Effect of Street Network Design on Walking and Biking

Wesley E. Marshall and Norman W. Garrick

The objective of this research was to investigate whether a relationship existed between street network characteristics and the transportation modes selected in a neighborhood. Factors such as street characteristics, vehicle volumes, activity levels, income levels, and proximity to limited-access highways and the downtown area were controlled for. The results suggested that all three of the fundamental characteristics of a street network—street connectivity, street network density, and street patterns—were statistically significant in affecting the choice to drive, walk, bike, or take transit. Both increased intersection density and additional street connectivity were generally associated with more walking, biking, and transit use. Street patterns with gridded street networks, which tended to have a higher-than-average street connectivity and a much higher street network density, were associated with much more walking and biking. These results suggested that street network patterns were extremely important for encouraging nonautomobile modes of travel. As the United States begins to focus on reducing vehicle miles traveled as a strategy to combat carbon production and cut energy use, it is increasingly imperative that this relationship between the built environment and mode choice be accounted for in the planning and design of the transportation system.

A transportation system that is based on multiple options for travel is generally thought to bring many benefits, including increased efficiency, enhanced flexibility, and equity for all users (*1*). The ability to choose the right travel mode for the right situation helps reduce congestion, as well as economic and environmental costs. In addition, a transportation system with a diverse set of travel options tends to be more flexible, in that it can accommodate sudden and unanticipated problems or situations, such as emergency evacuations or abrupt jumps in oil prices. More travel choices also help improve equity not only by offering mobility to young people and elderly individuals but also by providing options for people who may not be able to afford automobiles (*2*).

As planning for a more diverse set of travel options in the United States is begun, it is increasingly important that those factors that will facilitate the ready adoption of nonmotorized and public transit travel be researched and understood. The focus of the research described here is on how one aspect of the built environment, the street network, affects mode choice. The objective of the present study was to assess how street network characteristics, that is, street connectivity, street network density, and street patterns, influence mode choice in 24 California cities. The focus is on mode choice not only because these data are readily available but also because it is an indication of how people are actually using the transportation system on a daily basis. In addition, along with trip frequency and trip length, mode choice determines how much people drive (*3*).

Much of the existing research on travel patterns focuses on the impact of land use or street design characteristics (*3*). Those studies that have sought to associate street network measures with travel are few in number and generally fail to account for the full range of street network measures.

The present research carried out a spatial analysis of mode share in 24 medium-sized California cities. The cities were selected from an initial database of more than 150 California cities that best represent a geographically diverse collection of 12 medium-sized California cities with good safety records and 12 with poor safety records, according to the number of street fatalities per capita. The safety records of these cities were taken into consideration during the city selection process as part of the original investigation exploring street network and road safety outcomes (*4, 5*).

Street network measures were combined with street characteristics, socioeconomic data, and traffic flow information in a geographic information system (GIS) database. Statistical multinomial logistic regression mode share models were estimated at the census block group level of geography for more than 1,000 distinctly populated block groups. The goal of the research design was to capture the mode share implications of different street network patterns while controlling for variables such as vehicle volumes, income levels, and proximity to limited-access highways and the downtown area.

This study comes at an opportune time, because the need for a more definitive understanding of the impact of street networks on travel seems to be increasing. For instance, the Commonwealth of Virginia recently adopted a new street connectivity policy, in part to encourage the use of nonautomobile modes of travel (*6*). However, this policy focuses only on street connectivity, which is just one characteristic that defines a street network. It is not clear if this policy will be successful without a fuller understanding of the character of a street network that would come from also assessing the street network density and pattern of the street network. The problem is that little or no research is currently available to help to guide changes such as those in Virginia, which are intended to improve the performance of the street network.

The overall goal of this study is to begin to fill this gap in knowledge on how street design patterns affect mode choice and other issues, including safety, that impinge on the sustainability of communities. This paper focuses solely on the results pertaining to mode choice.

Center for Transportation and Urban Planning, Department of Civil and Environmental Engineering, University of Connecticut, U-37, Storrs, CT 06269-2037. Current affiliation for W. E. Marshall: University of Colorado, Denver, 1200 Larimer Street, Campus Box 113, Denver, CO 80217. Corresponding author: W. E. Marshall, wesley.marshall@ucdenver.edu.

Transportation Research Record: Journal of the Transportation Research Board, No. 2198, Transportation Research Board of the National Academies, Washington, D.C., 2010, pp. 103–115.
DOI: 10.3141/2198-12

LITERATURE REVIEW

Over the course of the last century, American street patterns and community design have shifted dramatically. Specifically, the traditional gridded layouts in place in the first part of the 20th century have transitioned to increasingly more dendritic, treelike networks of the post-1950 period (*7, 8*). In describing these changes, many observers focus on the shape and connectivity of the street networks but typically ignore another important factor, street network density, which progressively decreased over the second half of the 1900s.

Interestingly, the most influential effort at promoting newer types of street networks in the 1900s did not come from planners or engineers but from a quite unexpected quarter: the Federal Housing Administration (FHA). FHA was founded in 1934 and in the mid-1930s released Technical Bulletins 5 and 7 to recommend specific street patterns (*9*). The bulletins called the grid layout monotonous, with little character or appeal. They also said it was uneconomical and had safety issues (*8*). The publications endorsed hierarchical street layouts that minimized through traffic and singled out cul-de-sacs as being one of the most attractive and profitable street types.

In its first 15 years of existence, FHA played a role in overseeing the production of more than 22 million properties (*8*). As a result, its recommended design principles became accepted practice for developers and began to be included in many zoning regulations. In effect, the federal government became a driving force in determining the types of street networks getting built at the neighborhood level.

It was not until the early 1950s that transportation engineers began to actively recommend hierarchical cul-de-sac designs as the preferred street pattern. It is noteworthy that very little technical evidence or research supported this radical change in how street networks were designed and constructed. Nonetheless, in 1965, ITE published *Recommended Practice for Subdivision Streets,* which discouraged the use of gridded street patterns. The report recommended curvilinear local streets with discontinuities to discourage through traffic, replacing four-way intersections with T-intersections where possible, and the use of cul-de-sacs. Although in 1994 ITE published *Traffic Engineering for Neo-Traditional Neighborhood Design,* which promoted a return to more traditional patterns, the latest ITE guidelines for subdivision streets still maintain many of the same design principles discussed in the 1965 version (*8*).

The result was that from the 1940s through the late 1980s, few new developments in the United States featured a gridded street pattern; instead, hierarchical layouts became the standard (*8*). Despite their fall from favor, connected street networks are widely considered to have some advantages, including directness of travel and more route choice options. These advantages are often thought to encourage nonautomobile travel, including walking, biking, and transit (*1*). Some research in the literature has investigated the link between street pattern and various measures of travel behavior, including mode choice. This literature is reviewed below (*10*).

In one particularly influential study, Newman and Kenworthy charted the overall fuel consumption in 32 cities worldwide measured against the population density of those places (*11*). They found a distinct relationship between fuel consumption and density, with fuel consumption decreasing as the density of the city increases. Newman furthers this examination of energy use and urban form by examining in more detail the New York City and San Francisco, California, regions (*11*). In both locations, the amount of gasoline used increases exponentially with decreased density as one moves from the central city toward the outer suburbs, where the maximum amount of energy is used. Although these comparisons do not reveal what specific differences in urban form and travel patterns account for this relationship to fuel consumption, it is difficult to ignore the implication of these trends.

A number of studies have explicitly examined the relationship between travel patterns and various characteristics of the street network. The earliest of these studies were based on simulation programs and did not use measurements from real-life examples. For example, in 1984, Curtis et al. modeled mode choice and fuel savings of conventional hierarchical street patterns compared with those of several hypothetical street networks, including a grid network (*12*). The results suggested that the gridded street network would save up to 30% in fuel costs; however, the authors contended that this difference was in part due to higher vehicle speeds on the grid network. In the early 1990s, Walter Kulash did a similar study based on simulation models (*13*). Kulash's simulation was also based on the assumption that a gridded street network had higher average vehicle speeds. His simulations showed a 57% decrease in the number of vehicle miles traveled (VMT) for neighborhood travel on a gridded street network (*13*).

McNally and Ryan, in another hypothetical study, found similar advantages for a connected street network when it was compared with a less connected, more contemporary street network (*14*). In yet another simulation study, this one sponsored by ASCE, the findings were that street networks heavy on cul-de-sacs increased travel demand on arterial roads by 75% and on collector roads by 80%, whereas a gridded street design had 43% lower VMT (*7*).

The results of a number of more recent empirical studies seem to support those of the earlier simulation studies of street networks and travel. For example, the Puget Sound Regional Council found that in the King County, Washington, area VMT dropped by approximately 0.5% for every 10% increase in the number of intersections per mile, with all other variables being held constant (*15*). In another series of case studies, the Portland, Oregon, Metro found that an increase from low connectivity to moderate connectivity reduced the number of VMT by 2%, the trip length by 2%, and vehicle delay by 14% (*16*).

In a study specifically addressing street network measures, Cervero and Gorham found that denser and more connected transit-oriented street networks had much higher pedestrian mode shares than networks in what they considered to be more automobile-oriented neighborhoods (*17*). The authors suggested that their focus on work trips is a limitation of the study but point out that much of the research in the literature showed an even bigger influence of street network characteristics on nonwork trips (in particular, shopping trips). For example, they cite Handy, who, in looking at what she termed accessibility, suggested that people living in more accessible places drive as many as 40% fewer miles for shopping trips (*18*).

Cervero and Kockelman found not only that increased nonautomobile mode shares were associated with dense developments but also that gridded street networks, combined with parking restrictions, resulted in the biggest shift in mode choice and, in turn, the largest drop in VMT (*19*). Interestingly, they did not find the variable that they used for measuring the pedestrian environment to be strongly correlated with any mode choice shift. On the other hand, Hess et al., comparing sites matched for population density, land uses, and income, observed that urban places with shorter block lengths supported by good sidewalks had an average of three times higher pedestrian volumes than more suburban places with longer block lengths and an incomplete sidewalk network (*20*).

Not all of the research studies found street networks to be significant factors in affecting travel and mode choice. Holtzclaw's results showed that street patterns had no significant effect on total VMT per household (*21*). In another report, Crane suggested that the transportation benefits of denser and more connected street networks are being oversold because improving access to the point of increasing walking trips will also increase trip frequencies and perhaps even overall travel on the transportation system (*22*). This begs the question, especially if the overall goal is related to sustainability: Are more walking trips really a bad thing? Another study by Crane, this time with Crepeau, found no evidence that street patterns influenced differences in walking or driving for nonwork trips; however, they did not explicitly consider street network density (*23*).

A common problem with all the research reviewed above is that they do not account for all three of the fundamental street network measures: street connectivity, street network measures, and street patterns. The present study focuses on fully characterizing the differences between different types of networks and examines how the full range of street network design factors influences mode choice. The goal is to establish a clear picture of the street network characteristics that might affect mode choice.

OVERVIEW OF STUDY

The research described here is based on 24 California cities with populations of between 30,000 and 100,000 at the block group level of geography. According to the U.S. Census Bureau, a census block group is intended to average 250 to 500 housing units, and census block groups vary in area, depending on housing density. The present study has more than 1,000 distinctly populated block groups at an average of approximately 43 block groups per city. The study focused on California cities because of the large number and diversity of city types and to help maintain consistency in the data. For the initial study, the objective of city selection was to find 12 medium-sized cities with good road safety records and 12 with poor records, since the original goal of the research was to assess traffic safety. However, the authors also found that the city selection process resulted in a wide range of street and street network characteristics, in part because the average years of incorporation were 1895 for the safer cities and 1932 for the less safe cities. The safer cities selected were

- Alameda,
- Berkeley,
- Chico,
- Cupertino,
- Danville,
- Davis,
- La Habra,
- Palo Alto,
- San Luis Obispo,
- San Mateo,
- Santa Barbara, and
- Santa Cruz.

The less safe cities selected were

- Antioch,
- Apple Valley,
- Carlsbad,
- Madera,
- Morgan Hill,
- Perris,
- Redding,
- Rialto,
- Temecula,
- Turlock,
- Victorville, and
- West Sacramento.

Description of Spatial Data

Network-Level Data

The street network data were derived from a number of sources, including the U.S. Census Bureau TIGER/Line files, the California Spatial Information Library, and the California Department of Transportation (Caltrans) records. Street network measures for characterizing both street connectivity and street network density were calculated by use of the ArcGIS program. Proper characterization of the street network requires answers to three basic questions: How connected are the streets? How compact is the network? and What are the street network patterns? The approach used to characterize these properties is discussed in the following paragraphs.

One common measure used to determine the connectivity of a street network and the first that was sought to be measured here is the link-to-node ratio. The link-to-node ratio is calculated by dividing the number of links (road segments between intersections) by the number of nodes (or intersections) (*15, 24*). The node count represents the total number of intersections, including dead ends or cul-de-sacs. For example, addition of a dead-end cul-de-sac to a street network would add one link and one node to the total count, whereas connecting two existing dead-end cul-de-sacs would add one link without adding any additional nodes. Correspondingly, a new dead end would lower the link-to-node ratio, and connecting two dead ends would increase the link-to-node ratio; thus, the higher that the value of the link-to-node ratio is, the more connected the street network is. A score of 1.4 or higher is typically considered indicative of a walkable community (*15*).

The second characteristic of the street network that was sought to be measured was street network density. Intersection density is one way of characterizing street network density; it is typically measured by the number of intersections per unit area (the typical unit is often a square mile). Intersection density can be calculated separately for major streets and local streets, in an attempt to give an indication of the type of intersections that make up the street network. Other typical measures of intersection density included average block size, dead-end density, centerline street-mile density, and the connected node ratio. For additional background information on street network measures, refer to the authors' earlier paper (*5*).

Street network patterns are determined by use of an adaptation of Stephen Marshall's concept of macroscopic and microscopic street networks, shown in Figure 1 (*25*). The concept differs from the standard functional classification of arterial, collector, and local roads, in that Marshall's system is based on street network structure. The macrolevel, or citywide, street network distinguishes streets that are generally continuous over a substantial portion of the city and likely services travel from one part of the city to another and, in many cases, trips to or from the city. The microlevel, or neighborhood, street network generally serves residential neighborhood travel because these streets are on routes not continuous over a significant portion of the city. Marshall defines four types of citywide street network types: linear (L), tributary (T), radial (R), and grid (G) (the first letters of the abbreviations in Figure 1); he then combines this with two neighborhood street network types: tree (T) and grid (G) (the second letters of the abbreviations in Figure 1).

Marshall presents the chart shown in Figure 1 in his book as a way to discuss the hybrid types of street patterns and account for the

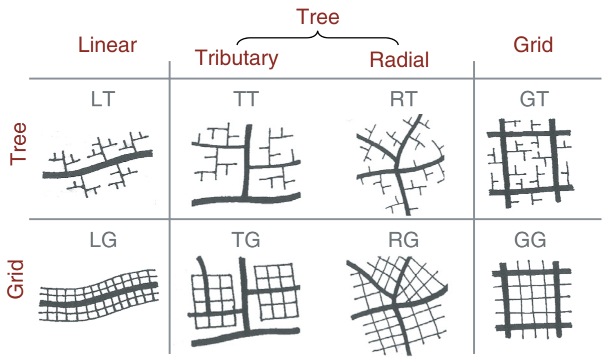

FIGURE 1 Citywide neighborhood street network classification system (*25;* used by permission).

different levels of streets in the network; the chart was not originally intended to serve as a way to classify actual street networks (*25*). The authors' preliminary evaluation of this scheme suggested that it would be a good approach for classifying street pattern types in the present study, since it was found that it was inclusive of most network types encountered while at the same time providing a good way of adequately representing the different levels of the street network.

However, to transition Marshall's pattern chart into a feasible street network classification system, a couple of obstacles had to be overcome. One drawback is the omission of curvilinear street types. Hence, a binary descriptor value representing whether the street network was generally curvilinear was added. Another drawback of trying to use Marshall's pattern chart in practice is that his streets fall into only two categories: citywide or neighborhood. This binary scheme is limiting and not consistent with how places and street networks are built in practice. As a result, Marshall's system was supplemented with an intermediate type of street that was neither a citywide street nor part of the neighborhood street network. This intermediate-level street enables movement between neighborhoods but is not necessarily useful for citywide travel; accordingly, these streets were labeled the interneighborhood streets.

To use this adapted classification method in the present study, the entire street network in the 24 cities evaluated in the present study had to be manually classified. By use of aerial photographs, the citywide streets in each city were designated by selecting streets that are generally continuous across a substantial portion of the city. In other words, the citywide street network consisted of those streets that were deemed to be significant connectors between distinct parts of the city. Streets adjacent to or leading to significant commercial or industrial land uses were also considered part of the citywide street network. The interneighborhood streets were selected to represent connections between adjacent neighborhoods or multiple neighborhoods.

Figure 2 depicts the process of classifying the major and local streets in Carlsbad, California, on the basis of the citywide, interneigh-

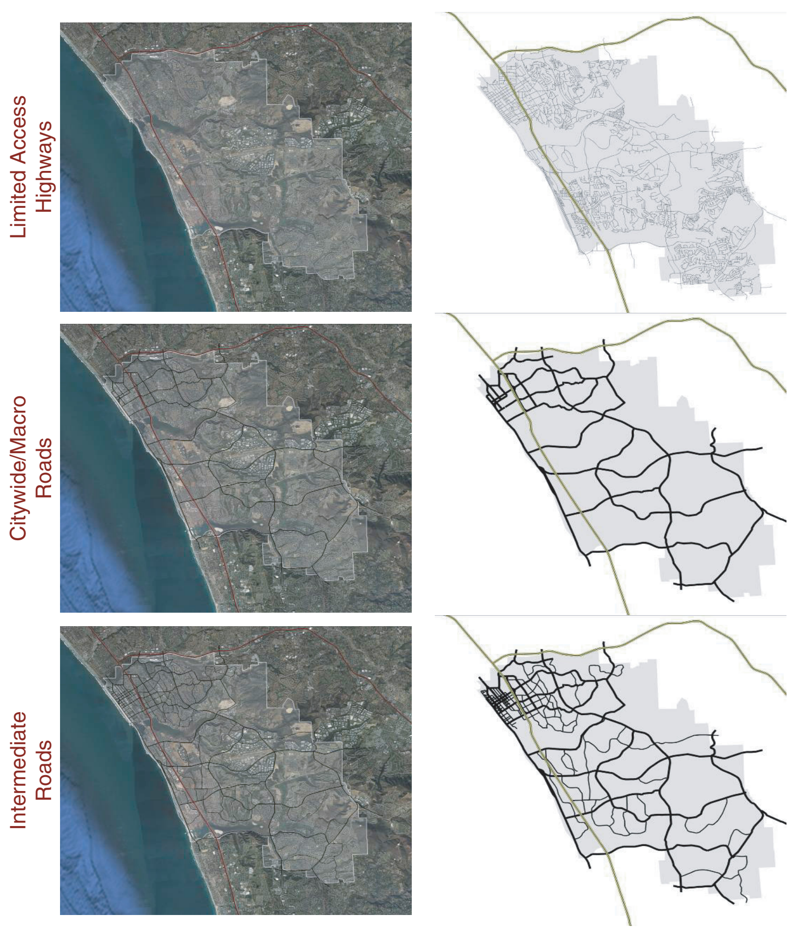

FIGURE 2 Citywide (macroscopic) versus neighborhood (microscopic) street classification in Carlsbad.

borhood, and neighborhood street system by the use of aerial photographs from Google Earth. The top images in Figure 2 display the limited-access highways in Carlsbad. The middle set of images in Figure 2 shows the citywide street network. This picture offers a good indication of what streets would accommodate longer-distance travel within Carlsbad and what streets would accommodate coming to or leaving Carlsbad. Although most of the citywide streets extend across a significant portion of Carlsbad, a few in the northwest corner of the city were selected because of their proximity to major commercial land uses. The bottom set of images in Figure 2 displays the interneighborhood streets. This begins to show the roads connecting the different residential neighborhoods of Carlsbad and starts to provide an impression of the street network structure at the interneighborhood street level. By this approach, each block group in the database was classified by the predominant street network pattern in that block group.

This classification system not only provided a visual representation of the street network but also facilitated the creation of more detailed street network measurements. For instance, intersection density can now be broken down by intersection type for the corresponding intersecting nodes for citywide street network intersections (the intersection of two citywide streets) or citywide street network–interneighborhood street network intersections (the intersection of a citywide street with an interneighborhood street).

Street-Level Data

The following street design characteristics were collected for every street segment in the citywide street network by use of Google Earth:

- Total number of lanes,
- Curb-to-curb distance,
- Outside shoulder width,
- Inside shoulder width (when a median is present),
- Raised-median width,
- Painted-median width,
- On-street parking (0 = no, 1 = yes, 0.5 = along one side of street),
- Bike lanes (0 = no, 1 = yes, 0.5 = along one side of street),
- Curbs (0 = no, 1 = yes, 0.5 = along one side of street), and
- Sidewalks (0 = no, 1 = yes, 0.5 = along one side of street).

Census Data

Census data from the year 2000 were collected and analyzed along with the street network data at the census block group level of geography. These data included mode shares, travel time to work, household income levels, and demographic information, such as age and race.

Traffic Data

Vehicle volumes, according to VMT, were estimated through the use of average annual daily traffic (AADT) counts carried out by each city. The AADT data were geocoded on the basis of the nearest intersection, and the average AADT for each street type—citywide, interneighborhood, and neighborhood—was calculated. This average AADT value was used to calculate VMT on the basis of total street length, by type. Since the number of AADT points on the neighborhood streets was relatively low, VMT on these streets was estimated by using an average AADT value of 845, which is consistent with the value that Caltrans uses for all local streets in its VMT assessment. However, this did not seem to be an appropriate value for dead-end streets, so an AADT value of 250 was used in these cases.

In general, zones with higher VMTs would be expected to be associated with more driving. However, the intent of including this variable is to control for the influence of high traffic volumes on mode choice.

To account for the overall level of activity in an area, a proxy measure based on a simplified gravity model strategy and the relative levels of population and employment that was originally conceived by Graham and Glaister (*26*) was used (*27*). The idea is to establish the relative activity of a zone in terms of the population and employment of that particular zone as well as the population and employment of other zones according to the distance between them. The following equation is a proxy for the amount of activity in each zone (*26, 27*):

$$\mathrm{PP}_i = \sum_j \frac{P_j}{d_{ij}}$$

$$\mathrm{PE}_i = \sum_j \frac{E_j}{d_{ij}}$$

where

PP_j = number of trips generated by block group j by the proximate population,
PE_j = number of trips generated by block group j by the proximate employment,
P_{ij} = level of population,
E_{ij} = level of employment, and
d_{ij} = centroid-to-centroid distance between block groups i and j (calculated in feet, with a distance of 1 ft being used to calculate the intrazone proxy values).

The proximate employment variable and proximate population variable were also used to calculate a proxy for the relative level of mixed land uses by dividing the proxy for employment by the proxy for population. At the block group level of geography, this value helps identify the relative mix of employment and population.

Statistical Methodology

The fundamental question trying to be answered with this research is the following: How are street network measures correlated to mode choice? Although mode choice modeling is best known for being used in transportation planning and the four-step travel demand model, the model described here focuses on how certain characteristics of the street and street network affect travel-to-work patterns by mode choice. In either case, the basic structure is the same and is typically based on the logit model. The following generalized logit equation establishes the probability of choosing a specific mode (*28*):

$$P_i = \frac{e^{u_i}}{\sum_{i=1}^{k} e^{u_i}}$$

where

P_i = probability of somebody choosing mode $i = 1, 2, \ldots, k$;
u_i = utility function describing the relative attractiveness of mode i; and
$\sum_{i=1}^{k} e^{u_i}$ = sum of the functions for all available mode alternatives

The probability of choosing a certain mode depends on this utility function relative to the utility functions for all other mode options. In a traditional four-step model, the utility function of the logit equation normally contains variables such as in-vehicle travel time, out-of-vehicle travel time, and the cost associated with each mode for a particular type of trip between two specific zones. The utility function in the present study primarily consists of street and street network characteristics.

Four types of modes were modeled in the present study: transit, walking, biking, and driving. To account for four separate categorical outcomes, a multinomial logistic regression model is used (*29*). A multinomial logistic regression simultaneously considers a binary logit model for every possible combination of outcomes; in this case, four different outcomes are equivalent to six binary logit models (*30*). One assumption of the multinomial logistic regression model is that the probabilities related to the choices sum to 1:

$$P(\text{transit}) + P(\text{walking}) + P(\text{biking}) + P(\text{driving}) = 1$$

For such a probability-based model, the multinomial logistic regression equation is as follows (*30*):

$$P(y_i = 1|x_i) = \frac{1}{1 + \sum_{j=2}^{J} e^{(x_i\beta_j)}} \quad \text{for } m = 1$$

$$P(y_i = m|x_i) = \frac{e^{(x_i\beta_m)}}{1 + \sum_{j=2}^{J} e^{(x_i\beta_j)}} \quad \text{for } m > 1$$

where

y = dependent variable,
J = number of categorical outcomes for four mode choices,
$P(y = m|x)$ = probability of choosing mode m given x,
x_i = independent predictor variable, and
β = estimated coefficient representing the effects of the independent variable.

Description of Experiment

The statistical relationship between mode choice and street network measures, including street connectivity, street network density, and types of street patterns, was investigated by using the multinomial logistic regression model. Also considered were design characteristics of the citywide streets, including the total number of lanes; the outside shoulder width; and the percentage of citywide streets with medians, on-street parking, bike lanes, and curbs or sidewalks. Interactions among the selected variables were also tested and analyzed; in particular, interactions among street connectivity, street network density, street network pattern, and citywide street design variables were tested.

The variables controlled for in the models include income levels, proximity to limited-access highways or the downtown area, the proxy variable for block group activity levels, the proxy for mixed land uses, and vehicle volumes. Because of the relative magnitude of the vehicle volume counts and average income compared with that for the rest of the data, the data for these two variables were scaled down and standardized to range from 0 to 1 so that the statistical coefficients could be estimated and the direction of the effect could be more easily observed. Consistent data representing the level of transit service were not available for all 24 cities in the database. Because transit use is linked to the level of transit available in an area, it is difficult to establish firm conclusions about the transit results because a measure of transit availability was not available; however, separation of transit use from the other nonautomobile mode shares allowed a better understanding of the association of the street network with the other modes to be obtained. Table 1 displays the summary statistics for the variables tested.

A number of variables were also tested but not used in the final models because they showed a high correlation with other variables already included in the model. The variables that were not included in the models because they were highly correlated with another variable include the following:

- Street network measures:
  - Centerline miles of street (total and by type),
  - Centerline miles of street per square mile (total and by type),
  - Percentage of streets by type,
  - Connected node ratio, and
  - Average block size;
- Street-level data (for citywide streets only):
  - Curb-to-curb distance and
  - Percentage of citywide street length with sidewalks; and
- Miscellaneous:
  - Population,
  - Population density,
  - Employment density,
  - Mode share data, and
  - Average travel time to work.

RESULTS

The results from the multinomial logistic regression are displayed in Table 2. Other than outside shoulder width on the Citywide Streets, every independent predictor variable in the data set turned out to be significantly associated with mode choice. Also significant were the interaction terms of the street pattern classification variable by intersection density, the link-to-node ratio, and the average total number of lanes. A three-way interaction of the street pattern type by both intersection density and the link-to-node ratio was also added and turned out to be significant. Because of all of the interaction terms, interpretation of the results directly from Table 2 is complicated. Therefore, in interpreting the results, the focus is on the change in mode share predicted by the models on the basis of a discrete change to a single variable. Rather than trying to reconcile three different coefficients for a variable such as intersection density, this approach allows all other variables to be held at their mean and observation of how modes shares would change if the intersection density were different. The results in Table 3 were calculated for the six most frequently occurring street patterns.

TABLE 1 Summary Statistics of Variables at Census Block Group Level

Variable	Mean	SD	Minimum	Maximum
Mode choice				
Transit mode share	0.0523	0.0681	0	0.4378
Walking mode share	0.0454	0.0812	0	0.9043
Biking mode share	0.0264	0.0442	0	0.3986
Driving mode share	0.8651	0.1427	0.0287	1
Street network measures				
Intersection density (intersections/mi^2)	176.0	98.8	7.9	559.0
Deadend density (dead ends/mi^2)	32.0	27.7	0	209.0
Citywide/interneighborhood intersection density	60.1	68.8	0	523.0
Link to node ratio (no. of links/no. of intersections)	1.20	0.20	0.40	2.00
Curvilinear (0, 1)	0.20	0.40	0	1
Street-level data for citywide streets				
Avg. total number of lanes	3.00	1.10	0	7.00
Avg. outside shoulder width	1.70	2.60	0	12.00
% of citywide street length with raised median	0.50	0.50	0	1
% of citywide street length with painted median	0.40	0.50	0	1
% of citywide street length with on-street parking	0.50	0.40	0	1
% of citywide street length with bike lanes	0.30	0.30	0	1
% of citywide street length with curbs	0.80	0.30	0	1
Traffic data				
VMT	30,440	36,586	1,475	502,272
VMT standardized from 0 to 1	0.10	0.10	0	1
Proxy for activity	0.30	0.30	0	1
Miscellaneous				
Distance from city center (mi)	1.8	1.4	0.0	9.0
Bisecting or adjacent limited-access highway (0, 1)	0.30	0.40	0	1
Income ($)	57,268	21,549	11,956	128,223
Income standardized from 0 to 1	0.40	0.20	0	1
Proxy for mixed land uses	0.40	0.00	0.30	1

Street Network Measures

Street Network Density

Intersection density had different effects, depending on both the mode being considered and the street pattern type. For transit, increased intersection density was associated with increased transit use only in the radial citywide street and gridded neighborhood street (RG) pattern, whereas for every other street pattern type, increased intersection density had little effect or a negative effect on transit mode share. For both walking and biking, increased intersection density was almost always associated with an increase in both of these nonmotorized mode shares.

With the tributary citywide street and treelike neighborhood street pattern type (TT pattern) as an example, the average walking and biking mode shares in a TT street pattern are 2.3% and 1.7%, respectively, as shown in Table 3. Table 3 also presents the predicted value for each mode share if, for example, the overall intersection density was changed from 81 to 144, 225, and 324 intersections per square mile (these levels correspond to the number of intersections that would be found in hypothetical square grids of 9×9, 12×12, 15×15, and 18×18 mi). The results suggest that the walking mode share would increase from 1.9% to 3.7% and the biking mode share would increase from 1.3% to 4.1% if the intersection density increased from the low level of 81 to the high level of 324 intersections per square mile. In other words, an increase in the intersection density from 81 to 324 in a tributary citywide street and treelike neighborhood street pattern type (TT pattern) is associated with an increase in walking and biking mode shares combined from 3.2% to 7.8%.

In addition to overall intersection density, the density of dead-end intersections as well as the density of citywide and interneighborhood intersections was tested to better understand the effects of the different mix of intersection types. Although the density of dead-end cul-de-sacs was statistically significant, it did not result in much of an impact on driving mode share. However, an increase in dead-end intersection density was generally associated with a decrease in both walking and biking mode shares and an increase in transit use. This result suggests that increases in the amounts of dead ends in a street network increase the likelihood of a trip requiring a circuitous route, resulting in a negative impact on walking and biking. Interestingly, the same trend was also seen with the citywide and interneighborhood intersection density variable. This suggests that a high number of major intersections in the network reduces the viability of walking or biking.

Street Connectivity

The overall trend for street connectivity was that an increased link-to-node ratio was associated with a decrease in the driving mode share for all street pattern types. This ranged from very small reductions in driving mode share for most street patterns to the much more substantial shift away from driving (from 93.0% to 82.5% for an increase in the link-to-node ratio from 1.1 to 1.55) for a tributary citywide street and gridded neighborhood street pattern type (TG pattern).

For transit, walking, and biking, the results for street connectivity were mixed, similar to those seen with dead-end density. For instance, in street pattern types TT, RT, and RG, the more transit use

TABLE 2 Multinomial Logistic Regression Mode Share Model

Variable	Transit Model (with respect to driving)			Pedestrian Model (with respect to driving)			Bicycling Model (with respect to driving)		
	Coefficient	SE	β/SE	Coefficient	SE	β/SE	Coefficient	SE	β/SE
Intercept	−15.8925	1.1954	−13.2947	−2.0963	0.7042	−2.9769	−8.2641	1.0566	−7.8214
Street Network Measures									
Street pattern type									
GG = citywide grid, neighborhood grid	1.2496	1.2610	0.9910	−11.9819	0.8249	−14.5253	−9.7152	1.2336	−7.8755
GT = citywide grid, neighborhood tree	6.3239	1.2801	4.9402	−4.3404	0.8498	−5.1076	−1.3507	1.2837	−1.0522
LT = citywide linear, neighborhood tree	9.1772	1.3614	6.7410	3.1124	0.8919	3.4896	1.0323	1.4508	0.7115
RG = citywide radial, neighborhood grid	15.1989	6.1852	2.4573	9.8073	7.9204	1.2382	34.3978	7.4238	4.6334
RT = citywide radial, neighborhood tree	7.3611	1.4490	5.0801	−0.9243	1.0358	−0.8924	−0.3918	1.6290	−0.2405
TG = citywide tributary, neighborhood grid	3.9161	1.4802	2.6457	−7.4373	1.2203	−6.0946	−7.4963	1.3955	−5.3718
TT = citywide tributary, neighborhood tree	7.7071	1.2090	6.3748	−4.1307	0.7317	−5.6453	0.3033	1.0777	0.2814
LG = citywide linear, neighborhood grid	—	—	—	—	—	—	—	—	—
Intersection density	0.0036	0.0005	6.8000	0.0013	0.0004	3.4759	0.0039	0.0006	6.8118
Interaction terms									
(Intersection density)(GG)	0.0166	0.0017	9.7076	0.0336	0.0018	19.0909	0.0262	0.0027	9.8868
(Intersection density)(GT)	−0.0093	0.0027	−3.4925	−0.0002	0.0027	−0.0803	0.0075	0.0041	1.8480
(Intersection density)(LT)	−0.0319	0.0063	−5.1040	−0.0250	0.0062	−4.0323	−0.0213	0.0088	−2.4315
(Intersection density)(RG)	−0.0410	0.0214	−1.9159	−0.0438	0.0285	−1.5368	−0.1149	0.0269	−4.2714
(Intersection density)(RT)	−0.0186	0.0041	−4.5146	−0.0132	0.0040	−3.3333	0.0128	0.0064	1.9907
(Intersection density)(TG)	0.0058	0.0041	1.3981	0.0141	0.0052	2.7115	0.0114	0.0043	2.6389
(Intersection density)(TT)	−0.0155	0.0013	−11.7424	0.0126	0.0013	9.5455	−0.0059	0.0015	−3.9730
(Intersection density)(LG)	—	—	—	—	—	—	—	—	—
Link-to-node ratio									
Interaction terms									
(Link-to-node ratio)(GG)	−1.2065	0.9278	−1.3004	8.4639	0.5983	14.1466	6.7743	0.9064	7.4739
(Link-to-node ratio)(GT)	−4.1615	0.9502	−4.3796	2.9288	0.6304	4.6459	1.0618	0.9672	1.0978
(Link-to-node ratio)(LT)	−6.7898	1.0526	−6.4505	−2.3966	0.7068	−3.3908	−0.0368	1.1827	−0.0311
(Link-to-node ratio)(RG)	−11.8143	4.4388	−2.6616	−7.8482	5.6852	−1.3805	−24.1000	5.3444	−4.5094
(Link-to-node ratio)(RT)	−5.4370	1.1035	−4.9271	0.0901	0.7906	0.1140	0.1136	1.2678	0.0896
(Link-to-node ratio)(TG)	−0.9865	1.0760	−0.9168	7.2047	0.8762	8.2227	6.3816	1.0204	6.2540
(Link-to-node ratio)(TT)	−5.2365	0.8944	−5.8548	3.2162	0.5400	5.9559	−0.4815	0.8047	−0.5984
(Link-to-node ratio)(LG)	—	—	—	—	—	—	—	—	—
Interaction terms									
(Intersection density) (link-to-node ratio)(GG)	−0.0141	0.0012	−12.0513	−0.0225	0.0012	−18.2927	−0.0198	0.0018	−10.7609
(Intersection density) (link-to-node ratio)(GT)	0.0041	0.0020	2.0553	0.0012	0.0021	0.5825	−0.0050	0.0031	−1.6052
(Intersection density) (link-to-node ratio)(LT)	0.0241	0.0055	4.4059	0.0160	0.0054	2.9412	0.0168	0.0075	2.2311
(Intersection density) (link-to-node ratio)(RG)	0.0284	0.0153	1.8562	0.0338	0.0204	1.6569	0.0806	0.0192	4.1979
(Intersection density) (link-to-node ratio)(RT)	0.0127	0.0033	3.8720	0.0126	0.0031	4.0777	−0.0081	0.0052	−1.5689
(Intersection density) (link-to-node ratio)(TG)	−0.0089	0.0029	−3.0941	−0.0125	0.0037	−3.3875	−0.0104	0.0030	−3.4899
(Intersection density) (link-to-node ratio)(TT)	0.0099	0.0010	10.2280	−0.0096	0.0011	−9.0000	0.0060	0.0011	5.3304
(Intersection density) (link-to-node ratio)(LG)	—	—	—	—	—	—	—	—	—
Dead-end density	0.0054	0.0003	15.8601	−0.0058	0.0004	−13.7264	−0.0041	0.0005	−8.3636
Citywide–interneighborhood intersection density	0.0005	0.0001	3.6090	−0.0022	0.0001	−15.5634	−0.0022	0.0002	−11.2953
Curvilinear (0, 1)	0.0213	0.0195	1.0923	−0.2643	0.0249	−10.6145	0.3163	0.0266	11.8910

(continued)

TABLE 2 *(continued)* **Multinomial Logistic Regression Mode Share Model**

Variable	Transit Model (with respect to driving)			Pedestrian Model (with respect to driving)			Bicycling Model (with respect to driving)		
	Coefficient	SE	β/SE	Coefficient	SE	β/SE	Coefficient	SE	β/SE
Street Level Data									
Avg. total no. of lanes	−0.2448	0.0108	−22.6667	−0.0414	0.0129	−3.2093	−0.0219	0.0155	−1.4129
Interaction terms									
(Avg. total no. of lanes)(GG)	0.3742	0.0160	23.3875	0.0980	0.0184	5.3261	0.2613	0.0232	11.2629
(Avg. total no. of lanes)(GT)	−0.0731	0.0190	−3.8474	0.0303	0.0213	1.4225	−0.1486	0.0283	−5.2509
(Avg. total no. of lanes)(LT)	0.1679	0.0281	5.9751	−0.0673	0.0342	−1.9678	−0.3748	0.0522	−7.1801
(Avg. total no. of lanes)(RG)	0.5391	0.0395	13.6481	0.1776	0.0606	2.9307	0.1804	0.0584	3.0890
(Avg. total no. of lanes)(RT)	0.0574	0.0248	2.3145	0.0756	0.0380	1.9895	−0.2627	0.0465	−5.6495
(Avg. total no. of lanes)(TG)	−0.4274	0.0466	−9.1717	−0.5726	0.0548	−10.4489	−0.1813	0.0520	−3.4865
(Avg. total no. of lanes)(TT)	—	—	—	—	—	—	—	—	—
(Avg. total no. of lanes)(LG)	—	—	—	—	—	—	—	—	—
Avg. outside shoulder width	0.0427	0.0024	17.5000	0.0698	0.0026	26.6412	−0.0123	0.0034	−3.5860
% of citywide street length with raised median	0.1096	0.0141	7.7730	−0.1735	0.0153	−11.3399	0.3134	0.0195	16.0718
% of citywide street length with painted median	−0.1480	0.0137	−10.8029	−0.2241	0.0162	−13.8333	−0.2542	0.0193	−13.1710
% of citywide street length with on-street parking	0.3403	0.0226	15.0575	0.2375	0.0259	9.1699	0.4639	0.0315	14.7270
% of citywide street length with bike lanes	0.0584	0.0203	2.8768	0.1982	0.0230	8.6174	0.6220	0.0266	23.3835
% of citywide street length with curbs	0.2808	0.0360	7.8000	0.5624	0.0398	14.1307	0.0073	0.0495	0.1471
Miscellaneous									
VMT (standardized from 0 to 1)	−0.6698	0.0914	−7.3282	1.2962	0.0899	14.4182	−1.9398	0.1833	−10.5827
Proxy for activity	1.8077	0.0350	51.6486	0.2195	0.0385	5.7013	−1.8507	0.0513	−36.0760
Proxy for mixed use	12.4131	0.2119	58.5800	9.5220	0.2106	45.2137	15.5296	0.2695	57.6237
Distance from city center (mi)	0.0351	0.0072	4.8750	−0.2934	0.0095	−30.8842	−0.3182	0.0122	−26.0820
Bisecting or adjacent limited access highway (0, 1)	−0.2727	0.0150	−18.1800	−0.1232	0.0167	−7.3772	0.2675	0.0197	13.5787
Income (standardized from 0 to 1)	−2.4035	0.0445	−54.0112	−4.8041	0.0542	−88.6365	−2.7475	0.0647	−42.4652

NOTE: Avg. = average; SE = standard error; degrees of freedom = 159; log likelihood = 62,198.92.

that was associated with an increase in street connectivity was also accompanied by less walking and biking. The overall driving mode share remained consistent; rather, it was the mix of transit, walking, and biking mode shares that shifted.

Street Patterns

On the basis of the results of the statistical models, street patterns are highly significant in mode choices. Evaluation of the data throughout Table 3 allows the influences of street pattern types to begin to be compared. However, a direct comparison is misleading because each of these street patterns is, in practice, built at different densities with a wide range of complementary features. Therefore, when mode share results are considered with respect to the street pattern classification system, one must keep in mind that, in actuality, certain street pattern types also tend to exhibit higher intersection densities, higher street connectivity, fewer lanes on citywide streets, more on-street parking, and a more complete network of curbs and sidewalks.

One interesting comparison that can be made is of the three network types with gridded neighborhood streets. Although all three types exhibit similar levels of street network density and street connectivity, the tributary citywide street and gridded neighborhood street pattern type (TG pattern) does not reach walking and biking mode shares nearly the same as the shares found in the other gridded neighborhood street pattern types. Because street pattern type TG has the least connected citywide street network, this result would suggest that both citywide street connectivity and neighborhood street connectivity are important in facilitating nonautomobile travel.

Data on Street Characteristics

The characteristics of the streets that were considered in the analysis included the total number of lanes, the outside shoulder width, as well as the presence of bike lanes, curbs or sidewalks, and raised and painted medians. Overall, the only one of these variables not significant in the mode choice models was the width of the outside shoulders. The results demonstrate that more lanes on the citywide streets may have conflicting effects on mode share, depending on the street network type. For instance, in the less connected treelike neighborhood street networks, the presence of more lanes on the citywide streets was associated with more driving. This was also the case for the tributary citywide street and gridded neighborhood street pattern type (TG pattern). In gridded pattern types RG and GG, however, a decrease in driving was found with more lanes on the citywide streets.

A possible explanation is that in the less connected street patterns, most nonautomobile travel must use the citywide street network for

TABLE 3 Expected Change in Mode Shares (Percent)

	Tributary Tree				Radial Tree				Grid Tree			
	Transit	Walking	Biking	Driving	Transit	Walking	Biking	Driving	Transit	Walking	Biking	Driving
Avg. mode share by street pattern type	3.66	2.28	1.71	92.35	1.80	0.95	0.54	96.71	2.35	2.01	0.98	94.66
Intersection Density												
81	3.81	1.94	1.29	92.96	1.80	0.82	0.38	97.00	2.49	1.65	0.65	95.21
144	3.65	2.30	1.74	92.31	1.80	0.99	0.60	96.62	2.38	1.93	0.90	94.79
225	3.44	2.85	2.56	91.15	1.79	1.25	1.05	95.91	2.24	2.36	1.37	94.03
324	3.18	3.69	4.06	89.07	1.76	1.66	2.10	94.47	2.07	3.00	2.29	92.65
Dead-End Density												
0	2.90	2.91	2.03	92.16	1.45	1.20	0.64	96.72	1.97	2.42	1.11	94.49
30	3.42	2.45	1.80	92.33	1.70	1.00	0.56	96.73	2.33	2.04	0.99	94.65
60	4.02	2.06	1.59	92.33	2.01	0.84	0.50	96.66	2.74	1.71	0.87	94.68
Citywide–Interneighborhood Intersection Density												
0	3.61	2.42	1.81	92.17	1.78	1.00	0.57	96.66	2.30	2.21	1.07	94.42
60	3.73	2.13	1.60	92.55	1.83	0.88	0.50	96.79	2.37	1.94	0.94	94.74
120	3.85	1.87	1.41	92.88	1.89	0.77	0.44	96.91	2.45	1.70	0.83	95.02
Link-to-Node Ratio												
1.1	3.42	2.40	1.74	92.44	1.60	1.05	0.62	96.74	1.88	1.96	1.04	95.12
1.25	4.17	2.05	1.65	92.13	1.97	0.88	0.48	96.67	2.41	2.02	0.97	94.60
1.4	5.06	1.75	1.55	91.63	2.43	0.74	0.38	96.46	3.08	2.08	0.90	93.94
1.55	6.14	1.50	1.46	90.91	2.99	0.62	0.29	96.10	3.93	2.13	0.84	93.10
Avg. No. of Lanes on Citywide Streets												
2	4.48	2.34	1.72	91.46	2.33	0.90	0.80	95.97	3.44	2.01	1.19	93.36
4	2.80	2.19	1.68	93.32	1.62	0.97	0.46	96.96	1.86	2.01	0.86	95.27
6	1.74	2.05	1.63	94.58	1.12	1.04	0.26	97.58	1.00	1.99	0.62	96.40
Bisecting or Adjacent to Limited Access Highway (0, 1)												
0	3.99	2.36	1.86	91.79	1.92	0.97	0.57	96.54	2.49	2.06	1.03	94.41
1	3.09	2.12	1.45	93.34	1.47	0.87	0.44	97.22	1.92	1.84	0.80	95.44
Distance from City Center (miles)												
0	3.30	4.03	3.18	89.49	1.55	2.59	1.61	94.24	2.17	3.29	1.67	92.86
1	3.48	3.06	2.36	91.11	1.62	1.96	1.19	95.24	2.28	2.49	1.23	94.01
2	3.65	2.31	1.74	92.30	1.69	1.47	0.87	95.97	2.38	1.87	0.90	94.85
3	3.82	1.74	1.27	93.17	1.76	1.10	0.64	96.50	2.48	1.40	0.66	95.45
4	3.98	1.31	0.93	93.78	1.83	0.82	0.46	96.88	2.58	1.05	0.48	95.88
% of Citywide Street Length with On-Street Parking												
0	3.24	2.10	1.44	93.22	1.63	0.89	0.47	97.01	2.01	1.81	0.79	95.39
50	3.79	2.33	1.79	92.08	1.93	0.99	0.59	96.49	2.37	2.02	0.99	94.63
100	4.43	2.59	2.23	90.75	2.27	1.11	0.74	95.88	2.78	2.25	1.23	93.74
% of Citywide Street Length with Bike Lanes												
0	3.61	2.15	1.42	92.81	1.76	0.88	0.42	96.93	2.33	1.93	0.85	94.90
50	3.69	2.36	1.92	92.03	1.81	0.97	0.58	96.64	2.38	2.11	1.15	94.35
100	3.76	2.58	2.59	91.07	1.86	1.07	0.79	96.29	2.44	2.32	1.56	93.68
% of Citywide Street Length with Curbs												
0	2.97	1.48	1.73	93.82	1.45	0.61	0.54	97.40	1.89	1.27	0.98	95.86
50	3.39	1.94	1.72	92.95	1.66	0.81	0.54	96.99	2.15	1.68	0.98	95.19
100	3.86	2.54	1.70	91.90	1.90	1.06	0.54	96.50	2.46	2.20	0.98	94.36
% of Citywide Street Length with Raised Medians												
0	3.46	2.51	1.45	92.59	1.68	1.06	0.44	96.82	2.22	2.21	0.82	94.74
50	3.65	2.29	1.69	92.37	1.77	0.97	0.51	96.74	2.34	2.03	0.96	94.67
100	3.84	2.10	1.97	92.09	1.87	0.89	0.60	96.64	2.47	1.86	1.12	94.55
% of Citywide Street Length with Painted Medians												
0	3.91	2.52	1.92	91.65	1.91	1.04	0.60	96.44	2.54	2.26	1.12	94.09
50	3.66	2.27	1.71	92.36	1.78	0.94	0.53	96.75	2.37	2.03	0.99	94.61
100	3.42	2.05	1.51	93.02	1.66	0.84	0.47	97.03	2.21	1.83	0.87	95.09

(continued)

TABLE 3 *(continued)* **Expected Change in Mode Shares (Percent)**

	Tributary Grid				Radial Grid				Grid			
	Transit	Walking	Biking	Driving	Transit	Walking	Biking	Driving	Transit	Walking	Biking	Driving
Avg. mode share by street pattern type	4.18	3.93	3.39	88.51	7.73	3.65	4.66	83.95	9.00	8.79	4.09	78.13
Intersection Density												
81	5.94	4.69	2.72	86.64	5.94	1.73	5.59	86.74	8.93	5.08	2.84	83.15
144	5.10	4.35	3.00	87.55	6.45	2.18	5.30	86.08	8.98	6.14	3.23	81.65
225	4.19	3.93	3.38	88.50	7.15	2.91	4.94	85.00	9.01	7.81	3.79	79.39
324	3.27	3.47	3.91	89.35	8.06	4.13	4.51	83.29	8.96	10.40	4.56	76.08
Dead-End Density												
0	3.67	4.48	3.71	88.14	7.03	4.04	5.01	83.92	8.27	9.54	4.33	77.85
30	4.34	3.78	3.29	88.59	8.27	3.39	4.42	83.91	9.80	8.06	3.85	78.30
60	5.12	3.18	2.92	88.78	9.70	2.84	3.89	83.57	11.53	6.77	3.40	78.30
Citywide–Interneighborhood Intersection Density												
0	3.98	4.60	3.96	87.47	7.16	4.65	5.92	82.27	8.07	11.55	5.35	75.03
60	4.13	4.07	3.50	88.30	7.45	4.12	5.25	83.18	8.46	10.31	4.78	76.45
120	4.29	3.59	3.10	89.02	7.74	3.64	4.65	83.97	8.85	9.17	4.27	77.70
Link-to-Node Ratio												
1.1	2.58	2.87	1.59	92.95	5.02	4.69	6.95	83.34	8.40	9.93	3.21	78.47
1.25	3.49	3.50	2.55	90.46	6.41	4.09	5.57	83.92	8.69	9.35	3.62	78.34
1.4	4.67	4.22	4.05	87.06	8.13	3.54	4.44	83.89	8.99	8.80	4.08	78.13
1.55	6.16	5.01	6.32	82.52	10.22	3.04	3.51	83.23	9.29	8.28	4.59	77.85
Average Number of Lanes on Citywide Streets												
2	7.15	6.38	3.80	82.66	6.71	3.45	4.36	85.48	8.28	8.57	3.45	79.70
4	2.10	2.10	2.85	92.95	11.18	4.20	5.53	79.09	10.16	9.09	5.27	75.48
6	0.57	0.64	1.97	96.82	17.93	4.90	6.76	70.40	12.26	9.48	7.93	70.33
Bisecting or Adjacent to Limited Access Highway (0, 1)												
0	4.53	4.06	3.67	87.74	8.02	3.70	4.83	83.45	9.37	8.91	4.25	77.47
1	3.54	3.68	2.88	89.91	6.32	3.39	3.83	86.46	7.45	8.23	3.40	80.92
Distance from City Center (mi)												
0	3.88	5.47	4.86	85.79	7.09	5.23	6.91	80.77	8.39	11.10	5.28	75.23
1	4.12	4.19	3.63	88.06	7.57	4.02	5.18	83.23	9.04	8.62	4.00	78.33
2	4.35	3.18	2.69	89.77	8.01	3.06	3.85	85.07	9.65	6.62	3.00	80.72
3	4.57	2.41	1.99	91.04	8.43	2.32	2.84	86.40	10.22	5.05	2.23	82.50
4	4.78	1.81	1.46	91.95	8.83	1.75	2.09	87.33	10.75	3.82	1.65	83.78
% of Citywide Street Length with On-Street Parking												
0	3.58	3.54	2.72	90.16	6.24	3.18	3.43	87.15	7.19	7.63	2.96	82.22
50	4.16	3.92	3.37	88.55	7.22	3.50	4.23	85.06	8.27	8.34	3.62	79.78
100	4.83	4.32	4.16	86.69	8.32	3.83	5.18	82.68	9.47	9.07	4.41	77.06
% of Citywide Street Length with Bike Lanes												
0	4.13	3.67	2.67	89.53	7.71	3.55	4.21	84.54	8.98	8.53	3.66	78.83
50	4.19	4.00	3.60	88.22	7.77	3.84	5.62	82.77	9.02	9.19	4.87	76.92
100	4.23	4.33	4.82	86.62	7.79	4.13	7.47	80.61	9.01	9.86	6.46	74.67
% of Citywide Street Length with Curbs												
0	3.36	2.47	3.45	90.72	6.23	2.29	4.78	86.69	7.29	5.43	4.31	82.96
50	3.81	3.23	3.42	89.54	7.05	2.99	4.72	85.24	8.16	7.00	4.21	80.64
100	4.32	4.21	3.37	88.10	7.95	3.88	4.64	83.53	9.07	8.95	4.08	77.90
% of Citywide Street Length with Raised Medians												
0	3.96	4.31	2.89	88.83	7.29	4.10	3.88	84.72	8.59	9.52	3.56	78.33
50	4.17	3.94	3.37	88.52	7.65	3.73	4.51	84.11	9.04	8.71	4.15	78.09
100	4.39	3.59	3.93	88.09	8.01	3.39	5.22	83.37	9.51	7.94	4.84	77.71
% of Citywide Street Length with Painted Medians												
0	4.44	4.33	3.79	87.45	7.84	3.73	4.78	83.64	9.28	9.27	4.35	77.10
50	4.17	3.92	3.38	88.53	7.39	3.39	4.28	84.94	8.81	8.47	3.92	78.81
100	3.92	3.54	3.01	89.53	6.96	3.07	3.82	86.14	8.34	7.73	3.52	80.41

travel over any significant distance; thus, more travel lanes might see lower nonmotorized mode shares because of a less desirable pedestrian or biking environment on these streets. Conversely, in the more connected street networks, walking and biking trips can be done on the neighborhood streets for longer-distance travel. Hence, more lanes on the citywide streets are less of a detriment than in the less connected street patterns.

Other street design features, such as the presence of on-street parking, bike lanes, and curbs or sidewalks, are all associated with less driving. This drop in driving was found for all street patterns and was generally associated with increases in all three nonautomobile modes of travel. Individually, the presence of any one of these factors seemed to result in a maximum 5% reduction in driving mode share.

Miscellaneous Variables

For the control variables, higher vehicle volumes were associated with more walking but less use of transit and bicycles. The proxy for the activity level associated with a block group was significant and was positively correlated with transit use and walking but negatively correlated with bicycling. The proxy for mixed land uses indicated that higher levels of mixed use were strongly associated with more transit, walking, and biking. For distance from the city center, the results indicated more walking and biking but less transit use when a block group was closer to the downtown area. A block group bisected by or adjacent to a limited-access highway was associated with more bicycling but less transit and walking. Higher incomes were also correlated with reductions to transit, walking, and biking mode shares.

CONCLUSION

The aim of the research described here was to learn more about how street networks influence the diversity of modes in a transportation system. The results suggest that all three of the fundamental measures of a street network—street connectivity, street network density, and street patterns—are highly significant and associated with influencing the choice to drive, walk, bike, or take transit. Although this research concentrated on journey-to-work mode share data, much of the existing literature showed an even greater influence of street network characteristics on nonwork trips. Performance of this inquiry controlled for a range of factors, including vehicle volumes, activity levels, income levels, and proximity to limited-access highways or the downtown area. The basis for this analysis was a GIS database encompassing more than 1,000 census block groups in 24 California cities.

Street pattern type played a considerable role in mode choice. However, because of several significant interaction terms, it is important to consider street pattern type in combination with street network density, street connectivity, and street characteristics. Increased street network density, according to the intersection density, was generally associated with more walking and biking. At the same time, increased street connectivity, measured by the link-to-node ratio, was generally associated with a decrease in driving. Although a higher intersection density generally equates to an increase in conflict points, more walking and biking in these street networks does not necessarily entail a reduction in safety; in fact, the results of the initial research on these cities indicate that the highest risk of fatal or severe road crashes occurs with a very low intersection density and safety outcomes improve as the intersection density increases (*4*).

The presence of street features commonly associated with more pedestrian- and bicycle-friendly places, such as on-street parking, bike lanes, and sidewalks, were generally correlated with more walking, biking, and transit use. However, the average number of lanes on the citywide streets had very different associations with transit, walking, and biking mode shares, depending on the street pattern type. Interestingly, although more travel lanes were associated with reductions in transit, walking, and biking mode shares in the less connected street pattern types, more lanes were also associated with increases in these mode shares for the more connected street pattern types.

For all types of street patterns, street network characteristics and street design factors play a major role in how people use the transportation system on a daily basis. The results presented here suggest that the dense, gridded street network with more urban street features is associated with much more walking and biking. Providing such a range of travel options in the transportation system increases efficiency, enhances flexibility, promotes equity, and is a better overall use of limited resources.

REFERENCES

1. Litman, T. *Transportation Cost and Benefit Analysis: Techniques, Estimates and Implications.* Victoria Transport Policy Institute, Victoria, British Columbia, Canada, 2009.
2. Feng, C.-M., and C.-H. Hsieh. Implications of Transport Diversity for Quality of Life. *Journal of Urban Planning and Development,* Vol. 135, No. 1, 2009, pp. 13–18.
3. Ewing, R., and R. Cervero. Travel and the Built Environment: A Synthesis. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1780,* TRB, National Research Council, Washington, D.C., 2001, pp. 87–114.
4. Marshall, W., and N. Garrick. Considering the Role of the Street Network in Road Safety: A Case Study of 24 California Cities. *Urban Design International Journal.* (Pre-print e-publication) DOI: 10.1057/udi.2009.31.
5. Marshall, W., and N. Garrick. The Shape of Sustainable Street Networks for Neighborhoods and Cities. *Proc., Congress for the New Urbanism XVII,* Denver, Colo., 2009.
6. Virginia Department of Transportation. *Secondary Street Acceptance Requirements,* 2009.
7. Taylor, J. *Transportation and Community Design: The Effects of Land Use and Street Pattern on Travel Behavior, Technical Report No. 11.* University of British Columbia, 2001.
8. Southworth, M., and E. Ben-Joseph. *Street and the Shaping of Towns and Cities.* McGraw-Hill, New York, 1997.
9. Tunnard, C. *Man-Made America.* Yale University Press, New Haven, Conn., 1963.
10. Litman, T. *Well Measured: Developing Indicators for Comprehensive and Sustainable Transport Planning,* 2005. www.vtpi.org/wellmeas.pdf. Accessed Feb. 9, 2007.
11. Newman, P., and J. Kenworthy. *Cities and Automobile Dependence.* Gower, Brookfield, Vt., 1989.
12. Curtis, F., L. Neilsen, and A. Bjornsor. Impact of Residential Street Design on Fuel Consumption. *Journal of Urban Planning and Development,* Vol. 110, 1984, pp. 1–8.
13. Kulash, W. *Traditional Neighborhood Development: Will the Traffic Work?,* 1990. http://user.gru.net/domz/kulash.htm. Accessed Nov. 29, 2009.
14. McNally, M. G., and S. Ryan. Comparative Assessment of Travel Characteristics for Neotraditional Designs. In *Transportation Research Record 1400,* TRB, National Research Council, Washington, D.C., 1993, pp. 67–77.
15. Litman, T. *Roadway Connectivity: Creating More Connected Roadway and Pathway Networks,* 2005. www.vtpi.org/tdm/tdm116.htm. Accessed Oct. 25, 2009.

16. *Street Connectivity: An Evaluation of Case Studies in the Portland Region.* Portland Metro, Portland, Ore., 2004.
17. Cervero, R., and R. Gorham. Commuting in Transit Versus Automobile Neighborhoods. *Journal of the American Planning Association,* Vol. 61, No. 2, 1995, pp. 210–225.
18. Handy, S. Regional Versus Local Accessibility: Implications for Nonwork Travel. In *Transportation Research Record 1400,* TRB, National Research Council, Washington, D.C., 1993, pp. 58–66.
19. Cervero, R., and K. Kockelman. Travel Demand and the 3 Ds: Density, Diversity, and Design. *Transportation Research Part D,* Vol. 2, No. 3, 1997, pp. 199–219.
20. Hess, P. M., A. V. Moudon, M. C. Snyder, and K. Stanilov. Site Design and Pedestrian Travel. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1674,* TRB, National Research Council, Washington, D.C., 1999, pp. 9–19.
21. Holtzclaw, J. *Using Residential Patterns and Transit to Decrease Auto Dependence and Costs.* Natural Resources Defense Council, San Francisco, Calif., 1994.
22. Crane, R. Cars and Drivers in the New Suburbs: Linking Access to Travel in Neotraditional Planning. *Journal of the American Planning Association,* Vol. 62, 1996, pp. 51–65.
23. Crane, R., and R. Crepeau. Does Neighborhood Design Influence Travel? Behavioral Analysis of Travel Diary and GIS Data. *Transportation Research Part D,* Vol. 3, No. 4, 1998, pp. 225–238.
24. Ewing, R. *Best Development Practices: Doing the Right Thing and Making Money at the Same Time.* APA Planners Press, Washington, D.C., 1996.
25. Marshall, S. *Streets & Patterns.* Spon Press, New York, 2005.
26. Graham, D., and S. Glaister. Spatial Variation in Road Pedestrian Casualties: The Role of Urban Scale, Density and Land-Use Mix. *Urban Studies,* Vol. 40, No. 8, 2003, pp. 1591–1607.
27. Noland, R., and M. Quddus. A Spatially Disaggregate Analysis of Road Casualties in England. *Accident Analysis and Prevention,* Vol. 36, No. 6, 2004, pp. 973–984.
28. Martin, W. A., and N. A. McGuckin. *NCHRP Report 365: Travel Estimation Techniques for Urban Planning.* TRB, National Research Council, Washington, D.C., 1998.
29. Ben-Akiva, M., and S. Lerman. *Discrete Choice Analysis: Theory and Application to Travel Demand.* MIT Press, Cambridge, Mass., 1985.
30. Long, J. S. *Regression Models for Categorical and Limited Dependent Variables.* Sage Publications, Thousand Oaks, Calif., 1997.

The Pedestrians Committee peer-reviewed this paper.