dissertation are primarily based on graph theory and are developed to capture certain aspects of network structure and design. However transportation networks are complex and are multi-faceted. The measures used here do not necessarily capture all aspects of network architecture that influence travel. Recent interest in network analysis has provided us with additional tools to uncover the structure or pattern of the transportation network. For example, Jiang (2007) suggest a named streets approach that represents street as vertices and street intersections as edges in topological analysis of networks. This approach is argued to be better at uncovering the topological patterns in street networks. Extensions to this research could include using new approaches to quantify network structure. For example better quantification of the shape of the network, the size of street blocks, the land constraints in a region, etc. would be valuable contributions to understanding the transportation network structure.

All analyses presented in this dissertation are cross-sectional comparisons of network and travel. Hence the results from this dissertation confirm a relation rather than causality between network structure and travel. As Marshall (2005) and Anas et al. (1998) point out, the current spatial structure of cities is based on the changes made to the transportation system in prior years. A good understanding of the influence of network structure on system performance therefore needs to consider the temporal aspect. The use of temporal data would allow us to identify how changes in network design can be used to bring about changes in travel patterns.

This dissertation focuses primarily on quantifying street networks but travel in an area is affected by other transportation modes. Derrible and Kennedy (2009)'s research on transit network design shows that key components of network design have significant impact on ridership and transit system performance. To obtain a comprehensive understanding of travel, it is important to consider other transportation modes and their networks.

While attempts were made to include as many relevant variables in the analysis, there are some measures that were not included due to data limitations. For example, the model of metropolitan travel (Chapter 7) could be improved by including variables that capture the directionality of demand.

The analyses in the dissertation mainly focus on the distance aspect of travel behavior such as trip length. It would be useful to extend this research to understanding how network design affects other aspects of travel such as trip frequency, trip chaining, etc. Also understanding how network design affect non-work trips would be a useful extension since non-work trips now comprise the majority of daily trips The above limitations provide future directions to this research. We expect that with such a comprehensive analysis, a clearer pattern will evolve. But the results that we have so far provide guidance about network design that can be used to support the higher-level objectives of transportation planners, developers, and policy makers.

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Appendix A

Summary of relevant research in travel behavior

Table A.1: Summary of Urban Form Measures

Measures	Author (Year)
Gross population density or Net population density	Boarnet & Crane (2001) Boarnet & Sarmiento(1996) Cervero & Kockelman (1997) Ewing, Haliyur & Page (1994) Frank & Pivo (1994) Handy (1992) Kockelman (1997) McNally & Kulkarni (1997) Moudon et al. (1997) Naess (2006)
Gross residential density or Net residential density	Cervero & Graham (1995 Cervero & Radisch (1996) Kitamura (2001)
Population centrality	Bento (2003)
	Continued on next page

Table A.1 – continued from previous page

Measures	Author (Year)
Employment density stratified by employment type	Boarnet & Crane (2001) Boarnet & Sarmiento(1996) Cervero & Kockelman (1997) Ewing, Haliyur & Page (1994) Frank & Pivo (1994) Kitamura (2001) Kockelman (1997)
Share or percentage of land uses within area	Cervero & Radisch (1996) Crane & Crepeau (1998) Ewing, Haliyur & Page (1994) McNally & Kulkarni (1997)
Distance or time measures	Cervero & Kockelman (1997) Crane & Crepeau (1998) Handy (1992) Meurs (2001) Naess (2006) Stead (2001)
Entropy index	Cervero & Kockelman (1997) Frank & Pivo (1994) Kockelman (1997)
Dissimilarity index	Cervero & Kockelman (1997) Kockelman (1997)
Texture measure for land use	Srinivasan (2002)
Accessibility index	Ewing, Haliyur & Page (1994) Hanson & Schwab (1987) Kitamura (2001) Kockelman (1997) Srinivasan (2001, 2002)

Continued on next page

Table A.1 – continued from previous page

Measures	Author (Year)
	Thill & Kim (2005)
Pedestrian accessibility (also refered to as convenience	Frank & Pivo (1994) Srinivasan (2002)
factor) Street network density	Bento(2003) Crane & Crepeau (1998) Handy (1992, 1996) Srinivasan (2001, 2002)
Neighborhood accessibility factor	Frank & Pivo (1994)
Street length	Handy (1992) Moudon et al. (1997)
Street pattern	Boarnet & Crane (2001) Boarnet & Sarmiento(1996) Crane & Crepeau (1998)
Percentage or ratio of intersection by type (3-way, 4-way intersections, cul-de-sacs etc)	Cervero & Gorham (1995) Cervero & Kockelman (1997) Handy (1992) McNally & Kulkarni (1997) Srinivasan (2002)
Intersection density	Cervero & Kockelman (1997) Cervero & Radisch (1996) Handy (1992) Srinivasan (2002)
Block density	Cervero & Kockelman (1997) Cervero & Radisch (1996) Handy(1992)
Block area	Hess et al. (1999)
Average Sidewalk width	Srinivasan (2001, 2002)

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Table A.1 – continued from previous page

Measures	Author (Year)
City Shape	Bento(2003)
Average Block length	Cervero & Kockelman (1997) Cervero & Radisch (1996) Moudon et al. (1997)

Table A.2: Summary of Network Structure Measures

Network Measures	Author (Year)	Definition	What it measures
Cyclomatic number	Kansky(1963), Garrison & Marble (1961)	Observed number of circuits	Connectivity
Diameter	Kansky(1963), Garrison & Marble (1961)	Maximum number of edges in the shortest distance path between each pair of vertices	Extent and connectivity of a network
Alpha index	Kansky(1963), Garrison & Marble (1961), Gauthier (1966)	Ratio between observed number of circuits to maximum number of circuits	Connectivity or Redundancy
Beta index	Kansky(1963), Garrison & Marble (1961)	Ratio between number of edges to number of vertices	Connectivity
Gamma Index	Kansky(1963), Garrison & Marble (1961), Gauthier (1966)	Ratio between observed number of edges to maximum number of edges	Connectivity

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Table A.2 – continued from previous page

Network Measures	Author (Year)	Definition	What it measures
Eta Index	Kansky(1963), Garrison & Marble (1961)	Ratio between the total mileage of the network to observed number of edges	Average edge length which indirectly measures connectivity
Pi	Kansky(1963), Garrison & Marble (1961)	Ratio between the total mileage of the network to the total number of miles of the network's diameter	Shape of the transportation system
Theta	Kansky(1963), Garrison & Marble (1961)	Ratio of the network as a whole to the observed number of vertices; network measured in terms of total traffic flow, freight volume, mileage etc	Structure, degree of connectivity and measure of network length
Iota	Kansky(1963), Garrison & Marble (1961)	Same as Theta measure except the number of vertices are weighted by their function	Structure, length and function
Associated number	Kansky(1963), Garrison & Marble (1961)	Maximum number of edges from a given vertex to each of the other vertices (maximum topological distance)	Topological distance or extent of the network

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Table A.2 – continued from previous page

Network Measures	Author (Year)	Definition	What it measures
Degree of Connectivity	Kansky(1963), Garrison (1960), Garrison & Marble (1961)	Ratio of the maximum number of edges to observed number of edges	Relative position of a given network's connectivity on a scale limited by minimum and maximum connectivity
Dispersion (Shimbel's measure)	Kansky(1963), Garrison & Marble (1961)	Distance measure expressing an overall property of the network	Extent of a network
Accessibility	Kansky(1963), Garrison & Marble (1961)	Distance measure similar to dispersion	Measures the relative location of a given element (vertex) to the remainder of the network
Circuity	Kansky(1963), Garrison & Marble (1961)	Squared difference between the network distance to straight line distance divided by the number of vertices; estimated relative to a given vertex	Measures the shape of the network

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Table A.2 – continued from previous page

Network Measures	Author (Year)	Definition	What it measures
Node connectivity based on Incidence matrix	Gauthier (1966)	Minimum number of edges that need to be cut to eliminate direct and indirect relations between the node and all others nodes in the network	Strength of the node's connection to the network
Node circuity based on the incidence matrix	Gauthier (1966)	Identify the nodes that are incident to the sequence of edges forming fundamental circuits	Redundancy in the network
Linkage Importance	Kissling (1969)	Number of times a certain link appears in a routeway sequence (path) connecting all the nodes in the network to each other, weighted by the importance of each routeway	Measures the relative importance of a link in a roadway network in terms of contribution to overall accessibility
Nodal Accessibility	Kissling (1969)	Number of appearances of routeways of all links incident upon a given node	Measures the relative accessibility of a node to the routeways in a network

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Table A.2 – continued from previous page

Network Measures	Author (Year)	Definition	What it measures
Betweenness centrality	Erath et al. (2009)	Similar to the above nodal accessibility measure; number of shortest paths between all other nodes that pass through a given node	Measures the relative accessibility of a node to the routeways in a network
Pedestrian route directness	Hess (1997)	Ratio of pedestrian network distance to Euclidean distance	Network connectivity, density and spatial structure
Circuity	El-Geneidy & Levinson (2007)	Ratio of the network distance to Euclidean distance	Network connectivity, density and spatial structure
Hierarchy	Xie & Levinson (2007)	Entropy measure for links or edges	Measures the heterogeneity in a network
Ringness	Xie & Levinson (2007)	Ratio between total length of arterials on rings to total length of arterials	Topology and connection patters in the network
Webness	Xie & Levinson (2007)	Ratio between total length of arterials on webs to total length of arterials	Topology and connection patters in the network

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Table A.2 – continued from previous page

Network Measures	Author (Year)	Definition	What it measures
Circuitness	Xie & Levinson (2007)	Ratio between total length of arterials belonging to circuits to total length of arterials; estimated as a sum of ringness and webness	Topology and connection patters in the network
Treeness	Xie & Levinson (2007)	Ratio between total length of arterials belonging to trees to total length of arterials	Topology and connection patters in the network
Beltness	Xie& Levinson (2007)	Ratio between total length of arterials on belts to total length of arterials	Topology and connection patters in the network
Discontinuity	Xie & Levinson (2007)	Discontuity along the shortest path between an origin and destination	Travelers perception of interconnectivity in a network

Appendix B

I-35 W Travel Surveys

B.1 Questionnaire of the computer based web-based survey after the bridge collapse (W-2007).

Getting Around Town

How do you usually get to work?

- Walk
- Bicycle
- Drive alone
- Carpool
- Bus
- Light rail
- Taxi/Shuttle
- Motorcycle/Moped

How long does your trip from home to work take?

minutes

What time do you usually leave home to go to work? (hh:mm)

Do you have to be at work at a fixed time?

- No
- Yes

If yes, what time do you **have to be** at work? (hh:mm)

How would you describe the traffic conditions on your trip to work?

- No congestion
- Fair
- Congested
- Very congested

How would you rate your commute experience on your trip to work?

- Unbearable
- Bad
- Tolerable/fair
- Good
- Excellent

How long would the same trip from home to work take on a Sunday morning?

Minutes

Where do you get travel information regarding your work commute?

- Personal experience
- Internet
- TV
- Radio
- Co-workers
- Other

Please specify:

How do you primarily get around town for non work trips?

- Walk
- Bicycle
- Drive alone
- Carpool
- Bus
- Light rail
- Taxi/Shuttle
- Motorcycle/Moped

Were your travels affected by the I-35W bridge collapse?

- No
- Yes

Next

I-35W Impacts

How often did you use the I-35 bridge on your work trips?

- Everyday
- A few times a week
- A few times a month
- Rarely
- Never

How often did you use the I-35 bridge on your non-work trips?

- Everyday
- A few times a week
- A few times a month
- Rarely
- Never

Did you make any changes to your work travels because of the bridge collapse
(please check all that apply and answer the follow up questions)

- Changed route
  - How many routes have you tried since the bridge collapsed?
- Changed travel mode (e.g. car to bus, bus to car etc.):
  - Before
  - Now
- Changed departure time from home
  - Before
  - Now
- Changed my work schedule (e.g. before 9 - 5, now 7 - 3)
  - Before
  - Now
- Travel time to work
  - Before
  - Now

Next

I-35W and travel frequency

How did you find out about the I-35W bridge collapse?

Did the I-35W bridge collapse affect the number of times you visit friends and family each week?

- It didn't affect it
- It decreased the frequency
- It increased the frequency
- Other

Please specify:

Did the I-35W bridge collapse affect the number of times you go shopping each week?

- It didn't affect it
- It decreased the frequency
- It increased the frequency
- Other

Please specify:

Did the I-35W bridge collapse affect the number of times you shop on the internet?

- It didn't affect it
- It decreased the frequency
- It increased the frequency
- Other

Please specify:

Next

B.2 Questionnaire of the paper-based survey after the bridge reopening (P-2008).

UNIVERSITY OF MINNESOTA

Prof. Henry Liu
Dept. of Civil Engineering
122 Civil Engineering Building
500 Pillsbury Dr. S.E.
Minneapolis, MN 55455

October 30, 2008

RE: Survey of Travel Behavior Impacts of I-35W Bridge Reopening

Dear participants:

We ask your help to participate in a survey on the travel behavior impacts of the I-35W Bridge reopening. The purpose of this survey is to advance our understanding of travel behavior. Participation in this study is voluntary. All information collected will only be used at a statistical level and for research purposes.

The survey is being conducted by the Department of Civil Engineering of the University of Minnesota. Please complete the questionnaire; then draw travel routes on the maps, following the instructions provided. Please place your survey responses and the maps in the prepaid envelope and drop the envelope in the mailbox. If you have any questions, please contact the principal investigator of this project, Prof. Henry Liu, at 1-651-314-4586. Thank you again for your participation.

Survey of Travel Behavior Impacts of I-35W Bridge Reopening

*Please complete the table, indicating the choice best describing your **MORNING COMMUTE** trip in the following time periods, and draw your route(s) on the attached maps.*

	Before Bridge Collapse *(e.g., in July 2007)*	**Before Bridge Reopening** *(e.g., Sept 17th, 2008)*	**After Bridge Reopening** *(September 18th, 2008)*	**Following Weeks** *(Sept. 19th to Oct. 23th)*	**Current Status**
Departure Time: (Typical departure time from home, to the nearest minute)					
Arrival Time: (Typical arrival time at work, to the nearest minute)					
Travel Mode: (The primary mode of travel) a) Drive alone b) Carpool driver c) Carpool passenger d) Bus/Light rail e) Bicycle f) Walk g) Other (Please specify)					
Route Choice: (Please draw your routes on the attached maps.)	Please mark line(s) on **MAP 1**	Please mark line(s) on **MAP 2**	Please mark line(s) on **MAP 3**	Please mark line(s) on **MAP 4**	Please mark line(s) on **MAP 5**
If you did not change route, please draw your route on at least one map.	*If you used more than one route at that time period, please indicate **ALL** of them in the same map.* (Please indicate the **Transit Route Number** if you chose Bus/Light rail)				
Route Familiarity: (How familiar are you with the routes you used)	*Please circle how familiar you are with each route on a scale of* 1-7, *with* 1 *representing not at all familiar and* 7 *representing very familiar*				
	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
Motivation for Changes in Travel Choices: Why did you change your route(s)? Please specify.					

Please answer the following questions.

Did the bridge collapse affect your travel? □ Y / □ N

If so, did you: cancel trip(s) □ Y/ □ N avoid certain destinations □ Y/ □ N
change departure time □ Y/ □ N change mode □ Y/ □ N
change route □ Y/ □ N work at home more frequently □ Y/ □ N

Did the bridge reopening affect your travel? □ Y/ □ N

If so, did you: avoid certain destinations □ Y/ □ N change departure time □ Y/ □ N
change mode □ Y/ □ N change route □ Y/ □ N

How much time savings would be required for you to change routes: .... Minutes

How much time savings would be required for you to change travel modes: .... Minutes

How did you find out about the I-35W Bridge reopening? ....

-- **OVER** --

Survey of Travel Behavior Impacts of I-35W Bridge Reopening

*Please complete the table, indicating the choice best describing your **MORNING COMMUTE** trip in the following time periods, and draw your route(s) on the attached maps.*

	Before Bridge Collapse *(e.g., in July 2007)*	**Before Bridge Reopening** *(e.g., Sept 17th, 2008)*	**After Bridge Reopening** *(September 18th, 2008)*	**Following Weeks** *(Sept. 19th to Oct. 23th)*	**Current Status**
Departure Time: (Typical departure time from home, to the nearest minute)					
Arrival Time: (Typical arrival time at work, to the nearest minute)					
Travel Mode: (The primary mode of travel) a) Drive alone b) Carpool driver c) Carpool passenger d) Bus/Light rail e) Bicycle f) Walk g) Other (Please specify)					
Route Choice: (Please draw your routes on the attached maps.)	Please mark line(s) on **MAP 1**	Please mark line(s) on **MAP 2**	Please mark line(s) on **MAP 3**	Please mark line(s) on **MAP 4**	Please mark line(s) on **MAP 5**
If you did not change route, please draw your route on at least one map.	*If you used more than one route at that time period, please indicate **ALL** of them in the same map.* (Please indicate the **Transit Route Number** if you chose Bus/Light rail)				
Route Familiarity: (How familiar are you with the routes you used)	*Please circle how familiar you are with each route on a scale of* 1-7, *with* 1 *representing not at all familiar and* 7 *representing very familiar*				
	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7	1 2 3 4 5 6 7
Motivation for Changes in Travel Choices: Why did you change your route(s)? Please specify.					

Please answer the following questions.

Did the bridge collapse affect your travel? □ Y / □ N

If so, did you: cancel trip(s) □ Y/ □ N avoid certain destinations □ Y/ □ N
change departure time □ Y/ □ N change mode □ Y/ □ N
change route □ Y/ □ N work at home more frequently □ Y/ □ N

Did the bridge reopening affect your travel? □ Y/ □ N

If so, did you: avoid certain destinations □ Y/ □ N change departure time □ Y/ □ N
change mode □ Y/ □ N change route □ Y/ □ N

How much time savings would be required for you to change routes: .... Minutes

How much time savings would be required for you to change travel modes: .... Minutes

How did you find out about the I-35W Bridge reopening? ....

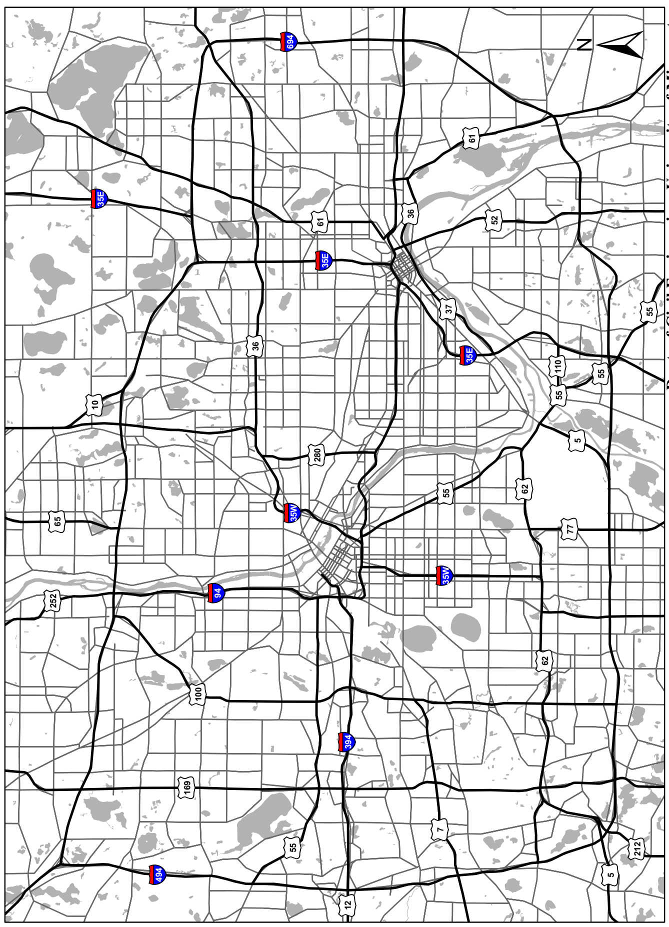
-- **OVER** --

You have completed the survey. Thank you very much for your participation!

Please return the questionnaire in the accompanying prepaid envelope to:

I-35W Travel Behavior Survey
University of Minnesota, Twin Cities
Department of Civil Engineering
500 Pillsbury Dr. S.E.
Minneapolis, MN 55455

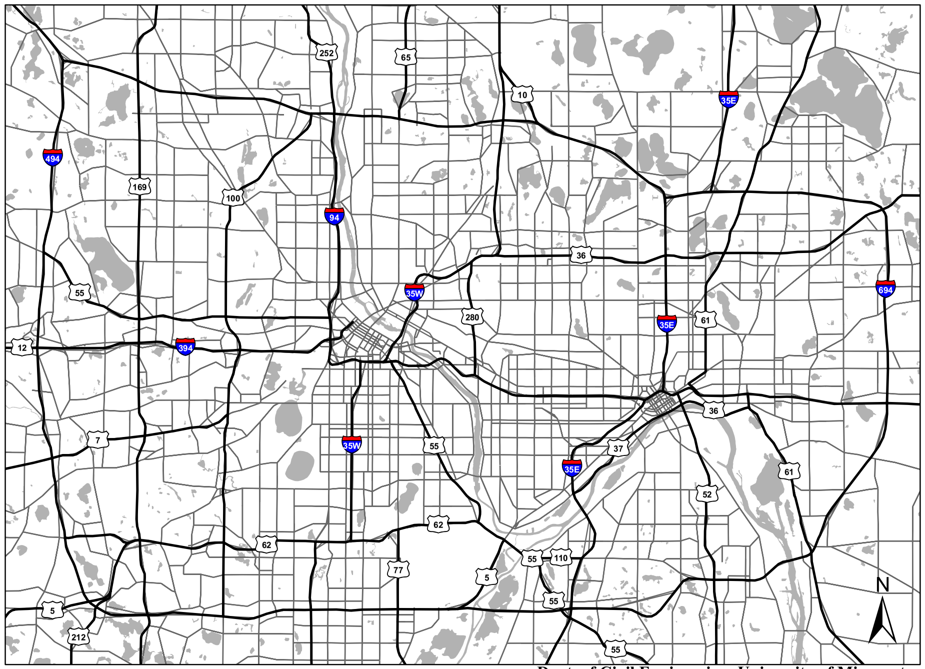
MAP 1: Please indicate your commute route **BEFORE** the I-35W Bridge **COLLAPSE**. THANK YOU!



Dept. of Civil Engineering, University of Minnesota

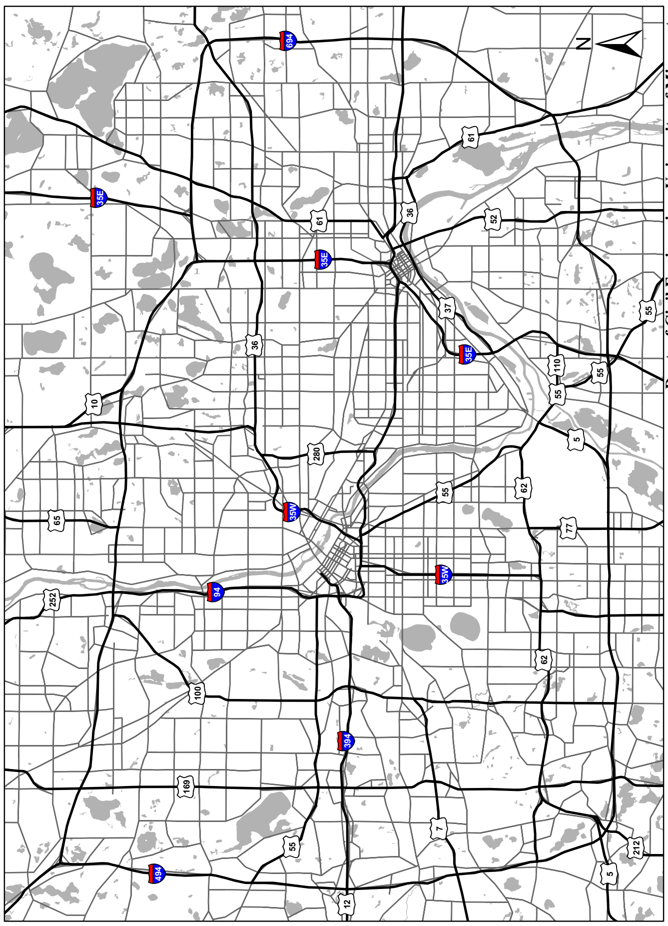
-- OVER --

MAP 2: Please indicate your commute route BEFORE the I-35W Bridge REOPENING. THANK YOU!



Dept. of Civil Engineering, University of Minnesota

MAP 3: Please indicate your commute route ON THE DAY of the I-35W Bridge REOPENING (September 18). THANK YOU!



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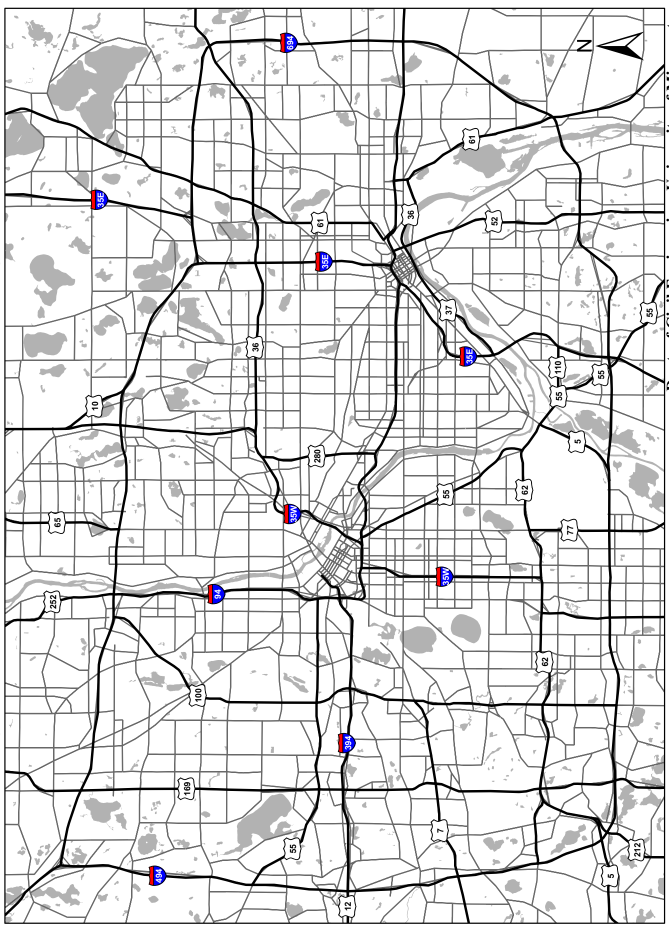
MAP 4: Please indicate your commute route in the WEEKS FOLLOWING the I-35W Bridge REOPENING. THANK YOU!



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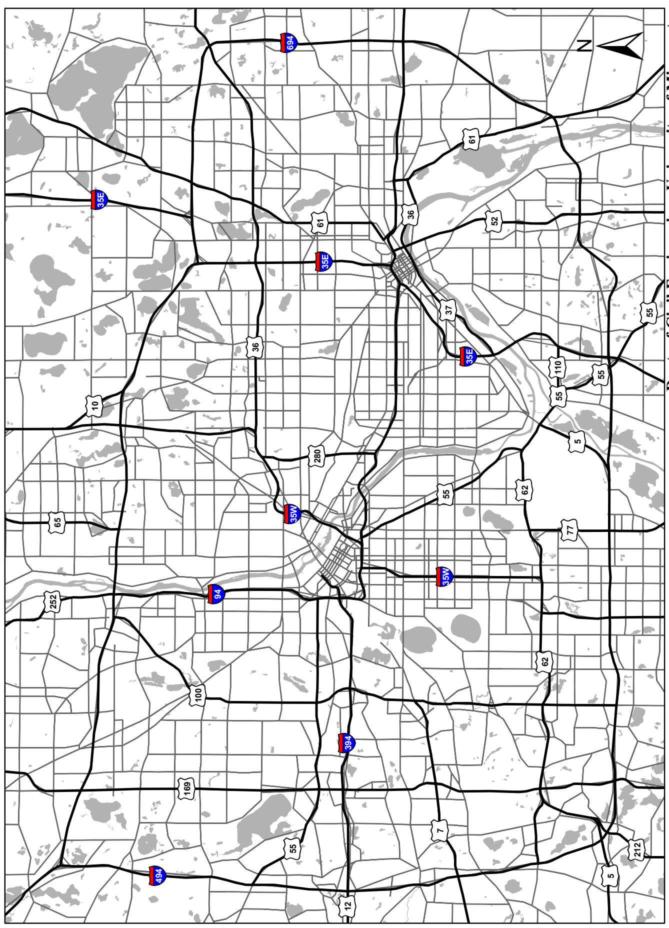
MAP 5: Please indicate your CURRENT commute route. THANK YOU!



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-- OVER --

Appendix C

Additional regression analyses conducted - Perception of travel time

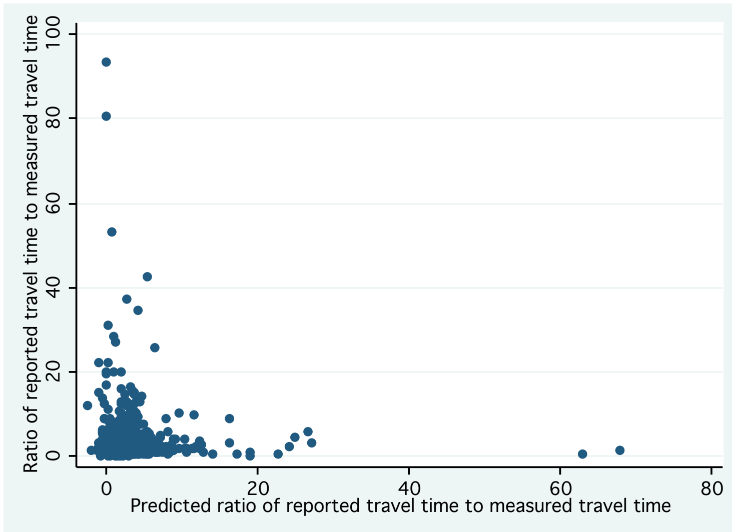

Figure C.1: Scatter plot of actual versus predicted ratio of travel time - TBI, commute trips; All commuters

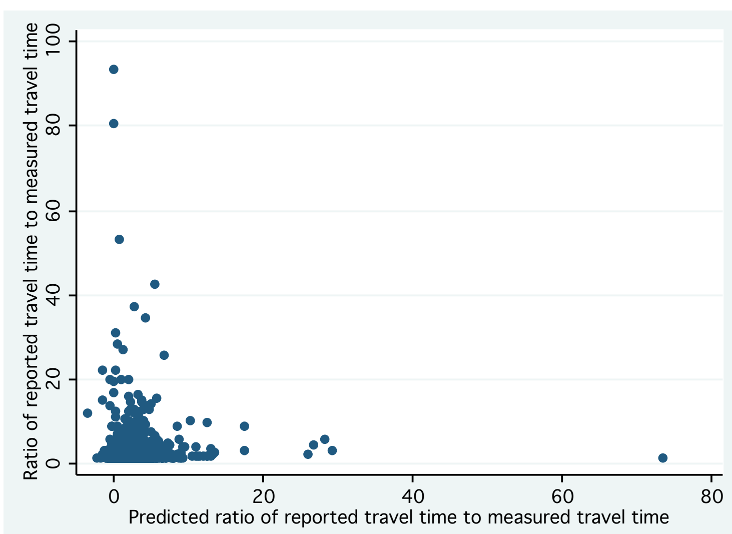

Figure C.2: Scatter plot of actual versus predicted ratio of travel time - TBI, commute trips; Commuters that overestimate travel time

Appendix D

Additional regression analyses conducted - Spatial Separation

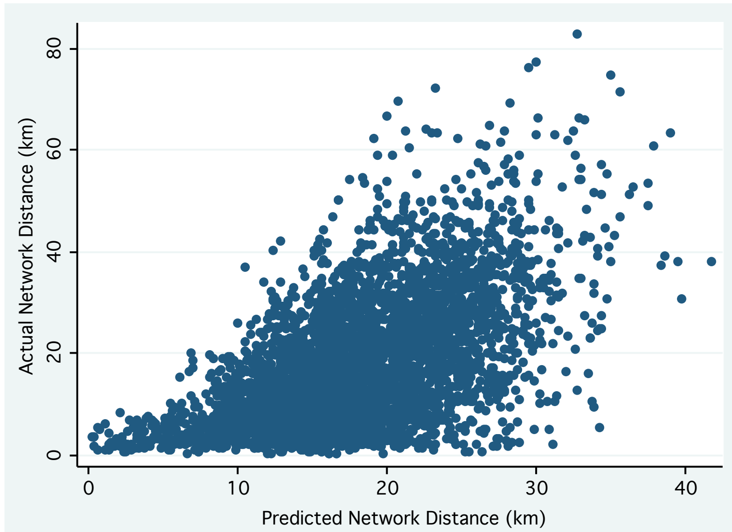

Figure D.1: Scatter plot of actual versus predicted network distance - Twin Cities work trips

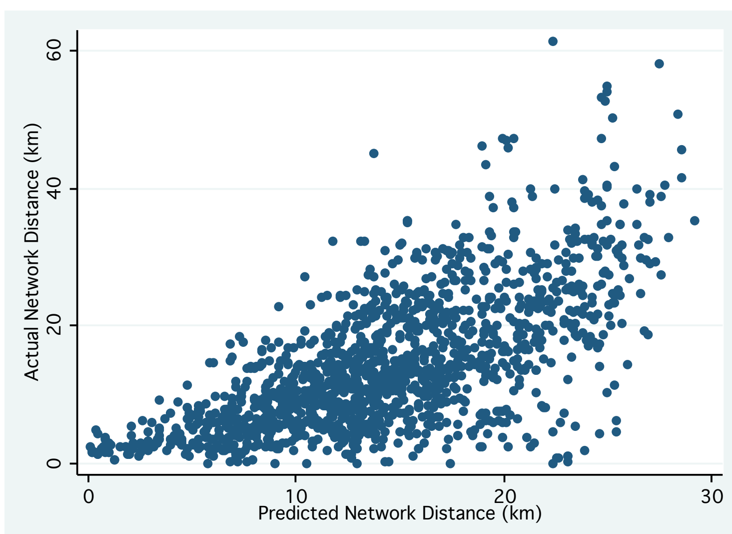

Figure D.2: Scatter plot of actual versus predicted network distance - South Florida work trips

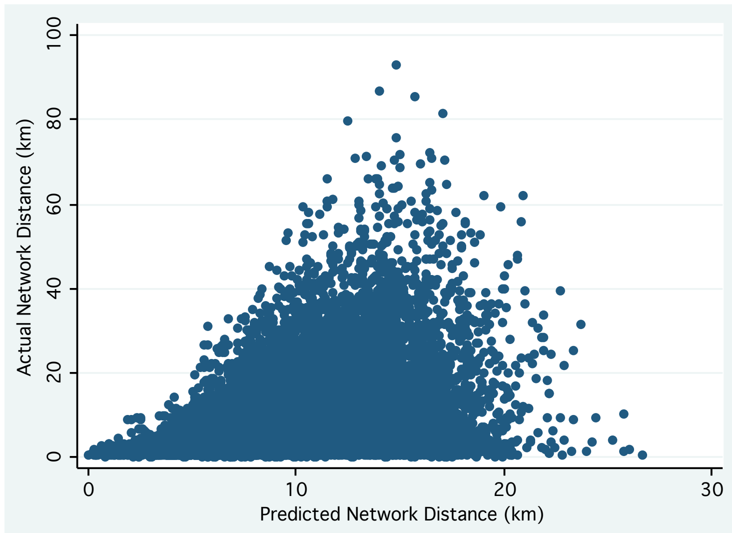

Figure D.3: Scatter plot of actual versus predicted network distance- Twin Cities non-work trips

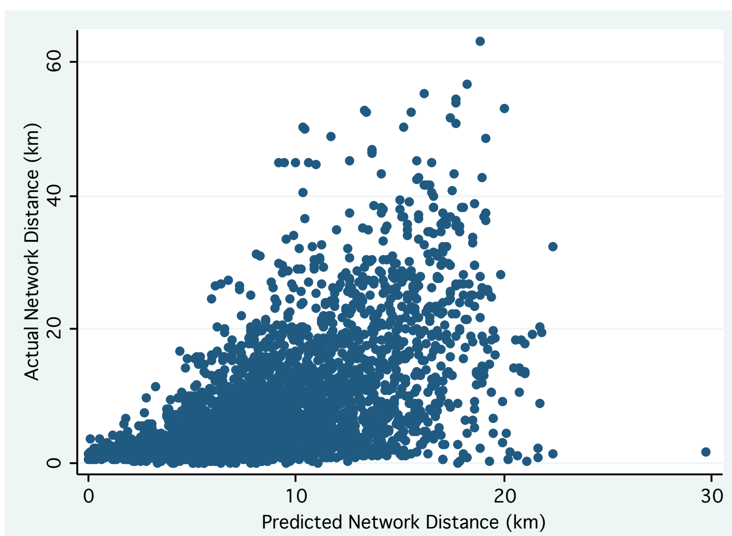

Figure D.4: Scatter plot of actual versus predicted network distance- South Florida non-work trips

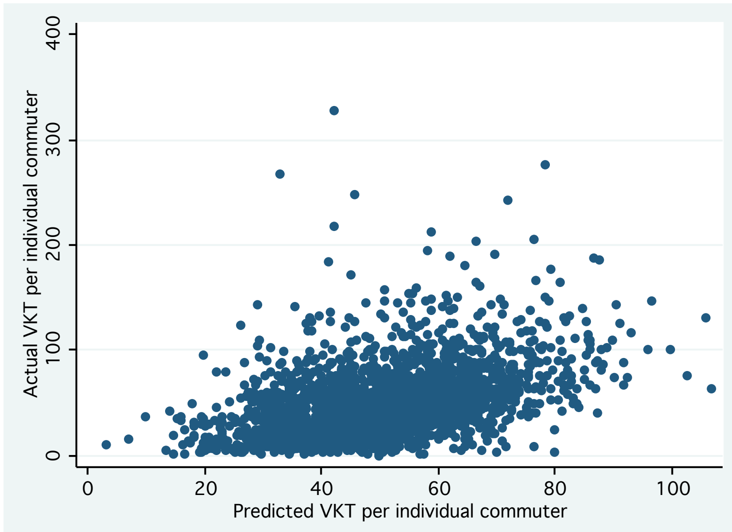

Figure D.5: Scatter plot of actual versus predicted VKT per individual commuter - Twin Cities

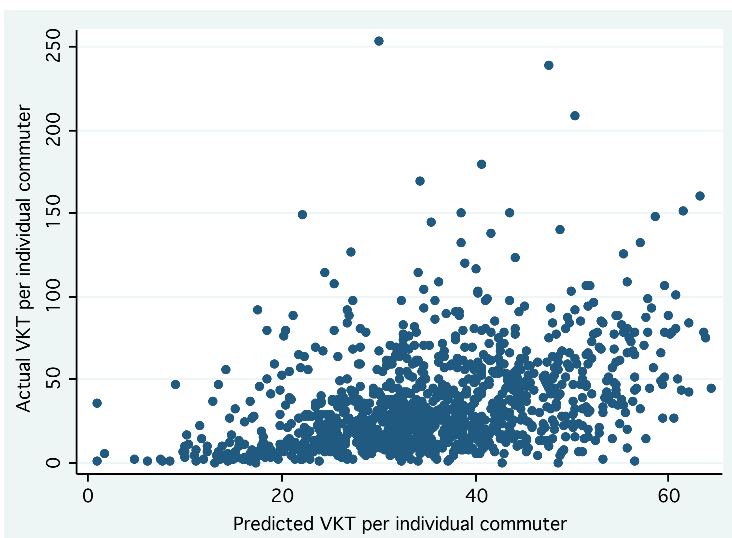

Figure D.6: Scatter plot of actual versus predicted VKT per individual commuter - South Florida

Table D.1: Prediction of work trip length, stratified by distance (km) - Twin Cities

	Trip lengths less than 20 km			Trip lengths between 20 km and 60 km			Trip lengths greater than 60 km		
Independent variables	Coef.	Sig	t	Coef.	Sig	t	Coef.	Sig	t
Distance to downtown Minneapolis	-0.07	***	-4.08	0.14	***	4.67	-0.02		-0.16
Distance to downtown St. Paul	-0.03	**	-2.07	0.04		1.39	0.07		0.54
Relative continuity	-3.21	***	-2.69	-21.24	***	-10.35	-78.31	**	-2.44
Proportion of limited access roads	21.55	***	6.96	54.04	***	8.06	55.31		1.36
Arterial Treeness	-17.22	***	-4.2	-5.84		-0.46	49.32		0.47
Trip circuity	-0.67	***	-6.5	-2.38	*	-1.91	-8.39	*	-1.78
P2A	-0.06		-1.37	-0.22	**	-2.11	0		0
Street density	-0.26	***	-8.08	-0.2	***	-2.81	-0.13		-0.26
Constant	18.89	***	12.82	38.76	***	10.77	79.3	*	1.89
N. of cases	2,606			1,469			30		
R-squared	0.161			0.164			0.256		
Adj.	0.158			0.16			-0.027		
* p<.10, ** p<0.05, *** p<.01									

Table D.2: Prediction of work trip length, stratified by distance (km) - South Florida

	Trip lengths less than 20 km			Trip lengths between 20 km and 65 km		
Independent variables	Coef.	Sig	t	Coef.	Sig	t
Distance to downtown Fort Lauderdale	0.02	***	4.76	0.09	***	6.54
Distance to downtown Miami	0.03	***	4.53	0.02		1.08
Relative continuity	-1.71	***	-3.41	-48.83	***	-12.68
Proportion of limited access roads	31.92	***	18.46	43.97	***	7.68
Arterial Treeness	-7.62		-1.13	54.19		1.22
Trip circuity	-0.48	***	-2.63	-2.47		-1.24
P2A	-0.21	***	-7.81	-0.43	***	-2.75
Street density	-0.35	***	-8.37	-0.31		-1.47
Constant	15.46	***	16.13	44.84	***	6.94
N. of cases	3,991			729		
R-squared	0.234			0.282		
Adj.	0.233			0.274		
* p<.10, ** p<0.05, *** p<.01						
Very few observations with trip lengths greater than 60 km; Hence only two categories used.						

Appendix E

Additional regression analyses conducted - Household Activity Spaces

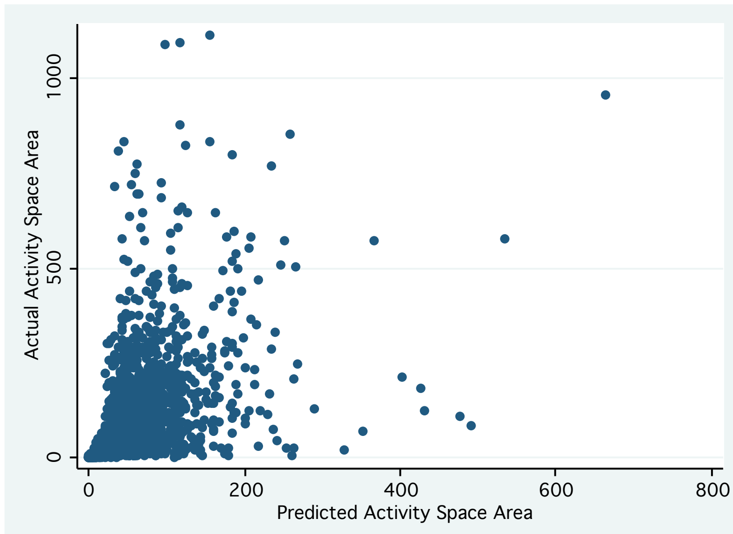

Figure E.1: Scatter plot of actual versus predicted activity space - Twin Cities

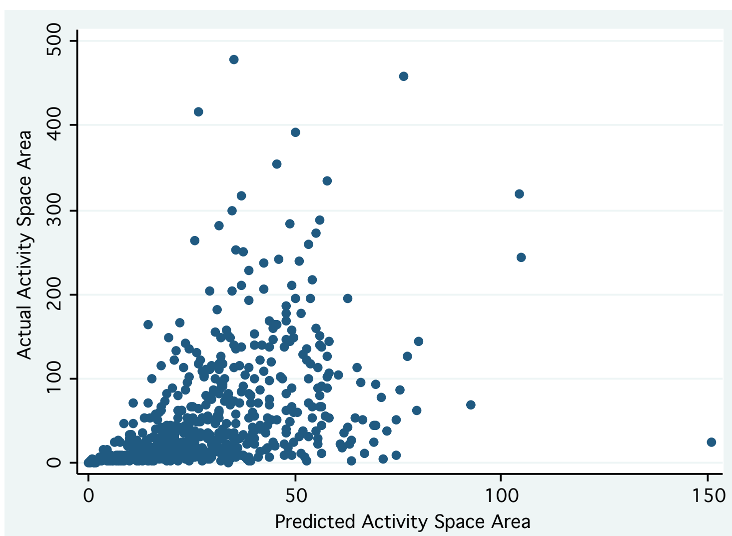

Figure E.2: Scatter plot of actual versus predicted activity space - South Florida

Appendix F

Additional regression analyses conducted - Metropolitan Mobility

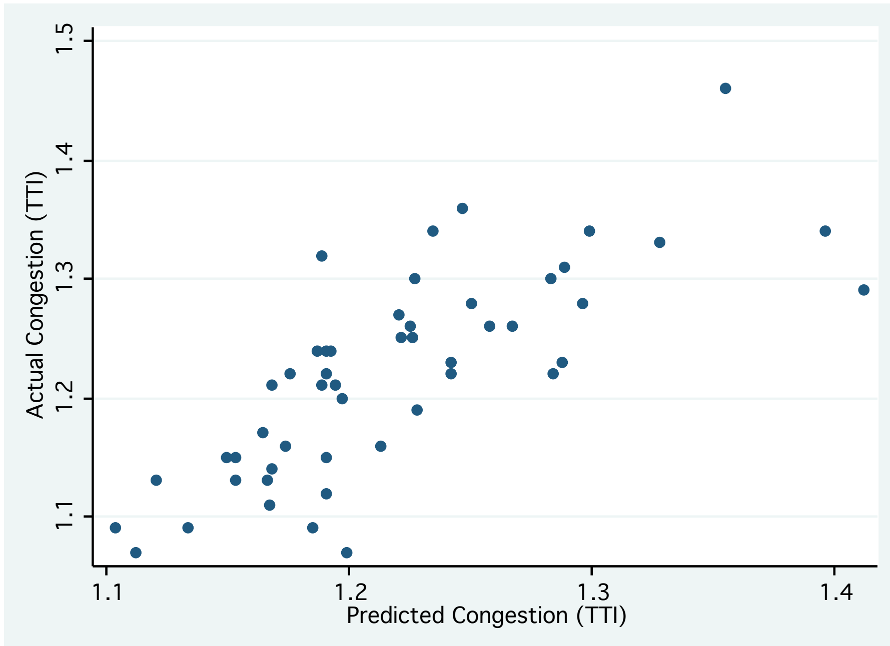

Figure F.1: Scatter plot of actual versus predicted congestion

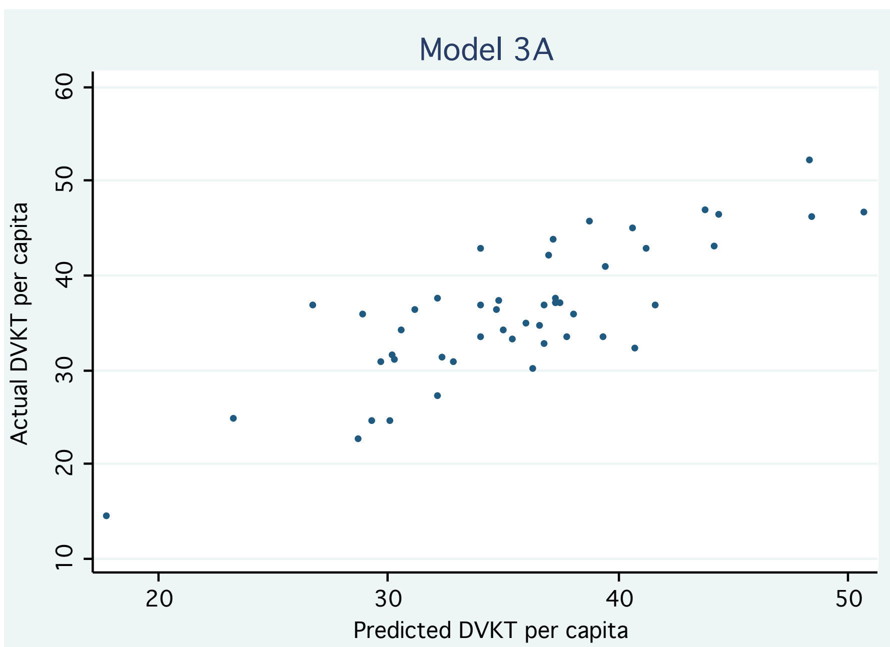

Figure F.2: Scatter plot of actual versus predicted DVKT per capita

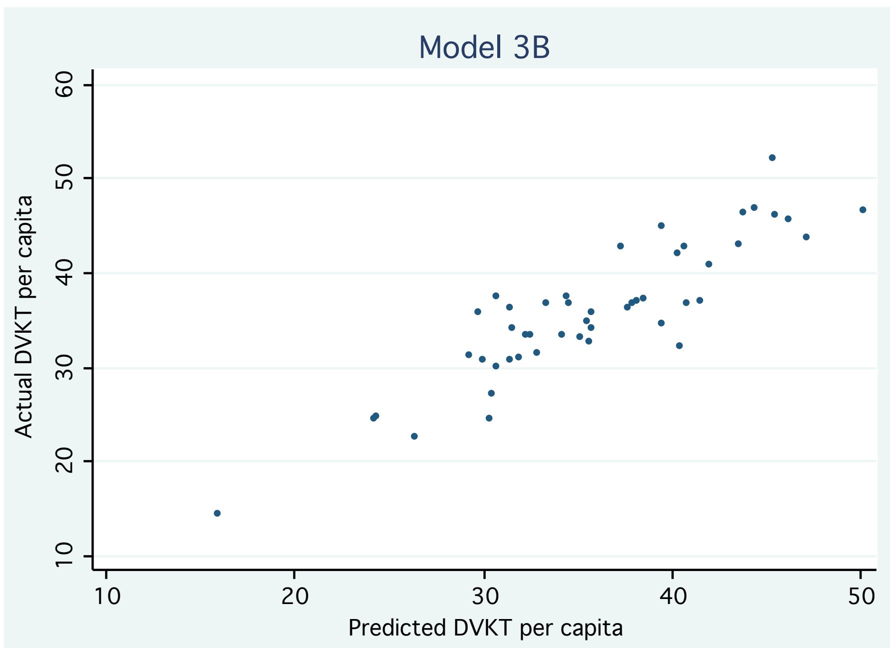

Figure F.3: Scatter plot of actual versus predicted DVKT per capita