The Influence of Network Structure on Travel Distance

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July 27, 2009

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Abstract

The objective of this research is to identify the role of network architecture in influencing individual travel behavior using travel survey data from two urban areas in Florida: Fort Lauderdale and Miami. Various measures of network structure, compiled from existing sources, are used to quantify roadway networks, capture the arrangement and connectivity of nodes and links in the networks and the temporal and spatial variations that exist among and within networks. The results from the regression models estimated show that network design influences how people travel and make decisions. Results from this analysis can be used to understand how changes in network can be used to bring about desired changes in travel behavior.

Introduction

Planners have traditionally shown keen interest in the use of land use and urban design strategies not only to bring about changes in travel behavior but as a way of providing a better quality of life for residents. Traditional neighborhood designs are asserted to be better than post-war suburban developments in terms of land use mix and greater accessibility to a variety of commercial establishments, grid-like arrangement of streets, traffic calming strategies, availability of sidewalks and other amenities suited to non-motorized travel.

While the use of urban design and associated accessibility to influence travel makes intuitive sense, researchers have found it extremely difficult to provide clear evidence on the existence much less the extent of this complex relationship. Review of the body of literature in this area shows many differences in the modeling methodologies used (Crane, 2000; Krizek, 2003). Apart from the differences in modeling methodologies, the research community has also been divided on the actual impact of urban design on travel patterns. On the one extreme, we have researchers who argue the existence of a significant relationship between urban form and travel (Cervero and Radisch, 1996; Frank and Pivo, 1994; Kockelman, 1997) and on the other extreme, we have researchers who counter that the impact of urban form on travel is weak at best (Boarnet and Crane, 2001; Crane, 2000). Researchers like Kitamura et al. (1997) and McNally and Kulkarni (1997) argue that attitudinal and socio-economic factors are greater indicators of travel patterns than land use variables and land use and urban design policies might not necessarily bring about measurable changes in travel behavior.

While many modeling methodologies and approaches have been proposed by researchers to analyze the relationship between urban form and travel behavior, consideration of the structure of the actual transportation network has been largely missing. The transport system, specifically the street system, plays the role of the primary structural element of any city. For example, as Marshall (2005) points out, the differences in modern cities such as New York or Los Angeles traces back to the transportation system in place during critical phases of growth for each city. An in-depth analysis of urban design and travel hence needs to explicitly consider the transportation network in terms of the structure, the actual layout of streets and routes.

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 only consider a coarse representation of easily measured metrics of the actual transportation network such as the density of the road network, the number of 3-way or 4-way intersections, cul-de-sacs, 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 the impact of these aspects on the performance of the transportation system.

The question of how travel behavior varies systematically with network structure is particularly important as network architecture is perhaps the slowest changing urban system. For that reason it is the most important to get right, as design of the network persists for centuries and is difficult to adjust, much less optimize. This paper aims to continue on the research interest in understanding travel behavior while explicitly accounting for the underlying highway network structure, using data from two urban areas (UA) in Florida: Fort Lauderdale and Miami. The results from this analysis 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.

The rest of the paper is organized as follows: The next section provides a brief review of relevant literature in this area. This is followed by the section on modeling methodology detailing the data and estimation of measures of roadway network structure. The statistical analyses conducted and the results are presented in the next section. The paper concludes with key findings from the study and future extensions to the current research.

Literature review

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 (2007) provides a similar definition of network topology as the arrangement and connectivity of the network. Gauthier (1966) classifies measures of network structure into two broad levels: 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.

Geographers have traditionally been interested in understanding the structure of a transportation network as an aspect of the geographical area. The reason for the interest is the complex and temporal nature of the spatial processes in transportation network, characterized by the nodes and their linkages along with the hierarchical relationships and associated flows. A topological approach based on graph-theoretic network analysis has typically been employed by geographers to understand the spatial aspects of transportation along with the underlying processes that created them (Haggett and Chorley, 1969; Rodrigue et al., 2006; Taaffe et al., 1996; Taaffe and Gauthier Jr., 1973).

Garrison (1960) utilized measures of graph theory to measure the connectivity of the Interstate Highway system, analyze the system as a whole and understand 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 $1,300 mile^2$ ($3,400 km^2$) 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.

Kansky (1963) utilized graph theory and statistical methods to develop 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 relationship between network structure and regional characteristics were analyzed through a cross-section in time and space using country level, state level, and county level data using regression analyses. 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 (1963)'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. The results of the regression analyses indicated a close relationship between the various structural network measures developed and characteristics of the area in which the transportation networks are located and technological development was a significant variable in influencing the transportation network structure.

Recently Li and Shum (2001) developed accessibility measures based on graph theory to analyze the impacts of the National Trunk Highway System (NHTS) program in China. The highway system was abstracted as a "valued graph" topologically and a nodal accessibility matrix based on the minimum distance was developed to quantify the accessibility at each nodal location and the change in accessibility over time, due to the construction of the NHTS system.

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. The authors indicate that an understanding of network topology and the stratification of a system into random (e.g. U.S highway system) or scale-free (e.g. U.S air transportation system) networks is essential to understanding the characteristics, development and behavior of complex systems. In a study evaluating pedestrian environments, Hess (1997) utilized quantitative measures of street network connectivity to explain the differences in pedestrian volumes between two neighborhoods (Wallingford and Crossroads) in the Seattle area. Hess (1997)'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 (Hess et al., 1999; Moudon et al., 1997).

Dill (2004) presented results from an ongoing research project evaluating various measures of network connectivity for the purposes of increasing walking and biking. Four selected connectivity measures (street network density, connected node ratio, intersection density and link-node ratio) were implemented to census tracts in the Portland, Oregon region as part of the preliminary analysis. While the selected measures were positively correlated, they did not provide the same measure of connectivity for a tract.

In a study looking at the journey to work, El-Geneidy and Levinson (2007) use circuity as a tool to better understand the relationship between residential location choice relative to work using data from the Twin Cities metropolitan region. Network circuity (also referred to pedestrian route directness in research on non-motorized modes) is defined as the ratio of the actual network distance to the Euclidean or straight line distance between an origin and destination. Network circuity measured for a random selection of origins and destinations was compared against the circuity measured for actual origins and destinations. The results indicate that a lower circuity for actual origins and destinations compared to random origins and destinations. Workers tend to select commutes with lower circuity applying their intelligence to locational decisions. The circuity measure has also been utilized at a national level using road networks from twenty six countries (Ballou et al., 2002) .

Jiang and Claramunt (2004) combined computational and experimental findings to conduct a topological analysis of large urban street networks. A functional graph approach was used, representing streets as vertices and nodes as edges, to estimate measures such as street connectivity, average path length and clustering coefficients. Estimation of the topological measures for large street networks indicated the presence of small-world properties combined with the absence of scale-free properties. 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: heterogeneity, connection patterns and continuity, were developed and tested on idealized test networks. The measures of connection patterns focuses specifically on the arterial network and utilizes the basic theory of the structure of planar transportation networks proposed by geographers (Haggett and Chorley, 1969). The proposed network measures were later applied to the Swiss road networks to trace the changes in network characteristics over time (Erath et al., 2007).

In a recent paper on network topology, Derrible and Kennedy (2009) study the relationship between graph theory based network topology measures and transit ridership using data on 19 subway systems worldwide. Three graph theory based topology measures: transit coverage, directness and connectivity, are developed and utilized in regression models predicting the annual number of boardings per capita. The results show a strong relationship between the topology measures and ridership indicating the importance of network design in attracting people to transit systems.

Modeling Methodology

The hypothesis of this research is that that the key measurable characteristics of network architecture of transportation networks, affect travel behavior, such as trip length, after controlling for attributes that are not explicitly network based, such as land use, urban scale and socio-demographic factors. The data for the analysis comes from two urban areas (UA) in Florida: Fort Lauderdale and Miami. The proposed statistical model used in the analysis is give below:

$$T = f(N, L, S) \tag{1}$$

where:
T = travel behavioral decision
N = network structure
L = land use

S = socio-demographic characteristics (e.g. gender, age, household size, residence type)

The data compilation process for each of the analyzed variables is detailed below:

Travel Behavior

The travel behavioral data for the two UA's comes from the 1999 Southeast Florida Travel Survey, maintained by the Florida Department of Transportation[1]. The travel survey provides information on the 1-day travel patterns of randomly selected residents in southeast Florida, comprising the counties of Palm Beach, Miami and Broward. The Southeast Florida travel survey consists of 33,082 trips undertaken by 4,603 households comprising 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 consists of 1,900 commute trips (home to work/work to home) while the 9,334 trips in the Miami area consists of 2,279 commute trips. Typical variables obtained from the travel surveys for analysis purposes include travel distance, trip mode choice and socioeconomic variables.

Highway Network

The highway network data for Fort Lauderdale and Miami are extracted from the 2000 Census TIGER/Line files[2]. 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, 2006). The extracted networks for the two UA's were cleaned and stratified into three main categories, arterials, interstates, and local streets, based on the Feature Class Codes (FCC) for the roadway segments provided in the Census TIGER/Line files. Figure 1 shows the arterial network of the two UA's considered for analysis.

The travel survey data provides information on the origin and destination of trips in the Fort Lauderdale and Miami area. The fastest path (computed over roadway segments weighted with given speeds) between the given trip origin and destination is identified for each trip in the survey dataset and a 1-km buffer is created around this path. Various measures of network structure within the 1-km fastest path buffer are then estimated using the complete street network (including interstates, arterials, and local streets). A similar analysis is carried out using a smaller arterial network consisting of just the interstates and arterials in the Fort Lauderdale and Miami area. A 2-km buffer around the fastest path is used in the arterial network to estimate measures of network structure. This network differentiation better captures the variations in network structure at different roadway hierarchies.

The variables characterizing the network structure can be broadly categorized into three main categories: hierarchy, topology, and morphology. The estimated measures

[1] http://www.fsutmsonline.net/

[2] http://www.census.gov/geo/www/tiger/

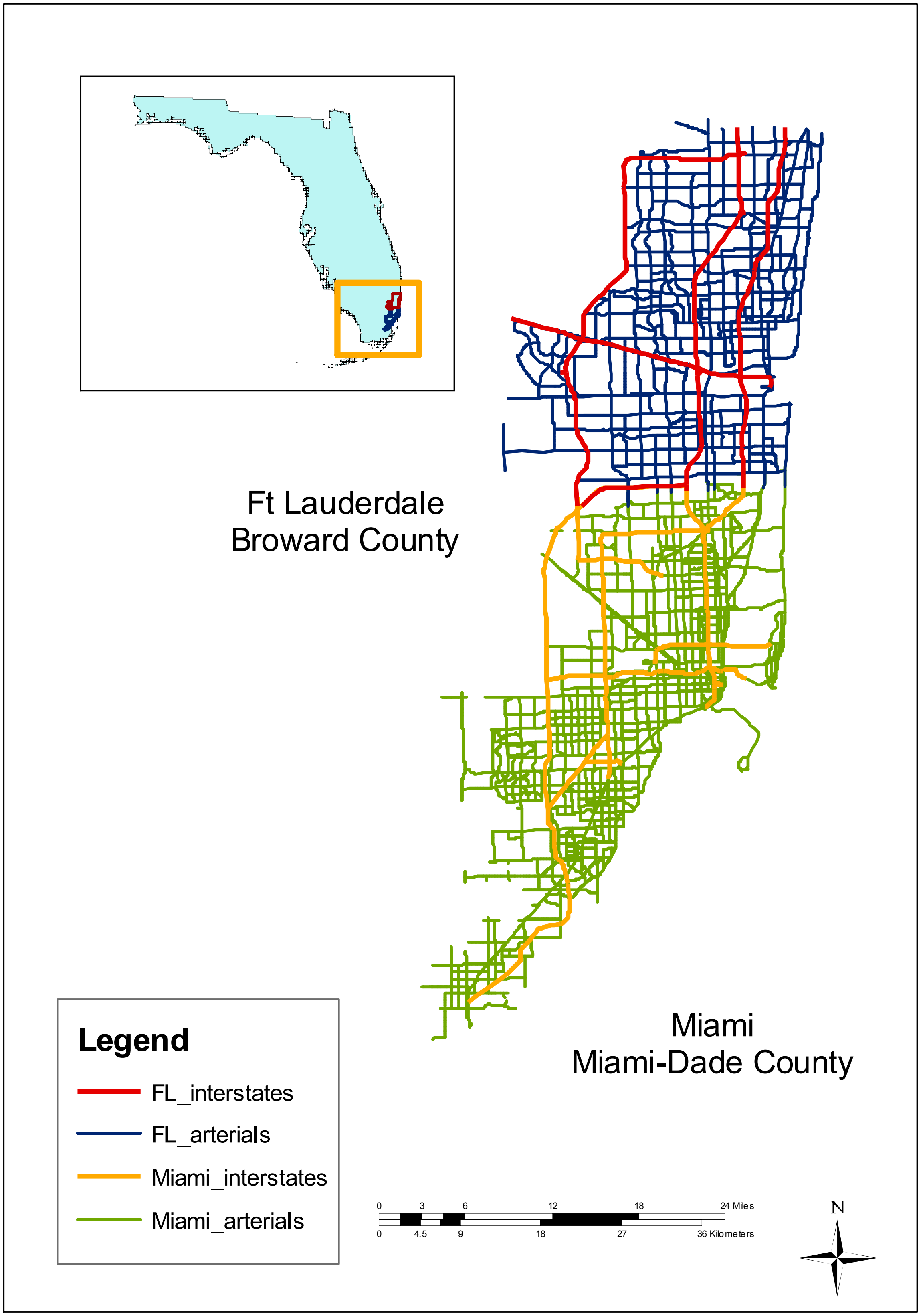

Figure 1: Fort. Lauderdale and Miami - Study Area

of network structure used in this analysis have been compiled from existing measures and are described below:

Hierarchy measures

The following attributes measure network heterogeneity:

- *Continuity and relative continuity*: This continuity measure quantifies the change in street hierarchy along the fastest path between the trip origin and destination while the relative continuity measure is the absolute change in street hierarchy divided by the trip length. These measures provide a measure of interconnectivity and heterogeneity in a road network as perceived by the traveler, and is estimated for the complete street network alone.
- *Nodal entropy*: This measure refers to the heterogeneity in node degree within the fastest path buffer, where the node degree is defined as the number of roadway links connected to the node. This measure is estimated for the complete street network and smaller arterial network and a larger nodal entropy value indicates greater heterogeneity of nodal degrees.
- *Mean nodal degree*: This is similar to the nodal entropy measure but estimates an average nodal degree within the buffer using the two street networks.
- *Percentage of road types*: This measure is similar to the entropy measure in identifying the heterogeneity in road types (interstates, arterials and local streets) using the complete street network.

$$\text{Percentage interstates} = \frac{\text{Length of interstates within the fastest path buffer}}{\text{Total length of roadways within buffer}} \tag{2}$$

$$\text{Percentage arterials} = \frac{\text{Length of arterials within the fastest path buffer}}{\text{Total length of roadways within buffer}} \tag{3}$$

$$\text{Percentage local streets} = \frac{\text{Length of local streets within the fastest path buffer}}{\text{Total length of roadways within buffer}} \tag{4}$$

Topology measures

The measures are typically based on elementary concepts of graph theory and provide a sense of connectivity and connection patterns in a network.

- *Intersection density*: This measure is estimated using the smaller arterial network as follows:

$$\text{Intersection density} = \frac{\text{Number of intersections within the fastest path buffer}}{\text{Total area of the buffer}} \tag{5}$$

- *Street density*: This is another topological measure, estimated for the complete street network.

$$\text{Street density} = \frac{\text{Total length of all roadways within the fastest path buffer}}{\text{Total area of the buffer}} \tag{6}$$

- *Treeness*: This measure is based on the two basic structures of a planar transportation network: circuit and tree (Haggett and Chorley, 1969). A regional network distinguished by closed circuits is called a circuit network where a circuit is defined a a closed path, with no less than three links, that begins and ends at the same node. A branching network is defined by a tree shaped structure and a tree is defined as a set of connected lines that do not form a complete circuit. Refer to Xie and Levinson (2007) for a complete description of this measure.

$$\text{Treeness} = \frac{\text{Length of arterials in a tree network within the fastest path buffer}}{\text{Total length of arterials within buffer}} \tag{7}$$

- **Circuity**: This measure is estimated between a given origin and destination as:

$$\text{Circuity} = \frac{\text{Network distance}}{\text{Euclidean distance}} \tag{8}$$

  The network distance is a realistic representation of the actual transportation network distance along the fastest path between the origin and destination in this analysis. The Euclidean distance measures the straight line distance between the origin and destination using the location coordinates (El-Geneidy and Levinson, 2007).

Morphological measures

This measure describes the regularity of street networks, their shape and fragmentation.

- *Shapefactor*: This measure captures the general impact of the street network and is estimated for both the complete street network and the smaller arterial network. The estimation of this measure involves identifying the polygon enclosed by the street network and is estimated as:

$$\text{Shapefactor} = \frac{\text{Perimeter of the polygon}^2}{\text{Area of the polygon}} \tag{9}$$

  A higher value of this measure indicates greater impedance in circumnavigating the identified polygon.

The above measures of network structure characterize roadway networks and capture many of topological and geometric variations that exist among networks, that affect individual's travel decisions.

Land Use

The land use variables act as control variables in the analysis of network structure on travel behavior. The following land use variables are compiled for the Fort Lauderdale and Miami area.

- *Population density*: The population data utilized in the analysis comes from the year 2000 census block level population maintained by the US Census Bureau[3].

[3] http://factfinder.census.gov

A 1-km buffer is created around each trip origin (destination) obtained from the travel survey datasets. The census blocks that lie within each 1-km buffer are identified and summed to get the total population, which is then divided by the buffer area to obtain the population density at each origin (destination).

$$\text{Population density} = \frac{\text{Total population within the 1-km buffer}}{\text{Area of the buffer}} \tag{10}$$

- *Employment density*: The employment data used in the analysis is the Transportation Analysis Zone (TAZ) level employment data obtained from the Southeast Florida Regional Planning Model (SERPM) and Miami-Dade County Transportation Model for Fort Lauderdale and Miami UA's respectively. The employment density at each trip origin (destination) is estimated as:

$$\text{Employment density} = \frac{\text{Employment within the TAZ}}{\text{Area of the TAZ}} \tag{11}$$

- *Land use heterogeneity*: The land use data utilized in this analysis is the generalized land use data maintained at the Florida Geographic Data Library[4]. The generalized land use data is compiled from the parcel specific land use data for each UA and consists of 15 land use classifications. Similar to the population density measure, a 1-km buffer is created around the trip origins (destinations) identified in the travel survey datasets. The land use that lie within the 1-km buffer are identified and an entropy measure of land use heterogeneity is estimated at each trip origin (destination). Please refer to Xie and Levinson (2007) for a complete description of the heterogeneity measure.

Each of the above identified network and land use measures are estimated seperately for the reported travel patterns in Fort Lauderdale and Miami area respectively.

Hypotheses

Hypotheses about the relationships between certain network structure measures and other subsystems have been developed based on a review of relevant research and an intuitive understanding of the transportation system and are presented below:

- An increase in the relative continuity measure indicates greater changes in street hierarchy per km along the fastest path route. This can lead to decreased actual distance traveled due to the travelers' perception of inconvenience (and thus greater perceived travel distance) associated with transferring between different roadway levels.
- An increase in network circuity will result in increased travel distance as travelers use more circuitous routes to reach their destination.
- An increase in the shapefactor indicates higher impedance to circumnavigate the polygon created by the street network, which in turn will lead to less travel distance.

[4] http://www.fgdl.org

- An increase in network treeness will increase travel distance as the ease of covering more places in a given time is lower in a tree network than a circuit network. The treeness in a network represents network connectivity with higher treeness indicating lower network connectivity.
- An increase in street density indicates higher connectivity, and more inconvenience (e.g. traffic signals) in the roadway network which leads to decreased travel distance.
- An increase in intersection density in the arterial network indicates higher connectivity and more disruption in the network which leads to shorter trips and less travel distance.
- An increase in the percentage of higher hierarchy links (interstates, arterials) should mean higher travel distance since interstates/arterials are usually faster and more suited for longer travel.
- An increase in the land use heterogeneity indicates greater mix of land uses which typically encourage greater shift to modal options other than automobiles, shorter trips and decreased travel.

Hypotheses for the socio-demographic variables aren't elaborated in this paper as the influence of socio-demographic variables on travel behavior isn't the main focus of this study and these variables are mainly used as control variables in this analysis.

Analysis

Two types of analyses are conducted using the travel survey data. The first analysis uses the trip distance between the origin and destination as the dependent variable and the second analysis uses the estimated vehicle kilometers traveled (VKT) per individual commuter as the dependent variable. The objective in both the analyses is to understand the influence of network measures on the dependent variable, after accounting for the land use and socio-demographic characteristics.

The first step in both the analyses is to identify the fastest route between each reported origin destination pair in the travel survey and estimate the network measures within east fastest path buffer. As explained previously, most of the measures are estimated for both the complete street network and the smaller arterial network. The complete street network consists of the interstates, arterial and local streets in the urban area while the arterial network is a subset of the complete network and consists of just the interstates and arterials. 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 land use measures of heterogeneity and population/employment density are calculated at both the origin and destination of each reported trip in the travel survey dataset. Summary statistics of the network, density and land use variables for Fort Lauderdale and Miami are provided in Tables 1 and 2. The correlation between the various network and land use measures are estimated to ensure that the variables capture different aspects of the network and are summarized in Tables 3 and 4.

Table 1: Summary statistics of network measures - Fort. Lauderdale

Variable	Unit	Mean	Std. Dev.	Min	Max
Relative continuity	1/km	0.320	0.471	0.000	7.581
Circuity		1.435	0.903	0.034	33.407
Nodal entropy (arterials)		0.907	0.161	0.000	1.522
Nodal entropy (all)		1.259	0.101	0.713	1.562
Intersection density (arterials)	1/km2	0.521	0.168	0.023	1.120
Shapefactor (all)		25.885	3.697	18.859	43.721
Shapefactor (arterials)		19.720	1.871	16.802	30.800
Treeness (arterials)		0.002	0.010	0.000	0.193
Street density (all)	1/km	0.013	0.002	0.006	0.019
Percentage Interstates		0.052	0.056	0.000	0.456
Percentage arterials		0.179	0.037	0.049	0.367
Mean degree for nodes (arterials)		3.612	0.147	2.750	4.000
Mean degree for nodes (all)		2.877	0.183	2.367	3.621
Population density (origin)	1/km2	0.002	0.001	0.000	0.006
Population density (destination)	1/km2	0.002	0.001	0.000	0.006
Employment density (origin)	1/km2	0.001	0.004	0.000	0.039
Employment density (destination)	1/km2	0.002	0.004	0.000	0.039
Land use heterogeneity (origin)		2.323	0.382	0.755	3.243
Land use heterogeneity (destination)		2.326	0.383	0.933	3.243
Number of observations		3,718			

Table 2: Summary statistics of network measures - Miami

Variable	Unit	Mean	Std. Dev.	Min	Max
Relative continuity	1/km	0.331	0.492	0.000	8.214
Circuity		1.384	0.932	0.075	30.047
Nodal entropy (arterials)		0.969	0.158	0.000	1.585
Nodal entropy (all)		1.314	0.082	0.910	1.601
Intersection density (arterials)	1/km2	1.127	0.719	0.031	6.273
Shapefactor (all)		23.109	2.659	17.771	41.062
Shapefactor (arterials)		22.367	4.969	16.465	53.268
Treeness (arterials)		0.009	0.033	0.000	0.671
Street density (all)	1/km	0.015	0.002	0.004	0.023
Percentage Interstates		0.065	0.055	0.000	0.305
Percentage arterials		0.180	0.045	0.000	0.418
Mean degree for nodes (arterials)		3.591	0.135	2.857	4.000
Mean degree for nodes (all)		2.990	0.229	2.435	3.644
Population density (origin)	1/km2	0.003	0.001	0.000	0.010
Population density (destination)	1/km2	0.003	0.001	0.000	0.009
Employment density (origin)	1/km2	0.004	0.013	0.000	0.186
Employment density (destination)	1/km2	0.004	0.014	0.000	0.186
Land use heterogeneity (origin)		2.046	0.363	0.553	3.132
Land use heterogeneity (destination)		2.052	0.364	0.553	3.140
Number of observations		3,195			

Table 3: Correlation of network measures - Fort. Lauderdale

	Relative continuity	Circuity	Nodal Entropy (Arterials)	Nodal Entropy (All)	Int. density (Arterials)	Shapefactor (All)	Shapefactor (Arterials)	Treeness (Arterials)	Street Density (All)	Ptage Interstates	Ptage Arterials	Mean degree for nodes (All)	Mean degree for nodes (Arterials)
Relative continuity	1												
Circuity	**0.208**	1											
Nodal Entropy (Arterials)	**-0.082**	**-0.065**	1										
Nodal Entropy (All)	**-0.039**	**-0.089**	**0.062**	1									
Intersection density (Arterials)	**0.037**	-0.027	**0.175**	**0.234**	1								
Shapefactor (All)	**-0.043**	**0.095**	**-0.231**	**-0.485**	**-0.502**	1							
Shapefactor (Arterials)	-0.014	**0.039**	**0.117**	**-0.072**	**-0.164**	**0.075**	1						
Treeness (Arterials)	0.007	**0.041**	**0.126**	**-0.328**	**-0.141**	**0.204**	**0.249**	1					
Street Density (All)	**0.102**	**-0.033**	0.023	**0.123**	**0.520**	**-0.465**	**-0.131**	**-0.151**	1				
Percentage Interstates	**-0.111**	**0.092**	**0.122**	**0.031**	-0.006	**0.164**	**0.234**	**0.180**	**-0.170**	1			
Percentage Arterials	**-0.044**	**0.027**	**-0.039**	**-0.072**	**0.136**	**0.256**	**-0.056**	**0.053**	**-0.239**	**-0.182**	1		
Mean degree for nodes (All)	**0.093**	**-0.057**	**0.146**	**0.076**	**0.456**	**-0.693**	**-0.117**	0.001	**0.574**	**-0.199**	**-0.262**	1	
Mean degree for nodes (Arterials)	0.011	**0.037**	**-0.445**	**-0.063**	**0.061**	**0.287**	**-0.333**	**-0.099**	**0.112**	**0.029**	**0.183**	**-0.160**	1

* - Significance at 90% confidence level

Table 4: Correlation of network measures - Miami

	Relative continuity	Circuity	Nodal Entropy (Arterials)	Nodal Entropy (All)	Intersection density (Arterials)	Shapefactor (All)	Shapefactor (Arterials)	Treeness (Arterials)	Street Density (All)	Percentage Interstates	Percentage Arterials	Mean degree for nodes (All)	Mean degree for nodes (Arterials)
Relative continuity	1												
Circuity	**0.226**	1											
Nodal Entropy (Arterials)	0.016	**-0.034**	1										
Nodal Entropy (All)	**-0.145**	-0.027	**0.087**	1									
Intersection density (Arterials)	**-0.037**	0.025	**0.082**	**0.302**	1								
Shapefactor (All)	**0.065**	**0.069**	0.008	**-0.332**	**-0.422**	1							
Shapefactor (Arterials)	**0.047**	0.010	**0.259**	**0.260**	**-0.132**	**-0.072**	1						
Treeness (Arterials)	0.015	**0.055**	**-0.182**	0.013	**0.140**	**-0.115**	-0.012	1					
Street Density (All)	**0.097**	**-0.052**	**0.054**	**-0.130**	**0.397**	**-0.266**	**-0.138**	**-0.096**	1				
Percentage Interstates	**-0.101**	**0.031**	**0.094**	**0.327**	**0.281**	**0.145**	**0.036**	**-0.065**	0.026	1			
Percentage Arterials	-0.004	0.028	-0.020	**0.185**	**0.453**	**-0.156**	0.002	**0.162**	**-0.234**	**-0.087**	1		
Mean degree for nodes (All)	**-0.074**	**-0.034**	**-0.032**	0.024	**0.302**	**-0.159**	**-0.295**	**-0.220**	**0.421**	**0.046**	0.000	1	
Mean degree for nodes (Arterials)	**0.031**	**-0.038**	**0.097**	**0.115**	**0.369**	**-0.845**	**0.166**	**0.117**	**0.431**	**-0.184**	**0.029**	0.121	1

Predicting trip distance

To obtain the dependent variable for the first analyses, the distances along the identified fastest path between each origin-destination pair are summed up to obtain the trip distance. Three regression models (robust standard errors) of trip distance are estimated separately for the two urban areas of Fort Lauderdale and Miami, predicting the trip distance as a function of network, land use and socio-economic variables. The three regression models of trip distance are:

- Non-commuter

  Regression of trip distance of non-work trips using non-commuter data

- Commuter

  Regression of trip distance of non-work trips using commuter data

  Regression of trip distance of work trips using commuter data

The reason for this stratification by traveler type (commuter/non-commuter) and by trip purpose (work/non-work) is to obtain a better understanding of the influence of network measures on distance and the variation of the influence across individuals and by trip type.

The results from the analysis of trip distance, conducted for both the urban areas of Miami and Fort Lauderdale are presented in Tables 5 and 6. The hypotheses formulated for the various network and land use measures and the results from the analysis are also summarized in Table 7. The socio-economic variables are used as control variables in this analysis and are hence not presented here for brevity.

Looking at the results of the three regression models of trip distance for the Fort Lauderdale area, it is clear that most measures of network structure are significant and influence trip distance as hypothesized, even after controlling for other independent variables. The measures of relative continuity, arterial intersection density, shapefactor of the complete street network/ arterial network and street density within the fastest path buffer have an expected negative influence on the trip distance while the percentage of interstates shows a positive influence on trip distance, corroborating our hypotheses.

Some network measures contradict our hypothesis: the measures of circuity and treeness while the percentage of arterials within the fastest path buffer shows no influence on trip distance in any of the regression models.

The contradicting negative influence of circuity can be related to the causality between trip distance and circuity with the trip distance affecting the level of circuity that a traveler undertakes. In their analysis of circuity and residential location, El-Geneidy and Levinson (2007) show that the circuity based on a selection of actual origins and destinations is lower than circuity measured for random origins and destinations, indicating that travelers apply intelligence to their locational decisions. The relation between circuity and trip distance will be explored further in extensions to the current research.

The treeness coefficient has a negative influence on travel distance contradicting the hypothesis. This could be due to the very small number of arterial roadway segments in the Fort Lauderdale area characterized as belonging to a tree network, due to which this variable might not influence travel the way hypothesized.

The nodal entropy and the average nodal degree of the arterial network show a significant positive influence on trip distance in all three regression models. The nodal entropy of the complete street network shows a positive influence on trip distance only for non-work trips undertaken by non-commuters and the mean nodal degree shows a negative influence on trip distance in all models except for non-work trips undertaken by non-commuters, pointing to a variation of the influence by trip purpose. Further research is required to disentangle the effects of similar network structure variables. The land use variables of population density, employment density variables and land use heterogeneity at the trip origin and destinations affect trip distance, but there doesn't seem to be any clear pattern of influence across the three regression models.

The results from the Miami analysis follows the same pattern of influence except for few variations. The treeness within a buffer shows a positive influence in two of the three regression models confirming our hypothesis that an increase in treeness increases the travel distance due to lesser connectivity, unlike the Fort Lauderdale analysis. The difference could be attributed to the higher number of roadway segments characterized as belonging to a tree network in the Miami area compared to the Fort Lauderdale area. Unlike the results from the Fort Lauderdale analysis, the street density within the buffer in the Miami urban area shows no significant influence on the trip distance The nodal entropy in both the complete street network and arterial network show a positive influence on trip distance across the three regression models while the influence of the average nodal degree (complete street network/arterial network) variable shows some minor differences by traveler or trip type. The influence of the land use measures of population density, employment density and land use heterogeneity is most pronounced on the work trips undertaken by commuters in the region. As expected, the land use heterogeneity at the origin/destination show a significant negative influence indicating that a more balanced distribution of activities results in shorter commute trips.

The above analyses indicates that network structure does affect the travel patterns in an area, even after accounting for other causal factors. The stratification of the trips by traveler type and purpose doesn't show major differences in the patterns of influence but indicate significant minor distinctions. The consistency of the results across traveler type, trip purpose and across urban areas show that network architecture affect individual travel behavior. The next analysis presented below looks at how network measures along a recurring trip (ex. morning commute) affect the total travel undertaken by an individual in an urban area.

Predicting VKT

The second type of 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 is used to identify the commuters in the two urban areas along with the trips undertaken by each commuter on the given travel day. As mentioned in the previous section, the network distance along the fastest path, between the given trip origin and destination, is identified for all trips in the travel survey dataset. The dependent variable, VKT per commuter, is then obtained by summing up the network distance for all the trips undertaken by an identified individual commuter on the travel day. This variable 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 regression of VKT per individual commuter is conducted for both the Fort Lauderdale and Miami urban areas and the results are tabulated in Table 8. The socio-economic variables are used as control variables in this analysis and are similarly not presented here for brevity. The results from the VKT per individual commuter in the

Table 5: Predicting trip distance between an origin and destination- Fort. Lauderdale

Dependent variable: Trip distance between origin and destination												
	Non-work trips, non-commuter				Non-work trips, commuter				Work trips, commuter			
	Coef.	Robust Std. Err.	t	Sig.	Coef.	Robust Std. Err.	t	Sig.	Coef.	Robust Std. Err.	t	Sig.
Network Variables												
Relative continuity	-2410.985	598.7738	-4.03	***	-3728.196	514.7349	-7.24	***	-8023.546	975.1832	-8.23	***
Circuity	-770.3035	251.2258	-3.07	***	-217.6707	98.9347	-2.2	**	-395.114	660.0844	-0.6	
Nodal Entropy (Arterials)	14235.73	2219.316	6.41	***	11516.03	1232.602	9.34	***	12557.01	2190.673	5.73	***
Nodal Entropy (All)	4675.651	1757.366	2.66	***	-2084.206	2295.547	-0.91		-728.7899	3394.316	-0.21	
Intersection density (Arterials)	-4514.618	1178.459	-3.83	***	-5954.08	1470.599	-4.05	***	-5623.572	2013.277	-2.79	***
Shapefactor (All)	-328.4436	76.24403	-4.31	***	-450.7474	89.67892	-5.03	***	-508.8851	158.9419	-3.2	***
Shapefactor (Arterials)	86.49044	104.7881	0.83		-339.757	116.0792	-2.93	***	-367.2012	169.8189	-2.16	**
Treeness (Arterials)	-104821	14164.34	-7.4	***	-51029.65	34015.08	-1.5		-120277	56298.9	-2.14	**
Street Density (All)	-1226566	143821.6	-8.53	***	-597987	158181.3	-3.78	***	-1021243	237966.7	-4.29	***
Percentage Interstates	62200.8	4778.741	13.02	***	46705.66	5588.863	8.36	***	64554.28	5513.186	11.7	***
Percentage Arterials	8250.048	6039.713	1.37		293.8544	6059.673	0.05		-924.9609	10063.91	-0.09	
Mean degree for nodes (All)	396.2135	1379.273	0.29		-4666.44	1656.82	-2.82	***	-5342.941	2424.791	-2.2	**
Mean degree for nodes (Arterials)	9997.671	2130.296	4.69	***	5818.887	1534.765	3.79	***	5775.265	2739.667	2.11	**
Land use variables												
Popn density (Org)	355791.9	272958.4	1.3		285553.8	254634.1	1.12		764330.7	293096.8	2.61	***
Pop density (Dest)	833380	265780.1	3.14	***	24107.07	275270.1	0.09		600602.1	273221.3	2.2	**
Emp density (Org)	76856.58	49810.47	1.54		123980.6	56128.57	2.21	**	105677.9	61750.74	1.71	*
Emp density (Dest)	91374.92	49380.12	1.85	*	121973.8	76880.32	1.59		68736	46483.62	1.48	
Land use heterogeneity (Org)	-1172.034	585.772	-2	**	-659.1123	589.4277	-1.12		-218.8286	662.3476	-0.33	
Land use heterogeneity (Dest)	-685.2689	545.3931	-1.26		-1214.711	577.0017	-2.11	**	-542.583	669.9204	-0.81	
Number of obs	1333				1206				1175			
F	14.14				79.62				15.38			
Prob > F	0.000				0.000				0.000			
R-squared	0.4365				0.3596				0.4143			
Root MSE	5930.7				6256.5				7276.5			

*** - Significance at 99% confidence level

** - Significance at 95% confidence level

* - Significance at 90% confidence level

Table 6: Predicting trip distance between an origin and destination- Miami

Dependent variable: Trip distance between origin and destination												
	Non-work trips, non-commuter				Non-work trips, commuter				Work trips, commuter			
Trip distance	Coef.	Robust Std. Err.	t	Sig.	Coef.	Robust Std. Err.	t	Sig.	Coef.	Robust Std. Err.	t	Sig.
Network Variables												
Relative continuity	-4659.47	448.8063	-10.4	***	-3555.477	723.4259	-4.91	***	-10618.5	1340.009	-7.92	***
Circuity	-1339.137	506.8252	-2.64	***	-46.91142	257.2972	-0.18		-3048.526	810.0126	-3.76	***
Nodal Entropy (Arterials)	13170.04	1386.452	9.5	***	12010.12	1695.552	7.08	***	13979.65	2025.869	6.9	***
Nodal Entropy (All)	22092.37	3968.031	5.57	***	27264.32	4263.654	6.39	***	23984.45	4911.143	4.88	***
Intersection density (Arterials)	-3570.387	577.8024	-6.18	***	-3130.105	623.0963	-5.02	***	-2894.027	820.565	-3.53	***
Shapefactor (All)	-540.9349	179.6503	-3.01	***	-732.5926	210.3157	-3.48	***	-771.0822	266.392	-2.89	***
Shapefactor (Arterials)	-244.4857	57.4559	-4.26	***	-301.1662	62.82405	-4.79	***	-156.5418	58.1848	-2.69	***
Treeness (Arterials)	21786	6612.17	3.29	***	17565.85	5147.11	3.41	***	12783	8285.906	1.54	
Street Density (All)	-99879	162410.5	-0.61		243031	189951	1.28		150412	176842	0.85	
Percentage Interstates	56371.25	6595.888	8.55	***	39299.09	6754.903	5.82	***	74163.15	6360.273	11.7	***
Percentage Arterials	23402.41	7202.051	3.25	***	334.9168	7367.441	0.05		1064.933	9501.726	0.11	
Mean degree for nodes (All)	-221.7084	2108.256	-0.11		-3387.163	2451.934	-1.38		-10256.07	2973.849	-3.45	***
Mean degree for nodes (Arterials)	3338.105	1850.058	1.8	*	-128.8883	2159.771	-0.06		683.8775	2737.35	0.25	
Land use Variables												
Popn density (Org)	48416.87	194993.2	0.25		-189049.4	209874	-0.9		-415444.4	181170.5	-2.29	**
Pop density (Dest)	-393183	215318.6	-1.83	*	-236155	223696.4	-1.06		-375977.3	173573.1	-2.17	**
Emp density (Org)	4955.938	14987.2	0.33		19985.09	21402.42	0.93		-35763.91	19638.93	-1.82	*
Emp density (Dest)	16152.23	13138.2	1.23		10143.16	28969.34	0.35		-26366.17	16775.24	-1.57	
Land use heterogeneity (Org)	-63.44943	872.1139	-0.07		92.69988	936.3344	0.1		-1740.493	718.9254	-2.42	**
Land use heterogeneity (Dest)	296.7831	931.519	0.32		-65.25453	880.1408	-0.07		-1388.509	775.9224	-1.79	*
Number of obs	1158				925				1097			
F	12.44				10.34				19.76			
Prob ¿ F	0.000				0.000				0.000			
R-squared	0.3364				0.2982				0.4188			
Root MSE	8728.5				8820.6				8140.8			

*** - Significance at 99% confidence level

** - Significance at 95% confidence level

* - Significance at 90% confidence level

Table 7: Summary of regression results

		Trip distance between origin and destination						**VKT per individual commuter**	
		Non-work trips, non-commuters		**Non-work trips, commuter**		**Work trips, Commuter**			
	Hypothesis	**Ft. Lauderdale**	**Miami**	**Ft. Lauderdale**	**Miami**	**Ft. Lauderdale**	**Miami**	**Ft. Lauderdale**	**Miami**
Network Variables									
Relative continuity	**-S**	-S	-S	-S	-S	-S	-S	-S	-S
Circuity	**+S**	-S	-S	-S	NS	NS	-S	NS	-S
Intersection density (Arterials)	**-S**	-S	-S	-S	-S	-S	-S	NS	NS
Shapefactor (All)	**-S**	-S	-S	-S	-S	-S	-S	NS	NS
Shapefactor (Arterials)	**-S**	NS	-S	-S	-S	-S	-S	NS	-S
Treeness (Arterials)	**+S**	-S	+S	NS	+S	-S	NS	NS	NS
Street Density (All)	**-S**	-S	NS	-S	NS	-S	NS	-S	-S
Percentage Interstates	**+S**	+S	+S	+S	+S	+S	+S	+S	+S
Percentage Arterials	**+S**	NS	+S	NS	NS	NS	NS	NS	
Land use Variables									
Land use heterogeneity (Org)	**-S**	-S	NS	NS	NS	NS	-S	-S	NS
Land use heterogeneity (Dest)	**-S**	NS	S	-S	NS	NS	-S	NS	NS
Number of observations		1,333	1,158	1,206	925	1,175	1,097	649	647

Fort Lauderdale (and Miami) indicate that while the influence of network structure on VKT per individual commuter isn't as pronounced as the results for travel distance, there is some influence of network structure measures on total travel. The network and land use variables in both the regression models confirm the formulated hypothesis and show the same patterns of influence except for some minor differences across the two urban areas. A summary of the formulated hypotheses and the results of the analysis are provided in Table 7.

Table 8: Predicting VKT per individual commuter

Dependent Variable: VKT per commuter								
	Fort. Lauderdale				Miami			
Variable	Coef.	Robust Std. Error	t	Sig.	Coef.	Robust Std. Err.	t	Sig.
Network Variables								
Relative continuity	-13519.34	3405.07	-3.97	***	-15913.18	5207.054	-3.06	***
Circuity	-466.7725	2146.16	-0.22		-5801.223	2238.604	-2.59	**
Nodal Entropy (Arterials)	28940.08	9482.25	3.05	***	31024.11	11811.64	2.63	***
Nodal Entropy (All)	9005.654	15889.7	0.57		62137.04	21690.32	2.86	***
Intersection density (Arterials)	-8835.665	9605.04	-0.92		-2203.545	3706.968	-0.59	
Shapefactor (All)	-619.4365	704.974	-0.88		879.0219	1480.49	0.59	
Shapefactor (Arterials)	-530.5161	893.166	-0.59		-885.2966	271.9592	-3.26	***
Treeness (Arterials)	-32335.3	421873	-0.08		7554.276	34266.88	0.22	
Street Density (All)	-2291905	1124654	-2.04	**	-1602352	860067.3	-1.86	*
Percentage Interstates	97213.76	26267.4	3.7	***	141216.5	25481.84	5.54	***
Percentage Arterials	12653.6	41574.8	0.3		14942.54	42772.83	0.35	
Mean degree for nodes (All)	-23091.06	10895.7	-2.12	**	1081.833	16117.08	0.07	
Mean degree for nodes (Arterials)	9063.621	11185.7	0.81		11293.53	14158.48	0.8	
Land use Variables								
Popn density (Org)	807638.5	1499781	0.54		-1544093	821214.4	-1.88	*
Pop density (Dest)	1372207	1603430	0.86		-399402.2	751544.2	-0.53	
Emp Density (Org)	-1789758	1241394	-1.44		-729218.9	408986.5	-1.78	*
Emp density (Dest)	134794.5	143074	0.94		-41636.42	61878.55	-0.67	
Land use heterogeneity (Org)	-5829.47	2845.46	-2.05	**	-3300.011	3448.741	-0.96	
Land use heterogeneity (Dest)	-1360.333	3505.68	-0.39		2709.005	3186.067	0.85	
Number of obs	649				647			
F(44, 604)	5.66				7.1			
Prob > F	0.0000				0.0000			
R-squared	0.2137				0.2340			
Root MSE	25221				29291.0			
*** - Significance at 99% confidence level								
** - Significance at 95% confidence level								
* - Significance at 90% confidence level								

In the Fort Lauderdale area, the variables in the urban areas that confirm the formulated hypotheses are relative continuity along the fastest path, density of street network, percentage of interstates and the land use heterogeneity at the trip origin. The nodal entropy of the arterial network shows a significant positive influence on VKT, similar to the results from the regression of trip distance. Similarly the average nodal degree of the complete street network has a significant negative influence on total VKT.

The analysis of VKT per individual commuter conducted for the Miami area shows the same pattern of influence of network measures as the Fort Lauderdale analysis. The only network variables that differ from the Fort Lauderdale analysis are circuity and the shapefactor of the arterial network. The circuity variable shows a negative influence on total VKT, similar to the results of regression models of trip distance, contradicting our hypothesis. The shapefactor variable in the arterial network has a negative influence confirming the hypothesis of less travel due to higher impedance in the network. The population and employment density at the trip origin show negative significance which could indicate that individuals living in a denser neighborhood are likely to have lesser travel since denser neighborhoods usually have a more balanced distribution of land uses.

Discussion

The objective of this research is to test the influence of measures of network structure on individual travel behavior using data from two UAs in Florida: Fort Lauderdale and Miami. The selection of measures of network structure used in this analysis are designed to capture the arrangement and connectivity of nodes and links in the networks and the temporal and spatial variations that exist among and within networks. It is expected that these network characteristics impact the performance of the transportation system and affect the way people make travel decision on these networks.

Two types of analyses were conducted for each urban area - the first looks at the influence of network measures on trip distance while the second analyzes the influence of network measures characterizing the home to work trip on the total travel (VKT) over the travel day. The analysis of trip distance was further stratified by traveler/trip type to capture any differences in the way networks affect individual travel. The results show that network structure does influence the travel behavior of individuals, even after controlling for the effect of other independent socio-demographic and land use variables and the patterns of influence of the network variables show consistency between the two UAs.

The results point to the importance of developing measures to quantify network structure and extends long standing interest in the relation between urban form and travel behavior. The inclusion of network structure, quantified using various measures, as a factor in influencing travel behavioral decisions differentiates this research from prior research in this field. The quantification of roadway networks structure allows easy comparison of different networks and a better understanding of spatial and temporal variations. Future extensions to the current analysis include considering structural measures of other transportation networks such as transit, non-motorized networks which could be used to test the impact of different transportation networks on travel mode choice. Estimating similar network measures for other metropolitan areas and analyzing the influence on travel patterns could help test the validity of the results across different regions. Inclusion of congestion as a factor in the analysis could be another improvement to the model and will provide a more realistic network representation since congestion affects individual travel patterns. Another planned extension is to conduct a macro-level or aggregate analysis looking at the travel in a metropolitan area as a function of the overall network characteristics.

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