Shifting Gears: A cross-regional analysis of bicycle facility networks and ridership

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Abstract

Cities promote strong bicycle “networks” to support and encourage bicycle commuting. However, the concept of a “network” of bicycle facilities is not very well studied. Previous work has found relationships between the amount of bicycle infrastructure in a city and bicycle ridership. This study shifts the focus from quantity of bicycle infrastructure to measuring the quality of bicycle infrastructure networks using network science concepts and measurement techniques from other transportation modes. It fills a gap in the bicycling literature by developing a standard methodology for measuring bicycle infrastructure network quality.

A dataset of bicycle facility network shapefiles was collected for 74 medium- and large-sized cities in the United States. ArcGIS was used to develop routines for systematically measuring and analyzing network connectivity in each of these cities using routines developed for ArcGIS. Factor analysis is employed to test how the network connectivity constructs fit into general network qualities: size, connectivity, directness, and fragmentation. These factors are used in regression models to test their association with bicycle commuting mode share and the gender balance of bicycle commuters. The results suggest that connectivity, and to some extent fragmentation, are important factors associated with both bicycle ridership and the percentage of female bicycle commuters, even when controlling for household size and structure, vehicle ownership, and city size.

These findings provide a framework for transportation planners and policymakers to evaluate their local bicycle facility networks and set regional priorities that support and encourage nonmotorized travel behavior.

Introduction

Cities have increasingly been promoting cycling as a transportation alternative to driving; arguing that mode shift away from the private auto provides region-wide congestion, environmental, and health benefits. (USDOT FHWA NTPP) In 2010 alone, the Federal Highway Administration invested over US$1 billion in non-motorized infrastructure projects with the hopes of inducing mode shift to bicycling and walking. (USDOT FHWA NTPP) Many of these projects are explicitly targeted at closing “gaps” in bike routes to form a more cohesive network. (Hennepin County Bicycle System Gap Study) This idea of a “network” of bicycle routes connecting the region is an important indicator of the shift in transportation priorities from auto dominance to accommodation of nonmotorized modes. While bicycles are permitted to use most components of the road network, bicycle-specific infrastructure provides safe, comfortable routes that many bicyclists prefer over riding in general mixed traffic. The network formed by bicycle-specific infrastructure, however, is not as expansive or complete as the underlying road network, so cyclists often have to detour or ride with mixed traffic in order to use the bicycle facilities.

Numerous studies have examined how individual cyclists interact with bicycle facilities and mixed traffic, and the relationship between the existence and size of bicycle infrastructure and a city’s bicycle mode share, but no study so far has examined what it means to have a “network” of bicycle infrastructure and how effectively this network supports current cyclists or attracts new riders. This paper aims to fill this gap in the literature by developing a protocol for evaluating bicycle infrastructure network structure and testing its predictive power on bicycle ridership and the gender split of bicycle commuters.

Understanding these relationships between bicycle commuting and network features will enable transportation and planning agencies to target investment in infrastructure components for optimum impact on existing riders and the “interested but concerned” population of would-be cyclists. Additionally, the persistent gender gap in bicycle commuting suggests that the infrastructure or other elements of bicycling as a mode of transportation are not serving women’s needs. Several theories have been posed in the literature for this gap: that women are more risk-averse than men, or that they typically have more complex travel needs due to societal roles within family structures. Understanding the relationship between network structure and the gender distribution of bicyclists will enable planners to design bicycle facility networks that serve a larger range of trip purposes and infrastructure needs.

This paper analyzes bicycle facility networks from 74 mid- to large-sized US cities to identify, quantify, and evaluate the underlying network structure. These network variables are positively and significantly correlated to the journey-to-work mode share for bicycling and percent of bicycle commuters that are women from the 2005-2009 American Community Survey (ACS). Network variables factor into five scales that describe the network's size, connectivity, directness, cohesiveness/fragmentation, and average fragment size. Regression models are used to test the relationship between these factors and (H1) bicycle commuters per 10,000 workers, (H2) female bicycle commuters per 10,000 female workers, and (H3) percent of bicycle commuters that are female (adjusted for gender distribution of workers), controlling for city population, land area, household structure, auto ownership, and median income. Connectivity significant in all models, and fragmentation is significant in H2 and H3. The household structure is a very strong predictor of ridership, but connectivity (H1, H2, and H3) and fragmentation (H2 and H3 only) remain significant even when these factors demographic variables are controlled.

Literature Review

The Federal Highway Administration recommends providing bicycle facilities that both serve existing bicyclists and encourage new cyclists to start riding. Wilkinson et al (1994), in their FHWA manual on roadway design treatments for bicyclists, divide cyclists into groups according to age and experience level and recommend certain design principles to serve each type of group. They claim that a supply-driven approach of facilities targeted at Group B (basic cyclists) and Group C (children) riders will encourage mode shift to cycling and use of the facilities. Group A cyclists have different needs and expectations from Group B and C cyclists; Group A cyclists value reduced travel time and directness and are willing to navigate higher traffic volumes to maintain their own higher travel speeds. Sufficiently wide shoulders and enforced speed limits on major arterials provide the space needed for Group A cyclists. Group B/C cyclists make detours to avoid uncomfortable road conditions; it is for these people that bicycle specific facilities are provided. Wilkinson et al recommend a "network of neighborhood streets and designated facilities" to connect Group B/C cyclists to their destinations (Wilkinson et al 1994, 2). Bike lanes, separated paths, and traffic calmed bike boulevards, they argue, provide the increased comfort and perceived safety desired by these less experienced cyclists.

The evidence for bicycle facilities inducing mode shift is weak, though bicycle infrastructure may facilitate new and different kinds of trip-making patterns. Pucher et al's 1999 review of bicycling literature failed to find statistically rigorous studies to support the FHWA guidelines encouraging infrastructure development to induce cycling. Large presence of cycling infrastructure correlated with high cycling levels in Europe, but the authors posited that facility development might follow cyclists rather than incite cycling. Barnes et al followed bicycle facility network expansion and mode share in a longitudinal study of the Twin Cities Metro Area and largely reached this same conclusion: bicycling infrastructure was installed in areas that already had much higher than average levels of cycling. That said, Barnes et al did not disprove the possibility that the addition of infrastructure induces mode shift to bicycling; indeed some of their evidence suggests that the U of M Transitway connecting St. Paul to the University made longer cycling commute trips more viable, enabling people to switch to cycling for their work or school commute.

Numerous subsequent studies have validated this conjecture that cyclists prefer to use bicycle-specific facilities over riding in normal traffic by identifying a correlation between the size of a city's bicycle network and the bicycle mode share in that city. Nelson and Allen (1997) identified a positive relationship between miles of cycling paths (class I facilities) in a city and bicycle ridership. Dill and Carr (2003) confirmed these findings across 35 major cities in the US, additionally studying bike lanes (class II facilities) and the density of bicycle infrastructure within a city (miles of bicycle facility per square mile of area). Dill's 2009 study of Portland cyclists discovered that a disproportionate share of bicycling occurred on streets with bicycle lanes, separate paths, or bicycle boulevards, and suggests that cyclists travel out of their way to use these facilities. Buehler and Pucher in 2011 again identified this association between the size of bicycle facility network and ridership in 90 of the 100 largest cities in the US.

Different network elements serve a wide range of bicyclist skill levels. Wilkinson et al recommend simultaneously ensuring that all major streets are suitable for experienced cyclists while developing and maintaining a network of bicycle-specific infrastructure and quiet residential streets to meet the needs of Group B/C cyclists. This recommendation is based on the assumption that Group A cyclists value travel time while Group B/C cyclists value perceived safety and comfort. Tilahun et al (2007) quantified the relative value of bicycle specific facilities in terms of how many extra minutes a cyclist would “spend” in order to use each type of facility; cyclists valued bike lanes highest, followed by streets without street parking and separated bicycle paths. Dill (2009) used GPS devices to track regular cyclists and discovered that a disproportionate share of all bicycling among her sample occurred on bike paths, bike boulevards, and streets with bike lanes. Since this sample was composed of regular cyclists, this suggests the conventional wisdom about what Group A cyclists value may be wrong. These experienced cyclists were presumably detouring from the shortest path in order to use bicycle specific facilities, suggesting that they do not in fact value travel time highest.

The persistent gender gap in bicycle commuting is oftentimes addressed from one of two distinct theories: gender and risk aversion, or gender and travel behavior complexity. Parker et al (2011) studied the addition of bike lanes in New Orleans and observed a disproportionate increase in female cyclists after implementation (133% increase vs. 44% increase). Gender gap studies about cycling have claimed that women tend to select less risky bicycling routes; this study supports these claims that perceived safety and comfort is particularly important for women. Alternatively, travel behavior studies consistently find that women have more complex trip-chaining patterns due to the unequal distribution of household and childrearing responsibilities within households and the propensity for single-parent households to be female-headed (Li, Guensler, & Ogle 2005). These additional temporal, spatial, and monetary constraints make cycling a less viable option (Blue 2011). For example, dropping off children at daycare before work adds distance and time to the journey to work trip, and requires the capacity to transport passengers. In any case, a strong network of dedicated bicycle facilities may alleviate some of these concerns by providing safe, comfortable routes outside of mixed traffic that connect important destinations.

Scholars have examined cycling network quality and connectivity at a local scale. Krizek and Roland (2005) assessed 30 discontinuities in on-street bicycle facilities in Minneapolis for their impacts on rider risk, comfort, and perceptions of safety. Birk and Geller (2005) studied bicycle mode share over a period of investments in critical points in Portland's bicycle facility network. As connections across the river improved, more completely connecting the network across the city, cycling rates increased. Barnes, Thompson, and Krizek (in Barnes & Krizek 2005) traced bicycle mode share in Minneapolis over time alongside bicycle facility infrastructure development. Tilahun, Levinson, and Krizek (2007) tested the relative value of different kinds of bicycle facilities (on-street, off-street, and the presence of other factors such as on-street parking) in terms of how many extra minutes a person would be willing to add to their travel time in order to use that type of facility.

Graph theory offers a number of ways to measure the quality of a given network. Rodrigue, Comtois, and Slack (2009) present techniques for assessing network quality. Xie and Levinson (2006) discuss measures of transportation connectivity and continuity, and model these metrics on test networks. They argue for a standardized ways to quantify road network structure and emphasize the importance of connectivity and congruity within the network. These ideas can be loosely transferred to bicycle networks: discontinuities in the network may have three potential consequences: (1) forcing the cyclist into mixed traffic, (2) requiring lengthy detours to avoid mixed traffic, or (3) discouraging cycling altogether. Planning for stand-alone bike paths or place-based bicycle accommodations without considering these pieces of infrastructure as links in a broader network undermines the potential utility of this infrastructure.

Berrigan, Pickle, and Dill (2010) applied many of these network measures to the built environment and its appropriateness for active transportation. They used spatial data within buffers around survey respondents' homes to measure the link-node ratio, gamma index, and alpha index of the local street grid, among other measures of connectivity. These measures factored into two principle variables of network quality that predicted propensity and duration of active transportation. Since these studies were so locally oriented, they did not capture the bicycle facility network quality. This study used all forms of active transportation interchangeably so the impacts of bicycle-specific network structure remains untested. Dill and Voros (2006) studied built environment features within buffers around survey respondents' home addresses, testing the effects of proximity to trails, bike lanes, freeways, street connectivity, downtown, and slope/terrain, but again: localized studies are not indicators of macroscopic network structure.

While previous work provides evidence for a relationship between bicycle facilities, ridership, and gender, there have been no major studies of the effects of bicycle infrastructure network structure across cities on levels of bicycling. This study draws on principles established in previous work on the importance and utility of bicycle facilities, structural features of bicycle networks, and the application of graph theory to transportation network to analyze and evaluate bicycle facility networks.

Methodology & Data Assembly

This study collected spatial data and American Community Survey (ACS) household, demographic, and journey to work data for 74 mid- to large-sized cities in the United States. Network connectivity variables were constructed from the spatial datasets using a geographic information system (GIS). These network measures and bicycle ridership characteristics were evaluated through a bivariate correlation to identify significant relationships. Factor analysis was used to reduce the network characteristic measures down to five scales. These factors and ACS household structure and demographic data were used in Ordinary Least Squares (OLS) regression models to test three hypotheses: that better-connected networks are associated with (H1) more bicyclists per 10,000 commuters, (H2) more female bicyclists per 10,000 commuters, and (H3) a more even distribution between male and female cyclists.

Commuting Behavior & Demographics

Bicycle mode share was measured using the 2005-2009 5-year ACS estimates. The ACS asks respondents by which mode they traveled to work the most in the past week, so it only measures the bicycle mode share for the journey-to-work trip. Recreational or non-work utilitarian trips were not included in this measure. The ACS provides these measures split by sex of worker, enabling a comparison of cycling behavior by gender. Due to the sample size of the ACS and the relatively low numbers of bike commuters in each city, the standard error on these measures are very high; nonetheless, the ACS remains the only nationwide survey of travel behavior that can be disaggregated reliably to compare bicycling across cities.

Table 1. Demographic Profile (ACS 2005-2009)

Variable	Mean	Std. Dev.	Min	Max
Population	488,184	1,089,012	61,866	8,302,659
Land Area (square km)	215.88	244.74	1.04	1,213.78
Cyclists (per 10,000 commuters)	59	103	2	635
Female cyclists (per 10,000 female commuters)	62	158	0	1,271
Male cyclists (per 10,000 male commuters)	128	210	9	1,638
Pct Female Cyclists (adjusted for gender split of commuters)	24.34 %	15.37 %	0 %	66.10 %
Pct of Households with Children	35.89 %	9.40 %	15.88 %	56.26 %
Pct of Households with Seniors	26.63 %	4.73 %	13.92 %	38.95 %
Avg Vehicles per Household	1.67	0.32	0.64	2.16
Median Household Income	$ 57,645	$ 13,937	$ 34,311	$ 97,160

Household structure, auto ownership rates, median household income, population, and land area measures were collected from the same 5-year ACS dataset for each city. Household structure was measured using the percentage of households with children under 18 and percentage of households with seniors over 60. Auto ownership rate was constructed from an aggregate number of vehicles owned in the city and the number of households.

Table 1 highlights demographic and commuting behavior among cities in the sample. The very low rates of bicycle commuting are apparent here: the highest mode share in the study is only 6.35 %. On average, twice as many men commute by bicycle as women. The sample included a diverse range of incomes, household structures, and vehicle ownership rates.

Spatial Data

Bicycle maps were collected from city, county, and MPO websites that made the data available in either keyhole markup language (KML) or ESRI Shapefile format. The initial sampling frame was the top 50 cities by population but due to limited data availability, the sample was expanded to include cities with populations over 100,00 with a small handful of smaller cities selected for their proximity to major cities included in the study. Networks were included for analysis if it was possible to identify existing Class 1 and Class 2 facilities from all other types (Class 3 and 4 facilities, unpaved trails, and planned or proposed routes). Some cities that had publicly available data were excluded for this reason; for example, North Carolina's DOT publishes the entire state's bicycle network, but it is impossible to distinguish facility types. The final sample included 22 cities among the top 50 and 52 additional cities (48 of which had a population greater than 100,000), for a total of 74 cities included in the study. These maps were imported into a geographic information system (ESRI ArcGIS) for spatial analysis.

Table 2 describes the population, mode share, and gender split for all 74 cities included in the final dataset.

Table 2. Sample Cities by Population, Mode Share, and Gender Split (ACS 2005-2009)

City	Population	Mode Share	Percent Female	City	Population	Mode Share	Percent Female
New York, NY	8,302,659	0.27%	27.91%	Oceanside, CA	167,915	0.21%	21.80%
Los Angeles, CA	3,796,840	0.33%	24.54%	Grand Prairie, TX	154,192	0.06%	10.53%
Chicago, IL	2,824,064	0.43%	30.04%	Santa Rosa, CA	154,017	0.57%	32.62%
Philadelphia, PA	1,531,112	0.59%	31.24%	Springfield, MA	153,170	0.04%	0.00%
San Diego, CA	1,297,618	0.41%	29.46%	Pomona, CA	151,552	0.31%	12.66%
Dallas, TX	1,269,204	0.08%	16.27%	Pasadena, CA	142,013	0.83%	17.45%
San Jose, CA	934,415	0.34%	28.00%	Lancaster, CA	140,409	0.09%	0.00%
San Francisco, CA	797,271	1.41%	36.96%	Lakewood, CO	140,379	0.31%	28.24%
Columbus, OH	753,572	0.34%	29.70%	Torrance, CA	139,976	0.39%	17.75%
Austin, TX	747,984	0.61%	34.50%	Palmdale, CA	138,595	0.04%	53.99%
Fort Worth, TX	679,077	0.08%	22.46%	Escondido, CA	135,687	0.17%	4.36%
Boston, MA	625,304	1.00%	38.16%	Mesquite, TX	130,751	0.04%	0.00%
Seattle, WA	594,005	1.55%	36.11%	Sunnyvale, CA	130,256	0.60%	10.66%
Washington, DC	588,433	1.22%	28.41%	Elk Grove, CA	130,007	0.16%	27.08%
Denver, CO	582,447	0.87%	33.40%	Carrollton, TX	123,620	0.04%	0.00%
Portland, OR	548,988	2.49%	40.31%	East Los Angeles, CA	122,386	0.12%	8.67%
Albuquerque, NM	515,107	0.54%	34.64%	El Monte, CA	120,960	0.36%	4.17%
Long Beach, CA	462,823	0.40%	21.47%	Concord, CA	120,775	0.46%	27.89%
Sacramento, CA	456,394	0.96%	29.27%	Vallejo, CA	115,073	0.05%	0.00%
Oakland, CA	398,793	0.73%	36.42%	Denton, TX	114,933	0.85%	36.41%
Minneapolis, MN	379,499	1.81%	37.98%	McKinney, TX	113,606	0.07%	66.10%
Arlington, TX	370,217	0.07%	23.22%	Thornton, CO	110,768	0.04%	63.17%
Bakersfield, CA	310,077	0.19%	13.24%	Roseville, CA	109,497	0.20%	20.65%
Aurora, CO	309,091	0.14%	13.68%	Santa Clara, CA	108,075	0.53%	40.07%
St. Paul, MN	278,342	0.48%	32.30%	Downey, CA	107,178	0.18%	20.27%
Plano, TX	261,902	0.06%	14.33%	Westminster, MA	106,313	0.22%	17.35%

City	Population	Mode Share	Percent Female	City	Population	Mode Share	Percent Female
Orlando, FL	227,961	0.52%	19.82%	Cambridge, MA	106,255	4.14%	28.76%
Garland, TX	217,317	0.02%	0.00%	Arvada, CO	105,801	0.19%	15.92%
Chula Vista, CA	215,447	0.09%	29.34%	West Covina, CA	105,547	0.09%	0.00%
Fremont, CA	200,932	0.14%	63.45%	Lowell, MA	103,077	0.16%	39.25%
Irving, TX	197,830	0.05%	19.72%	Burbank, CA	102,364	0.67%	19.05%
Glendale, CA	195,876	0.27%	15.02%	Richmond, CA	101,098	0.09%	0.00%
Mobile, AL	191,936	0.08%	25.37%	Berkeley, CA	100,877	4.21%	39.70%
Worcester, MA	178,397	0.12%	26.33%	Daly City, CA	100,254	0.02%	41.49%
Providence, RI	172,519	0.37%	28.94%	Richardson, TX	100,045	0.14%	13.43%
Santa Clarita, CA	168,538	0.16%	8.75%	Frisco, TX	87,712	0.07%	0.00%

Data Cleaning and Manipulations

Some maps came from larger regional networks, such as the San Diego Association of Governments, Association of Bay Area Governments or Mid-Ohio Regional Planning Council. These were disaggregated to create one shapefile per city containing only Class I and Class II. A model routine in GIS was developed to iterate over each shapefile in the dataset, conduct spatial manipulations and measurements, and export network summary measures.

The trim, extend, generalize, and repair tools were used to address minor errors (+/- 30 meters) in the geometry of each network file. Many files contained pieces of infrastructure that were digitized free hand, leaving miniscule “gaps” or “dangles” in the represented network that probably do not exist in the actual network. Some cities also left gaps where a bike lane disappears through intersection but exists on either side of the cross street; for the purposes of network connectivity, these pieces of bike lane function as one contiguous link in the network.

Network Measures

Graphs are composed of edges (e) (in this study, links of bicycle infrastructure) and vertices (v) (junctions/intersections or endpoints in bicycle infrastructure). Subgraphs (p) can be thought of as disconnected “mini-networks” within the city’s larger network. These three components, along with information about the length of edges in the network, can be transformed to measure several different types of general, network-level connectivity.

Basic descriptive statistics of each network included the number of links in the network, average link travel length, and total graph travel length (L). The model process then calculated the x and y coordinates of the starting and ending points for each edge in the network in order to compute the "direct" length and each edge's deviation from the shortest path. An "overall" detour measure was then calculated from the sum of the direct lengths divided by the sum of the travel lengths.

To compute the number of vertices and the distribution of vertex degrees, I created a point file for each city containing points for each endpoint of every link in the network. Multiple endpoints stacked on top of one another at the same point represented vertices with degree equal to the number of stacked endpoints. Singular endpoints represented terminal points in the network, vertices with degree of 1. Sequential frequency operations exported the counts of vertices in each network with degree values of 1, 2, 3, 4, 5, or 6.

The number of subgraphs proved tricky to identify. The dissolve functions in ArcGIS retain breaks at intersections, so it is difficult to systematically count the number of distinct, non-adjacent subgraphs in the network. A model process was developed to buffer the network by a very small margin (5 meters), index the resulting polygons, and then use a spatial join function to associate links in the network with the index value of whichever subgraph they belong to. A summary was then exported for each network, including the number of subgraphs, average subgraph size (length), and min and max subgraph sizes.

Berrigan, Pickle, and Dill's 2010 study set a precedent for using the beta index, gamma index, and alpha index to evaluate connectivity for nonmotorized transportation modes. The beta index is a ratio of edges to vertices $\beta = \frac{e}{v}$. Higher values of beta indicate a more complex network. A collection of disconnected edges that do not intersect would have a beta value of 0.5 (two vertices/endpoints for each edge in the network). Higher values of beta in a network of bicycle infrastructure signify more route choice within the network. Lower values suggest that a bicyclist would be more likely to require mixed traffic connections where the bicycle network fails to connect points of interest. The gamma index is the ratio of observed edges to the theoretical maximum number of edges $\gamma = \frac{e}{3(v-2)}$ with values ranging from 0 to 1. Higher values of gamma indicate greater internal connectivity and increased redundancy in the network, providing a bicyclist with greater route choice and opportunities to choose a shorter path.

A cycle in a network is a chain of edges with the same starting point and ending point. The number of cycles u in a network corresponds to a higher level of complexity and development within the network. Simple networks have no cycles. The number of cycles in a network is estimated through the formula: $u = e - v + p$. The alpha index compares this estimated number of cycles to the theoretical maximum possible number of cycles through the formula: $\alpha = \frac{u}{2v-5}$. Like the gamma index, the values range from 0 to 1 and values approaching 1 are highly unlikely due to excessive redundancies. Unlike the gamma index, this measure is independent from the number of nodes and thus should be less size-dependent.

A simpler if less precise way to conceptualize network connectivity is through the distribution of vertices by vertex degree. Larger shares of vertices that are 3- or 4-way intersections suggest higher levels of internal connectivity, affording users greater route choice and lower potential for excessive detours within the network, than a hub-and-spoke structured network.

Directness in this study is evaluated at two levels: the directness of each edge, and the overall network. Higher length ratios indicate less deviation from the shortest path. The minimum length ratio value, a measure at the individual edge level, represents the “worst”, or least direct, link in the network. Higher values of minimum length ratio obviously set a higher minimum standard of directness for the entire network. However, the minimum length ratio is also negatively correlated with the number of edges in the network, so any potential benefit that might be derived from having more direct links in the network is obscured by importance of having more edges in the network.

One notable feature of many bicycle infrastructure networks is that they have numerous disconnected subgraphs. Higher levels of fragmentation may make the network less useful for longer or more complex trips, if the fragmentation results “islands” of bicycle infrastructure connected by hostile roads not conducive to bicycling. The largest subgraph and the average subgraph size can be examined both for their overall size and for the percent of the network contained in each. A high percentage of the network contained in the largest subgraph indicates a more cohesive “main” network with small, disjointed fragments. An “average” subgraph size that comprises a relatively high percentage of the overall network indicates a network that is more evenly distributed between several smaller but substantial subgraphs.

These subgraph measures do not take into account the types of environment between subgraphs (whether Class III bicycle facilities, residential streets, major arterials, impassible topological features, and the sheer distance between subgraphs). These environments will obviously interact with the distribution of the network among subgraphs, making the fragmentation more or less of an obstacle to bicycling. Even without these environmental measures, however, this depiction of network fragmentation may still explain some variance in bicycle mode share or gender split of cyclists if fragmentation.

Table 3 lists all the measures and constructed network variables included in the correlations, factor analysis, and regression models.

Results & Discussion

Correlations

To identify measures associated with bicycle mode share and gender split of bicycle commuters, a Pearson correlation was conducted on variables of interest. Table 4 highlights these results. These correlations suggest that ridership is in general correlated with network size, connectivity, detours, and household profile. Gender split is additionally related to network density and fragmentation.

The three dependent variables are all correlated with each other: Bicycle commuters in 10,000 and female bicycle commuters in 10,000 are very strongly correlated. Percentage of female cyclists has a

Table 3. Network Measure Summary

Description	Mean	Std. Dev.	Min	Max
Length of the network (km)	311.16	450.24	1.54	2,204.22
Cumulative direct length of the network (km)	275.70	408.57	1.38	1,987.12
Number of vertices	202	239	2	1,028
Number of edges	191	247	1	1,034
Number of subgraphs	32	35	1	168
Number of vertices with degree>=3	76	115	0	495
Length of largest subgraph (km)	144.60	249.30	0.99	1,621.75
Alpha index	0.03	0.05	-0.07	0.17
Gamma index	0.29	0.05	0.19	0.43
Pct. of vertices with degree>=3	26.0%	16.9%	0.0%	64.2%
Beta index	0.81	0.20	0.50	1.28
Number of cycles	20	47	-63	188
Average detour ratio	91.2%	8.6%	42.1%	100.0%
Overall detour ratio	86.5%	11.0%	42.1%	100.0%
Pct. of network contained in average subgraph	14.8%	23.7%	0.6%	100.0%
Pct. of network contained in largest subgraph	48.7%	25.7%	12.7%	100.0%
Minimum detour ratio	28.4%	35.2%	0.0%	100.0%
Length of average subgraph (km)	11.84	21.29	0.77	155.12
Length Density (km per square km)	4.64	23.71	0.03	204.12
Vertex Density (vertices per square km)	5.03E-03	2.86E-02	5.58E-06	2.46E-01
Edge Density (edges per square km)	4.06E-03	2.14E-02	2.79E-06	1.84E-01
Subgraph Density (subgraphs per square km)	8.16E-04	4.40E-03	2.79E-06	3.74E-02

somewhat weak but significant positive correlation with both mode share variables.

Mode share was positively correlated with the number of edges and number of intersections (size), network measures (alpha index, gamma index, beta index, and number of cycles), and percentage of vertices with degree of at least 3. It was negatively correlated with the minimum length ratio (worst detour ratio in the network), percentage of households with kids, and vehicles per household. Female mode share was similar; it was also positively correlated with the number of vertices, and not correlated with the number of vehicles per household. Gender split was positively correlated with the number of edges, vertices, subgraphs, and intersections, as well as the alpha index, beta index, and ratio of vertices with degree of at least 3. It was negatively correlated with the percent of network contained in the average subgraph, minimum length ratio, percent of households with kids, and vehicles per household. It was positively correlated with density measures: length of bicycle facility per unit area of the city, vertices per area, edges per area, and subgraphs per area.

Factor Analysis

Many of the independent variables were strongly correlated with each other since they were ultimately constructed from the same network measures.

Conceptually, each of these measures mapped to an underlying concept: network size, internal connectivity, fragmentation, etc. Thus this study used an exploratory principle component analysis to reduce these 18 measures into five factors. Four extractions had eigenvalues greater than one, but after reviewing the factor loadings and scree plot, a fifth factor was added to better differentiate directness, fragmentation, and fragment size.

The five factors correspond to the network's (1) size and scope, (2) internal connectivity and complexity, (3) directness, (4) fragmentation/ cohesiveness, and (5) fragment distribution. These five factors explain 91% of the variance among the network variables. Table 5 shows scree plot and the rotated component matrix for these factors. Two of the five factors have a statistically significant

Table 4. Correlations

Description ***Correlation with:***	**Bicycle commuters**	**Female bicycle commuters**	**Pct Female Cyclists**
Bicycle commuters in 10,000	-	0.898 ***	0.319 **
Female bicycle commuters in 10,000	0.898 ***	-	0.315 **
Percent female cyclists	0.319 **	0.315 **	-
Length of the network (km)	0.017	0.055	0.173
Cumulative direct length of the network (km)	0.025	0.063	0.176
Number of vertices	0.181	0.215 ^	0.307 **
Number of edges	0.216 ^	0.264 *	0.285 *
Number of subgraphs	0.009	-0.011	0.283 *
Number of vertices with degree>=3	0.239 *	0.302 **	0.237 *
Length of largest subgraph (km)	0.096	0.159	0.131
Alpha index	0.197 ^	0.231 *	0.286 *
Gamma index	0.202 ^	0.268 *	0.182
Pct. of vertices with degree>=3	0.281 *	0.318 **	0.359 **
Beta index	0.274 *	0.303 **	0.351 **
Number of cycles	0.224 ^	0.287 *	0.142
Average detour ratio	0.174	0.125	0.107
Overall detour ratio	0.082	0.069	0.079
Pct. of network contained in average subgraph	-0.184	-0.129	-0.354 **
Pct. of network contained in largest subgraph	0.031	0.144	-0.182
Minimum detour ratio	-0.205 ^	-0.193 ^	-0.371 **
Length of average subgraph (km)	0.005	0.085	0.036
Population	-0.047	-0.04	0.082
Percent of households with kids	-0.561 ***	-0.37 **	-0.33 **
Percent of households with seniors	-0.12	-0.149	-0.167
Vehicles per household	-0.337 **	-0.133	-0.203 ^
Median household income	-0.013	-0.016	0.105
Land Area	-0.138	-0.107	0.087
Length Density (km per square km)	0.001	0.047	0.314 **
Vertex Density (vertices per square km)	0.01	0.046	0.314 **
Edge Density (edges per square km)	0.048	0.093	0.324 **
Subgraph Density (subgraphs per square km)	-0.036	-0.02	0.294 *

****** significant at the 0.001 level***
***** significant at the 0.01 level***
**** significant at the 0.05 level***
^ significant at the 0.1 level

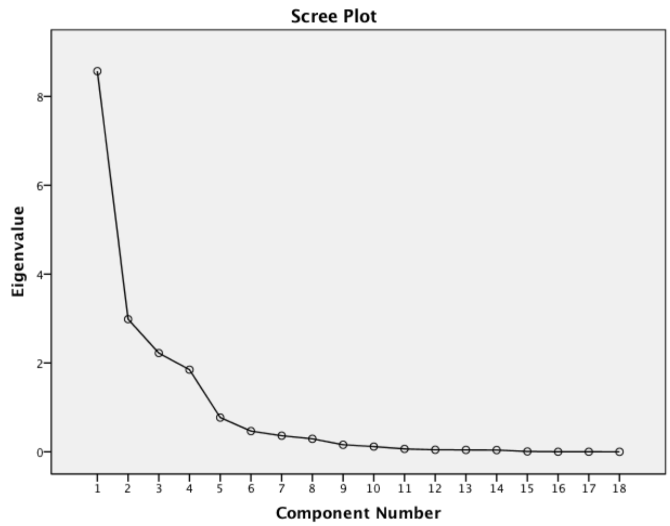

Figure 1. Plot of Eigen Values by Component

correlation with the dependent variables, as shown in Table 6.

Factor 2, measuring internal connectivity and complexity, is positively and significantly correlated with bicyclists per 10,000 commuters, female cyclists per 10,000 commuters, and percent female cyclists. This is not surprising given that many of the components of this factor (beta index, alpha index, gamma index, cycles, and percent of vertices with degree of at least 3) were also positively and significantly correlated with these dependent variables. Factor 4, fragmentation/cohesiveness, is negatively and significantly correlated with the gender split variable only. At face value, it looks like a more fragmented network is associated with a more even gender split of bicyclists, but the percent of the network contained in the largest subgraph and an "average" subgraph are both negatively correlated with the number of subgraphs, so this factor may be picking up on some latent preference for denser, more developed networks - not "fragmented" networks. More work is needed to disentangle these measures and identify the latent network variables.

Table 5. Rotated Component Matrix[a]

	Component				
	1	2	3	4	5
Length of the network (km)	.919				
Cumulative direct length of the network (km)	.914				
Number of vertices	.909				
Number of edges	.880				
Number of subgraphs	.839				
Number of vertices with degree>=3	.823	.522			
Length of largest subgraph (km)	.741				
Alpha index		.904			
Gamma index		.896			
Pct. of vertices with degree>=3		.885			
Beta index		.878			
Number of cycles	.621	.662			
Average detour ratio			.947		
Overall detour ratio			.941		
Pct. of network contained in average subgraph				.855	
Pct. of network contained in largest subgraph				.746	
Minimum detour ratio				.606	
Length of average subgraph (km)					.698

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 8 iterations.

Regression Models

This study used 10 OLS regression models to test three hypotheses:

H1: Bicyclists per 10,000 commuters

$Model\ H1.1: Mode\ share = f(Factor1, Factor2, Factor3, Factor4, Factor5)$

$Model\ H1.2: Mode\ Share = f(Factors\ 1-5, Size\ of\ city)$

$Model\ H1.3: Mode\ Share = f(Factors\ 1-5, Size\ of\ city, Demographics)$

H2: Female bicyclists per 10,000 female commuters

$Model\ H2.1: Female\ mode\ share = f(Factor1, Factor2, Factor3, Factor4, Factor5)$

$Model\ H2.2: Female\ Mode\ Share = f(Factors\ 1-5, Size\ of\ city)$

$Model\ H2.3: Female\ mode\ Share = f(Factors\ 1-5, Size\ of\ city, Demographics)$

H3: Percent female bicyclists (adjusted; assuming even gender split of commuters)

$Model\ H3.1: Pct.Female = f(Factor1, Factor2, Factor3, Factor4, Factor5)$

$Model\ H3.2: Pct.Female = f(Factors\ 1-5, Size\ of\ city)$

$Model\ H3.3: Pct.Female = f(Factors\ 1-5, Size\ of\ city, Demographics)$

$Model\ H3.4: Pct.Female = f(Factors\ 1-5, Demographics)$

For each of these hypotheses, I tested three models: one including only the five network factors, one with the network factors controlling for geographical size of the city, and one with network factors, area, and sociodemographic controls. The addition of land area to the models evaluating H3 caused a decrease in the Adjusted R Square value, so I tested a fourth model with the network factors and sociodemographic controls without land area.

Table 6. Correlations between Factors and Dependent Variables

Description	***Correlation with:***	**Bicycle commuters**	**Female bicycle commuters**	**Pct Female Cyclists**
Factor 1: Size		0.037	0.077	0.142
Factor 2: Connectivity/Complexity		0.284 *	0.328 **	0.256 *
Factor 3: Directness		0.077	0.051	0.004
Factor 4: Fragmentation/ Cohesiveness		-0.096	-0.005	-0.339 **
Factor 5: Fragment Size		-0.03	0.02	0.016

**** significant at the 0.001 level*
*** significant at the 0.01 level*
** significant at the 0.05 le*
^ significant at the 0.1 level

H1: Bicyclists per 10,000 commuters

Factor 2, connectivity/ complexity, was significant in all three models used to evaluate H1 with a relatively consistent coefficient across all three models. The adjusted R Square value was very low for Models 1 and 2.

The addition of socio-demographic and household structure variables increased the adjusted R Square value from less than 0.05 in Models 1 and 2 to 0.424 in Model 3. This is largely driven by a strong and significant negative relationship between percent of households with kids or seniors and ridership. When household structure was controlled for, Factor 3, the directness factor, was also revealed to be significant. According to Model 3, a 1% increase in connectivity or a 1% increase in directness in the network, all else being equal, corresponds to an increase of about 25 bicycle commuters per 10,000 commuters, or about a 0.25% increase.

Table 7: Models H1.1, H1.2, and H1.3

	Model 1	Model 2	Model 3
(Constant)	59.153 ***	78.328 ***	548.207 ***
Factor 1: Size	3.761	14.743	-11.117
Factor 2: Connectivity	29.086 *	27.143 *	25.441 *
Factor 3: Directness	7.917	3.047	25.211 *
Factor 4: Fragmentation	-9.858	-14.736	17.330
Factor 5: Size of Fragments	-3.072	-2.317	4.612
Pct of HH with kids			-865.088 ***
Pct of HH with seniors			-724.873 **
Vehicles per HH			64.364
Median HH income			-0.001
Population			0.000
Land Area		-0.000	-0.000
Adjusted R Square	0.032	0.048	0.424

Table 8: Models H2.1, H2.2, and H2.3

	Model 1	Model 2	Model 3
(Constant)	61.611 ***	85.052 **	674.620 ***
Factor 1: Size	12.149	25.574	-17.200
Factor 2: Connectivity	52.007 **	49.631 **	50.669 **
Factor 3: Directness	8.103	2.148	34.582 ^
Factor 4: Fragmentation	-0.870	-6.833	33.367 ^
Factor 5: Size of Fragments	3.127	4.050	10.990
Pct of HH with kids			-1381.684 ***
Pct of HH with seniors			-1298.728 **
Vehicles per HH			283.618 **
Median HH income			-0.044 *
Population			0.000 *
Land Area		-0.000	-0.000 t
Adjusted R Square	0.052	0.057	0.311

**** significant at the 0.001 level*
*** significant at the 0.01 level*
** significant at the 0.05 level*
^ significant at the 0.1 level

H2: Female bicyclists per 10,000 female commuters

Like H1, factor 2 was significant in all three models. The adjusted R Square value was also very low in Models 1 and 2, and improved considerably in Model 3. All of the sociodemographic variables were significant in Model 3. Notably, household structure is negatively associated with ridership, as in H1, but auto ownership is positively associated with ridership.

H3: Percent Female Bicyclists

Factors 2 (connectivity) and 4 (fragmentation) are significant in Models 1 and 2. Model 1 has a moderate adjusted R Square value, 0.142. Adding the land area control in Model 2 and Model 3 decreases the adjusted R Square value, so Model 4 tests the five network factors with household structure, vehicle ownership, income, and population without land area. These controls marginally increase the adjusted R

Square value, but none of the controls come out significant. Model 4 suggests that a 1% increase in connectivity is associated with a 3.2 percentage point increase in percent of bike commuters that are female (adjusted for gender split of commuters). A 1% increase in factor 4 is associated with a 3.8 percentage point decrease in percent female cyclists. As discussed previously, factor 4 includes components that ostensibly measure "fragmentation", but this is possibly driven by other factors, such as network density.

Table 9: Models H3.1, H3.2, H3.3, and H3.4

	Model 1	Model 2	Model 3	Model 4
(Constant)	0.243 ***	0.251 **	0.537 **	0.530 **
Factor 1: Size	0.022	0.026	0.019	0.019
Factor 2: Connectivity	0.039 *	0.038 *	0.032 ^	0.032 ^
Factor 3: Directness	0.001	-0.001	0.010	0.010
Factor 4: Fragmentation	-0.052 **	-0.054 **	-0.039 ^	-0.038 ^
Factor 5: Size of Fragments	0.003	0.003	0.011	0.011
Pct of HH with kids			-0.252	-0.245
Pct of HH with seniors			-0.583	-0.560
Vehicles per HH			-0.061	-0.067
Median HH income			0.000	0.000
Population			-0.000	-0.000
Land Area		-0.000	-0.000	
Adjusted R Square	0.142	0.132	0.139	0.152

**** significant at the 0.001 level*
*** significant at the 0.01 level*
** significant at the 0.05 level*
^ significant at the 0.1 level

Discussion

These tests suggest that there is a positive, significant relationship between network connectivity, levels of bicycle commuting, and the gender split of bike commuters, but more study is needed to tease out how exactly cyclists experience these network components and the relative significance of different network measures. The factor analysis process simultaneously highlighted the strength of a "connectivity and complexity" factor among the many network measures collected and the challenges associated with trying to understand the meanings and relative importance of concepts like "fragmentation".

Models H1.3 and H2.3 revealed the substantial relationship between household structure and bicycle commuting. The effects of network structure, while significant in the model, seem insignificant next to the magnitude of these relationships.

Applications for Practice

A better understanding of how cyclists use bicycle facility networks and which network elements serve various types of trips will enable planners to target nonmotorized transportation investments in ways that add value to the existing system and meet the needs of people living near the network.

Network connectivity and complexity was positively and significantly associated with mode share and percent female cyclists in all statistical tests conducted in this study. This provides planning professionals with a framework for evaluating their own bicycle infrastructure network. Since bicycling is so much more sensitive to distance than driving, it may make more sense for planners to target investments in building up internal connectivity before trying to expand the scope of the network.

From the findings of this study, it would be difficult to overemphasize the importance of household structure in predicting journey-to-work bicycle commuting. This is not a “free pass” for planners to assume neighborhoods with lots of children or senior adults do not want or need bicycle infrastructure; further study is needed to fully explain infrastructure barriers to cycling with children and to identify what kinds of bicycle trips, if not the commute trip, could be made accessible through the strategic building-out of the bicycle network.

This study also sheds light on the desperate need for standardized data collection and management practices for bicycle infrastructure networks and travel behavior. Road and rail networks are readily accessible from the US Census Bureau and other public agencies. No such equivalent exists for bicycle networks, so the availability of spatial data about bicycle infrastructure was heavily dependent on each individual city’s willingness to share the data and unique system for managing the information. Given the limited number of bicycle commuters, the American Community Survey is a crude tool for measuring bicycle mode share at the city level. That said, there is no other standard method for collecting this information across multiple cities. The Alta Planning bicycle count protocol and data collection project is limited by voluntary participation from cities, weak predictive models, and non-standard implementation across cities. As previously mentioned, the national household travel survey has too small of a sample size to identify trends at the city level. If federal, state, and local governments are interested in providing infrastructure to serve the needs of cyclists and would-be cyclists, their efforts will be significantly enhanced by a complementary push for consistent nation-wide infrastructure evaluation and mode-share measurement.

Limitations & Areas for Further Study

This study opens up many opportunities for continued research on bicycle facility networks. The sample size for this study was limited in two ways: (1) by the number of cities that make their spatial data on bicycle infrastructure available publicly, and (2) the limits of ACS journey to work data for smaller cities. Addressing either of these concerns, either by acquiring more spatial data or developing a better way to measure mode share, would enable a larger sample that could validate or refute some of the relationships identified here.

It is probable that regions with more cyclists and more interest in cycling are more likely to make their bicycle networks easily available online. Some of this selection bias may be alleviated by using regional bicycle networks that include spatial data for all cities in the region whether they have bicycling infrastructure or not, but even these cities may see higher rates of bicycling due to spillover effects from neighboring cities. A broader sample of cities from a more consistent source would mitigate these concerns, but this kind of information is difficult to come by. OpenStreetMap, for example, has some data on bicycling infrastructure, but its user-edited content is difficult to validate without an official data source for comparison and intimate knowledge of the area.

The ACS data are limited in that they only measure the percent of people who commute regularly by bicycle. This does not capture the number of people who make other kinds of utilitarian trips by bicycle: riding to school, running errands, etc. Matching network features with other kinds of ridership data may provide more insight into the different kinds of utility an infrastructure network can serve. This would facilitate identifying how different kinds of riders use the infrastructure, and which network structures are best suited for specific needs.

Statistical techniques could be used to manage the high standard errors on bicycle mode share in the ACS (particularly for small cities). Buehler and Pucher (2011) used log-log OLS regression models to address the skewed distribution of bicycle mode share. A Monte Carlo process could be devised using the standard errors on bicycle mode share for increased confidence in the dependent variables. This study controlled for land area but did not include network density measures constructed from the land area variable in the regression models; these should be included in future iterations of the model to see if they increase their explanatory power.

This study treated Class 1 and Class 2 facilities as interchangeable because they provide a separate space for bicycles outside of or adjacent to mixed traffic. Existing research shows, however, that riders value these two types of infrastructure differently. Tilahun et al's findings suggest that cyclists will travel upwards of 20 minutes out of their way to reach a separated bike path, with different (and lesser) values attached to wide shoulders, bike lanes, and the absence of street parking. Further study should maintain the distinction between Class 1 and Class 2 facilities to test the relative impact of each kind of facility or the complementarity of both on ridership and gender split.

Only a very small minority of a city's population will live and work immediately adjacent to bicycle infrastructure. Inevitably, almost all bicyclists will have to interact with mixed traffic at some point in their journey. Future work should consider access *to* the bicycle network as well as the network structure itself. This could be in the form of Class III/IV bike facilities or a network distance buffer of local streets around the bicycle infrastructure network. Reforming data management technique at the government agency, matching with street map data, or enlisting local knowledge to geocode the infrastructure with better detail would increase the robustness of measurements at the individual city level.

References

Barnes, G., Thompson, K., and Krizek, K. 2005. Longitudinal approaches to examining the effects of bicycle facilities on mode share. In: Barnes, G. and Krizek, K., 2005. *Tools for Predicting Usage and Benefits of Urban Bicycle Network Improvements*.

Berrigan, D., Pickle, L. W., and Dill, J. 2010. Associations between street connectivity and active transportation. *International Journal of Health Geographics*, 9: 20. DOI: 101.1186/1476-072X-9-20.

Birk, M. and Geller, R. 2006. Bridging the gaps: How quality and quantity of a connected bikeway network correlates with increasing bicycle use. *Transportation Research Board Annual Meeting*, Paper #06-0667.

Blue, E. 20 June 2011. "Bicycling's Gender Gap: It's the economy, stupid." Grist. Available from http://www.grist.org/biking/2011-06-20-bicyclings-gender-gap-its-the-economy-stupid. Accessed October 2011.

Buehler, R. and Pucher, J. 2011. Cycling to work in 90 large American cities: New evidence on the role of bike paths and lanes. *Transportation*. In press. DOI: 10.1997/s11116-011-9355-8.

Dill, J. 2009. Bicycling for transportation and health: The role of infrastructure. *Journal of Public Health Policy*, 30: S95-S110. DOI: 10.1057/jphp.2008.56arme.

Dill, J. and Carr, T. 2003. Bicycle Commuting and Facilities in the Major U.S. Cities: If you build them, commuters will use them. *Transportation Research Record: Journal of the Transportation Research Board*, 1828: 116-123. DOI: 10.3141/1828-14.

Dill, J. and Voros, K. 2007. Factors affecting bicycling demand: Initial survey findings from the Portland, Oregon, region. *Transportation Research Record: Journal of the Transportation Research Board*, 2031: 9-17. DOI: 10.3141/2031-02.

Duthie, J., Brady, J.F., Mills, A.F., and Machemehl, R.B. 2010. Effects of On-Street Bicycle Facility Configuration on Bicyclist and Motorist Behavior. *Transportation Research Record: Journal of the Transportation Research Board* 2190. DOI: 10.3141/2190-05.

Hennepin County, MN. Bicycle System Gap Study. Hennepin County Website. Available from http://hennepin.us/portal/site/HennepinUS/menuitem.b1ab75471750e40fa01dfb47ccf06498/?vgnextoid=48af5d9b29ad4210VgnVCM10000049114689RCRD. Accessed October 2011.

Hunter, W.W., Stewart, J.R., and Stutis, J.C. 1999. Study of Bicycle Lanes Versus Wide Curb Lanes. *Transportation Research Record* 1674.

Krizek, K.J. and Roland, R.W. 2005. What is at the end of the road? Understanding discontinuities of on-street bicycle lanes in urban settings. *Transportation Research Part D*, 10: 55-68. DOI: 10.1016/j.trd.2004.09.005.

Krizek, K.J., Johnson, P.J., and Tilahun, N. 2004. Gender differences in bicycling behavior and facility preferences. *Transportation Research Board Conference Proceedings 35: Research on Women's Issues in Transportation.* Volume 2: Technical Papers.

Li, H., Guensler, R., and Ogle, J. 2005. Comparing Women's and Men's Morning Commute Trip Chaining in Atlanta, Georgia, by Using Instrumented Vehicle Activity Data. *Transportation Research Board Conference Proceedings 35: Research on Women's Issues in Transportation.* Volume 2: Technical Papers.

Nelson, A.C. and Allen, D. 1997. If you build them, commuters will use them: Association between bicycle facilities and bicycle commuting. *Transportation Research Record: Journal of the Transportation Research Board*, 1578: 79-83. DOI: 10.3141/1578-10.

Parker, K.M., Gustat, J., and Rice, J.C. 2011. Installation of Bicycle Lanes and Increased Ridership in an Urban, Mixed-Income Setting in New Orleans, Louisiana. *Journal of Physical Activity and Health*, 8(Suppl 1), S98-S102.

Pucher, J., Komanoff, C., and Schimek, P. 1999. Bicycling renaissance in North America? Recent trends and alternative policies to promote bicycling. *Transportation Research Part A* 33(7/8), 625-654.

Rodrigue, J., Comtois, C., and Slack, B. 2009. *The Geography of Transport Ssytems, 2nd Ed.* Routledge: New York, NY.

Stinson, M.A. And Bhat, C.R. 2005. A comparison of the route preferences of experienced and inexperienced bicycle commuters. *TRB 2005*, Paper # 05-1434.

Tilahun, N.Y., Levinson, D.M., and Krizek, K.J. 2007. Trails, lanes, or traffic: Valuing bicycle facilities with an adaptive stated preference survey. *Transportation Research Part A*, 41: 287-301. DOI: 10.1016/j.tra.2006.09.007.

US Department of Transportation Federal Highway Administration: Nonmotorized Transportation Pilot Program. Available from http://www.fhwa.dot.gov/environment/bikeped/ntpp.htm. Accessed September 2011.

Wilkinson, W.C., Clarke, A., Epperson, B., and Knoblauch, R. 1994. *Selecting Roadway Design Treatments to Accommodate Bicycles.* Federal Highway Administration publication FHWA-RD-92-073.

Xie, F. and Levinson, D. 2007. Measuring the structure of road networks. *Geographical Analysis*, 39(3): 336-356. DOI: 10.1111/j.1538-4632.2007.00707.x

Data Sources

US Census Bureau American Community Survey
Bay Area Metropolitan Transportation Commission (CA)
City of Albuquerque (NM)
City of Austin (TX)
City of Bakersfield (CA)
City of Chicago (IL)
City of Houston (TX)
City of Mobile (AL)
City of New York (NY)
City of Orlando (FL)
City of Philadelphia (PA)
City of Portland (OR)
City of Seattle (WA)
Denver Regional Council of Governments (CO)
Los Angeles Metro Transit (CA)
Massachusetts Department of Transportation (MA)
Mid Ohio Regional Planning Council (OH)
North Carolina Department of Transportation (NC)
North Central Texas Council of Governments (TX)
Rhode Island Department of Transportation (RI)
Sacramento Area Council of Governments (CA)
San Diego Association of Governments (CA)
Twin Cities MetroGIS (MN)
University of Wisconsin, Milwaukee (WI)
Washington, D.C.