GEOSPATIAL ANALYSIS OF BICYCLE NETWORK "LEVEL OF TRAFFIC STRESS", BICYCLE MODE CHOICE BEHAVIOR, AND BICYCLE CRASHES FOR RISK FACTOR IDENTIFICATION

FINAL PROJECT REPORT

by

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16. Abstract Small and medium-sized cities need publicly acceptable criteria for bicycle infrastructure improvements. This report explores the effectiveness of one proposed system of bicycle infrastructure criteria using data from a state-of-the-art travel survey, the Oregon Household Activity Survey (OHAS), and census journey-to-work data for the Salem-Keizer metropolitan area. In addition, this report also attempts to explore the geospatial correlation between bicycle level of traffic stress and where bicycle crashes happen. Results show that commuters (i.e., employees and students) with low-stress connectivity to work and school are more likely to commute by bicycle, but also show that some demographic variables like race and income correlate with households' low stress connectivity. The count model of household bicycle trip production in the Salem-Keizer region produced in this report illustrates that the size of a household's adjacent "island" of low-stress bicycle connectivity correlates positively with bicycle trip production. In contrast, modeling with census data fails to show any correlation between bicycle commute mode share at the "is -land" scale and low-stress network connectivity. The mixed results suggest the range of a commuters' low-stress bicycle network alone may not be a primary factor in the decision to bike. In combination with existing literature, we consider how the effect of low-stress connectivity on cycling to destinations relies on travelers' awareness of low stress connections between origins and destinations. Further research should identify level of service criteria that can predict cycling rates yet remain cost effective for small communities to map.			
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List of Abbreviations

ACS: American Community Survey
LEHD: Longitudinal Employment Household Data
LTS: Level of Traffic Stress
MPO: Metropolitan Planning Organization
MWVCOG: Mid-Willamette Valley Council of Governments
ODOT: Oregon Department of Transportation
NHWBA: New Hampshire Bike Walk Alliance
OHAS: Oregon Household Activities Survey
PacTrans: Pacific Northwest Transportation Consortium
SAW: Simple Additive Weighting
ZINBR: Zero Inflated Negative Binomial Regression

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1. Introduction

Cities and planning agencies with limited budgets and a commitment to increasing bicycle mode share require empirically grounded yet publicly communicable tools to evaluate bicycle investments. These tools need to identify projects that offer the greatest gain in bicycle network connectivity, accessibility, and safety. This report tests one such method, the level of traffic stress (LTS) criteria proposed by Mekuria, Furth, & Nixon (2012), using both census data and a variable-rich household travel survey to examine if LTS networks can explain bicycle mode share, trip rates and crash rates. The results presented in this report are mixed, with evidence LTS can predict household bicycle trip rates, but not neighborhood bicycle mode share or intersection crash rates. Results draw from two sets of case studies from different sides of the country.

The authors conducted the analysis of LTS predicting trip rates and mode choice on the adjacent cities of Salem and Keizer in Oregon using the 2011 Oregon Household Activity Survey, a demographic-variable rich household travel survey with a representative sample of households in that metropolitan area. Census journey-to-work data were pulled from the 2007-2011 American Community Survey. This case study, having a population just over 200,000 residents, represents the type of smaller MPOs that may not have the resources to build other, more data-intensive bicycle level of traffic stress models. Building off Mekuria et al., (2012), the authors constructed and identified "islands" of low-stress connectivity surrounding households as representations of each observations' potential range of low stress access. It should be noted however that due to the low number of households that produced bicycle trips on the survey day, the results from this test should be considered with caution, especially given contradictory census-based results. Models are then presented to study the effect that size and range of the street network of households that have low stress access to on the households' bike trip rates using the zero-inflated negative binomial regression. This is an advanced and punitive count-modeling tool.

The second case study examining LTS and bicycle crash rates includes the central cities of several MPOs in southern New Hampshire that are similarly sized at between 200,000 and 300,000 residents. The authors explored the geospatial relationship of LTS netowrks and bicycle crash data by visually inspection to determine if LTS models could potentially be used to improve crash prediction models. This analysis was done using bicycle crash data and LTS models for four cities prepared by New Hampshire Bike-Walk Alliance (NHBWA).

1.1 Report Objective

The purpose of this research is to (1) explore the significance of level of traffic stress (LTS) for bicyclists in explaining bicycle mode share and bicycle trip rates of households in medium-sized cities and (2) explore the correlation between LTS and bicycle crashes. The authors selected Salem and Keizer, Oregon, two contiguous cities with over 200,000 residents combined, for low-stress bicycle mode choice analysis. The Oregon Household Activities Survey (OHAS) data provided a unique opportunity to investigate bicycle mode share and bicycle trip rates as the authors could pinpoint households' exact locations in a road network and define the range of the road network each household could access at low stress levels. The authors then used the state-of-the-art, zero-inflated negative binomial regression (ZINBR) to quantitatively define relationship between the level of traffic stress values and cycling trip rates. Additionally, the authors explored the geospatial relationship of LTS networks and bicycle crash data by visually inspection to determine if LTS models could potentially be used to improve crash prediction models. This analysis was done using bicycle crash data for four cities provided by New Hampshire Bike Walk Alliance (NHBWA).

1.2 Report Organization

Chapter 2 provides a summary of current research in the area of bicycle infrastructure design, modeling, crash severity, and analysis relevant to identifying levels of service or stress for cyclists. Chapter 3 describes data used and the overall methodology. Chapter 4 discusses the results from two different case studies involving LTS and the correlation of LTS to bicycle mode choice behavior using the Oregon Household Activities Survey (OHAS) and the American Community Survey. Chapter 5 concludes the report and provides suggestions on how the research could be improved for future studies.

2. Literature Review

2.1 The Case for LTS

Prior research on the effectiveness of level of traffic stress (LTS) categorizations in explaining travel behavior come from studies relying on both stated and observed data of how cyclists' route choices respond to changes in the built environment. Mekuria et al., (2012) produced the LTS criteria tested in the report "Low-Stress Bicycling and Network Connectivity." The authors selected this approach because it provides consistent criteria for creating a network links and nodes that policy makers and the public can readily understand.

LTS networks are defined by automobile speeds, number of lanes, and cycling infrastructure improvements with the goal of creating a cost-effective tool for identifying ways to bridge gaps between "islands" of low-stress cycling connectivity. Any jurisdictions looking to develop maps for bicycle policy evaluation would need access to each of these variables. First among these variables are the infrastructure improvements that undoubtedly correlates with higher cycling rates at the household, neighborhood, and municipal level (Dill & Carr, 2003; Monsere et al., 2014). Infrastructure also determines the route choice, with individuals willingly taking longer routes to stay on lower stress and improved infrastructure paths (Arentze & Molin, 2013; Hood, Sall, & Charlton, 2011; Tilahun, Levinson, & Krizek, 2007), bicycle sharing system to address geographic inequalities through pricing (Goodman & Cheshire, 2014), and the user destination choice preference of bicycle sharing system (Faghih-Imani & Eluru, 2015). When having to ride in mixed traffic, cyclists appear to prefer riding along residential streets to riding on major streets with higher speeds and more lanes in an order that mirrors the LTS classification system (Caulfield, Brick, & McCarthy, 2012; Habib, Mann, Mahmoud, & Weiss, 2014). In multiple countries scholars report the importance of automobile speeds and number of lanes in determining subjects' perceptions of service levels (Kang & Lee, 2011; Providelo & da Penha Sanches, 2011).

Additionally, the authors utilize a popular four-group classification of urban bicyclists to define their level of traffic stress system, a demographic system developed in Portland, Oregon (Geller, 2013). This classification system categorizes residents based on their cycling comfort levels rather than skill level, which enables planners to think about stress level classifications as catering to three groups. The first group is a small, fearless section of the population that will choose to cycle in any conditions along any road-way. The second is typical, confident adult bicyclists who will only be comfortable on major arterials with bike lanes or small, slower roads without bike lanes. The last group consists of the vast majority of the population that would bike but has very low tolerance levels for negotiating vehicle traffic above small, residential street speeds.

The method defined by Mekuria et al., (2012) also does not require the detailed data requirements as Landis, Vattikuti, & Brannick, (1997), which includes vehicle volumes and share of heavy vehicles (trucks) on each node. As such, the Mekuria et al., (2012) study is a less data intense approach which enables a complete classification of a city's entire bicycle network. How road segments are classified from very low stress level one to highest stress level five is delineated in Table 2-1.

Table 2-1 Criteria for Level of Traffic Stress in Mixed Traffic (Mekuria et al., 2012)

	Street Width		
Speed Limit	**2-3 lanes**	**4-5 lanes**	**6+ lanes**
Up to 25 mph	LTS 1* or 2*	LTS 3	LTS 4
30 mph	LTS 1* or 2*	LTS 4	LTS 4
35+ mph	LTS 4	LTS 4	LTS 4

Links and nodes classified as LTS 1 are those that Mekuria et al., (2012) suggest a rider would feel safe riding on with children. Likewise, LTS 1 and LTS 2 links and nodes are designed to represent riders in Portland's "Interested But Concerned" riders, roughly two-thirds of the population (Geller, 2013). Upon classifying a network, a jurisdiction can identify "islands" of low-stress connectivity and prioritize infrastructure investments that bridge these islands so that "Interested but Concerned" residents have increased accessibility at levels of stress they are comfortable with.

2.2 The Case against LTS and A Review of Alternatives

The literature also offers several reasons to doubt the effectiveness of LTS accessibility in predicting cycling mode share or trip production. Some of the latest research on route choice using GPS data found that traffic volumes are critically important to understanding route choice (Broach, Dill, & Gliebe, 2012). This variable is left out of the LTS to minimize the data intensiveness of building a LTS model. Traveler awareness of connectivity is as important as the availability of bicycle connectivity of a network itself, as Lundberg & Weber (2014) note from a survey of commuters to the University of Alabama and Wierda & Brookhuis (1991) found that wayfinding is a central cognitive task for cyclists.

Travel experience by bicycle or other modes may limit an individuals' knowledge of alternative cycling routes because they significantly shape individuals' personal cognitive map of their communities (Campbell & Lyons, 2008). The importance of wayfinding inspired the production of the London Cycle Map, a grassroots mapping of cycling routes in London with implications for city politics (Sherwin & Melia, 2012). The "islands" of low stress connectivity approach evaluated here sidesteps these human cognitive factors in travel behavior entirely. Planners may be able to see a "bridge" between two low-stress islands on a road network using geographic information science (GIS) tools, but if such links are hidden in subdivisions with light traffic, residents' sense of their own personal islands of low stress bicycle routes may be significantly smaller than what local planners assume them to be. This may negate the potential for LTS accessibility to be useful in predicting residents' propensity to cycle.

Milakis & Athanasopoulos, (2014) expand beyond wayfinding in a case study of Athens, Greece to also incorporate ride difficulty measures like elevation into a cycling infrastructure evaluation system. The study also incorporated the intensity of junctions and intersections, including the effect of signalization, which may slow down rider (Broach et al., 2012; Providelo & da Penha Sanches, 2011; Sener, Eluru, & Bhat, 2009; Titze, Stronegger, Janschitz, & Oja, 2008). Their methods also includes several other aspects of a cycle trip that may play a significant role in route and even mode choice: built environment variables like architecture (Cervero & Duncan, 2003), natural environment variables like views of trees and green space, and accessibility to a variety of activities and transit stations. Milakis & Athanasopoulos (2014) then invited a sample of experience cyclists to weight the criteria and utilized the weights to examine the relative importance of all variables. It was found that centrality, difficulty, junction density, and the mental legibility of routes were more important to residents than speed (Milakis & Athanasopoulos, 2014). Although this system is superior to the LTS system in terms of comprehensiveness Mekuria et al., (2012), it suffers from the same problem that makes other infrastructure evaluation systems difficult for small and medium sized cities to produce. It requires a large amount of data inputs that smaller communities may be unwilling or unable to pay for. That said, the survey results completed by Milakis & Athanasopoulos, (2014) on the relative greater importance cyclists place on centrality and junction density could be easily incorporated into the LTS using data local planning and public works departments may have readily available.

Lastly, the LTS system excludes two aspects of the riding experience understood in the literature as important to cyclists: traffic volumes and cycling crash rates. Volumes are left out because they can be costly to obtain for across an entire network (Mekuria et al., 2012) even if the volumes can increase stress and significantly alter riders' route decisions (Li, Wang, Liu, & Ragland, 2012; Winters, Davidson, Kao, & Teschke, 2011). Larsen, Patterson, & El-Geneidy, (2013) provide a GIS-based approach to prioritizing bicycle network investments that included an additional variable not covered by Mekuria et al., (2012) or in the cycling crash rates collected by Milakis & Athanasopoulos (2014). Their approach allowed for a spatial comparison of how different criteria can prioritize infrastructure improvements in different or similar areas, illustrating the different trade-offs inherent in including different criteria. While this is undoubtedly beneficial, it represents yet another layer of data cities may not be able to afford. As research predicting bicycle crash rates grows, a simple stand-in variable that highly correlates with crash rates may emerge that small jurisdictions can utilize in the planning process.

2.3 The Limited Research Explicitly Evaluating Classifications

While research on cycling preferences and behavior inform LTS models, little research attempts to validate the usefulness of these broad, simplified classification systems back onto observed travel data. Rybarczyk & Wu, (2010) developed overlay supply and demand models for bicycling in Milwaukee, Wisconsin. The study applied the bicycle level of traffic stress developed by Landis et al. (1997) to categorize and analyze bicycle supply. That system computes a six-level categorization which downgrades the bicycle level of service (BLOS) on a link as the following input variables rise: volume of directional traffic, the percentage of heavy vehicles, and road surface conditions as defined by the FHWA's five-point scale (Landis et al., 1997). Additionally, the score for each link is increased as the effective width of the outside through lane increased. The output is defined through a linear combination of these variables derived from a regression equation produced by Landis et al. (1997). Rybarczyk & Wu, (2010) contrast the results with an analysis of bicycle demand using a simple additive weighting (SAW) method to calculate relative demand potential for each link versus the rest of the network. It was concluded that a combined demand and supply analysis enables better planning decision making, noting a mismatch in their case study between presumably high demand neighborhoods and neighborhoods with effective low-stress network coverage. While this approach may be more effective in predicting outcomes, the LTS framework offers much less complicated metric using criteria that cyclists, citizens, and local officials may readily understand. Additionally, data on vehicle volumes, the percentage of volumes from heavy vehicles, and road conditions may not be available or feasible to collect for small and medium sized jurisdictions.

2.4 Bicycle Crash Severity Studies

There are several crash severity studies that have found multiple factors which impact the severity of a crash involving a bicycle including the geometry of the roadway, the design of the intersection and its' approach, the weather at the time of the accident, and the lighting condition. These factors are important to recognize because they can improve crash prediction models based on roadway characteristics but are not considered in LTS modeling.

2.4.1 Roadway Geometry

Geometry plays a huge role in collision of vehicles-bicycles. In published literature, researchers have analyzed factors such as number of traffic lanes adjacent to bicycle traffic, road curvature, and the shoulder characteristics or the presence of a bike lane in depth.

Greibe (2003) found that when there were 2 lanes there were more accidents. In addition, there were more accidents in the same direction on single lane with no centerline markings, attributes not measured in the LTS. This study also noted that many of the roadways geometry characters had strong correlation with each other. When considering pedestrian-vehicle crashes, Lee & Abdel-Aty (2005) found that 1 lane reduced the amount of pedestrian crashes by 400%

when it is the pedestrian's fault and when a road had 2 lanes, these crashes were reduced by 25%. It was also found that more crashes occurred on undivided roads with more number of lanes than divided roads with less number of lanes (Lee & Abdel-Aty, 2005). Petritsch, Landis, Huang, & Challa, (2006) considered a side path safety model design and found that the more lanes that are on the roadway, the more motorists focus on the opposing travel lanes and turning traffic as oppose to the activity on a side path. Additionally, on two lane roads, motorists look for cyclists on the side of the street and the roadway and cyclists using a side path may only concern themselves with traffic in the nearest travel lanes (Petritsch et al., 2006).

Pai (2011) found that horizontal and vertical curves can contribute to bicycle accidents. Schepers & den Brinker (2011) considered potential visual barriers that different road geometry causes cyclists and found that cyclists collide with a bollard or road narrowing or rides off the road in a curve. This type of crash was found to occur more than when cyclists hit an obstacle because they were looking at something on the side of the road but not more than cyclists looking behind them. The biggest takeaway from the study was that focal operations play a more important role in crashes involving a curve. Dixon et al. (2012) found that 'no horizontal curves' should be a SPF that is included when calculating the unadjusted crash prediction model for the base conditions for a rural two-lane, two-way road segment. Eluru et al. (2008) found that crashes at curved/non-flat roadways tend to have more severe injury. Using a multinomial logit model, Kim et al. (2007) found that curved rounds significantly increase the chance that a fatal or incapacitating injury will occur during a vehicle-bicycle accident.

There are a number of different types of facility designs for bicycles and each has an impact on bicycle safety such as the presence of bicycle lanes, the grade of the roadways/bicycle track, and if there are any different pavement markings or colors (Oh et al. 2008; Vandenbulcke, Thomas, and Int Panis 2014). Vandenbulcke et al. (2014) considered different cycle facilities and found that there is an increased risk of accident when associated with a specific type of intersection. This study found that right-of-way intersections equipped with cycle lanes tends to have higher accident risk for cyclists, due to vehicles not respecting the right-of-way (i.e. right-hook crashes). The researchers also found that cyclists riding on marked cycle lanes in roundabouts and signalized intersections with marked cycle lanes had higher accident risks for cyclists and attributed the higher risk to the cyclists being in drivers' blind spots (Vandenbulcke et al., 2014).

Schepers et al. (2011) found that more crashes where the bicycle has the right-of-way on a through movement occur at intersections with two-way bicycle tracks that are well marked and are reddish in color. However, this study found a cycle track where the approach is deflected 2-5 meters (6-10ft) from the intersection decreased the risk for the cyclist. Walker (2007) considered the effect of lanes on how drivers overtake bicyclists on the road and discussed that more narrow roads might lead to vehicles passing cyclists closer which might cause more risk.

Petritsch et al. (2006) created the Sidepath Safety Model in order to determine if a side-path, or separated bicycle track, would be a viable option for a given road segment or how to improve an existing side-path with multiple crashes. This model found that the path width has an impact on the safety and recommends that paths be built wide enough to accommodate multiple users along a segment but restricted at conflict points to calm traffic. It also found that the distance between the side-path and the roadway, the speed of the adjacent roadway, and the number of lanes on the adjacent roadway were also key safety factors.

2.4.2 <u>Intersection</u>

The design of the intersection has an impact on bicycle safety in multiple ways as concluded by Wang & Nihan (2004). For intersection and network movement, hazardous crossings, right hook, left sneak, and complicated interactions are potentially dangerous to cyclists. Intersection safety was influenced by vehicle volume, vehicle speed, percent of heavy vehicle, and many other factors for both the major and minor roads (Dixon, Monsere, et al. 2012).

Oh et al. (2008) conducted a study based on surveys collected at 151 signalized intersections and found that average daily traffic volume, presence of bus stops, sidewalk widths, number of driveways, presence of speed restrict devices, and presence of crosswalks are all statistically significant factors that influence the risk level of bicycles. It has also been found that complex intersections (high number of road legs, road users, high number of signs, dense traffic crossings, etc.), and therefore complex traffic situations, increase the risk for bicycles (Vandenbulcke et al., 2014)

Abdel-Aty & Keller (2005) considered three types of variables in different probit models for signalized intersections; (1) based on collision types, (2) based on intersection characteristics, and (3) based on a complete set of significant variables. These models found that the division of the minor road, as well as a higher speed limit on the minor road, was found to lower the expected injury level while a median on the minor road may prevent more head-on crashes, which were found to be more severe crashes (Abdel-Aty & Keller, 2005). Additionally, a higher speed limit on the minor road may cause the speed differential between vehicles on intersecting roads to be smaller, likely resulting in a decrease in the crash severity level (Abdel-Aty & Keller, 2005).

Another study looked at two types of crashes across 540 un-signalized intersections; (1) through bicycle related collisions where the cyclist has right of way, and (2) through motor vehicle related collisions where the motorist has right of way (J. P. Schepers et al. 2011). The results showed that Type 1 crashes occurred more when the two way bicycle tracks is well marked, and there are reddish colored bicycle crossing. Fewer crashes occur when there are raised bicycle crossings (speed humps) or other speed reduction measures (J. P. Schepers et al. 2011). Haleem & Abdel-Aty (2010) considered the number of lanes for un-signalized intersection and found that the traffic volume on the major approach, the number of through lanes on the minor approach (surrogate measure for traffic volume), the upstream and downstream distance to the nearest signalized intersection, left and right shoulder width, number of left turn movements on the minor approach, and number of right and left turn lanes on the major approach were significant factors that influence bicycle risk.

2.4.3 Weather and Lighting

Bicycle crashes inherently have their own factors that are specific to bicycle crashes. The two more impactful factors are bad weather such as fog, snow, or rain, and the lighting of the road when it is dark outside. Moahn et al., (2006) recognizes that weather conditions and darkness are risk factors that influence crash involvement. One study found that bad weather (e.g. rain, snow, fog, etc.) increases the probability of fatality by 128% and darkness with no streetlights increases the probability of fatality by 110% (Kim et al., 2007).

Pai (2011) found that adverse weather, wet roads, and unlit streets in darkness were most common in rear-end crashes. Mountain and Jarrett (1996) stated that weather, quality of street lighting, and condition of the road surface used in a regression model will still have different underlying mean accident frequencies due to unique and unmeasured site characteristics. Stone & Broughton (2003) found that darkness increased the accident incidence rates and fatality rates. Martínez-Ruiz et al. (2013) considered bicycle defects and found that bicycles with brake defects were at a higher risk of being involved in a crash with a vehicle. Weather will need to be accounted for in statistical evaluations of the relationship between LTS and crash rates when data are gathered over a long period of time. That said, endogeniety between weather and LTS should not be present as presumably the entire community is uniformly facing the same weather conditions at all times.

3. Data & Methodology

3.1 Salem-Keizer Data

The Oregon Department of Transportation (ODOT) and Mid-Willamette Valley Council of Governments (MWVCOG) provided the data necessary to construct the bicycle network according Mekuria et al. (2012). This system defines level of traffic stress criteria for nodes and links based on the presence of bike lanes and on-street parking, number of lanes, and speed limit or prevailing speeds. The authors adapted the standards for bicycle lanes, originally developed in an application in San Jose, CA, to Oregon standards for bike lane widths.

Each of the 13,670 trips from the Oregon Household Activities Survey (OHAS) in Salem and Keizer were associated to an origin census block and a destination census block. If a trip's origin and destination blocks are in the same low-stress island, they were flagged as having low-stress connectivity. This does not mean the trip maker actually took a low stress route, it simply means that the trip-maker could make the trip on an entirely low-stress route. Home, employment, and school locations were pulled from the OHAS dataset, associated with census blocks already joined to islands, and merged to identify connectivity with households using the 'join' function in ArcGIS. Households were similarly defined as connected to specific islands using the 'join' function. As with trips, if a household (origin) and its trip maker's affiliated work site or school (destination) were in the same low-stress Island, they were flagged as having low stress connectivity.

The authors first explored the share of trips with low-stress accessibility by mode, and then explored respondents' stated "usual" work and school modes by low-stress access to employment and schooling destinations. These cross tabulations and figures were calculated in R, an open-source statistical package. Then two variables were selected to measure low stress connectivity for a household based on the size of the households' island of low stress connectivity. These variables included the population within each island of connectivity and the number of jobs within each island of connectivity. Population data came from the 2010 Census and employment data came from the 2011 Longitudinal Household Employer Dynamics (LEHD) dataset for Oregon. These variables represent the amount of employment, activity and space accessible to households given their low-stress network.

In theory, these variables could be biased if a household's low-stress island extended to distances residents would not be expected to bike to, e.g. an island over five miles long, however no islands in the Salem-Keizer area presented this problem. The other limitation of these variables is the inability to account for time differences within and across islands. Some islands of low-stress connectivity with high numbers of cul-de-sacs and stop signs might have higher cycling times than those with grid layouts and faster arterials with bike infrastructure.

To properly conduct this analysis, the OHAS travel survey data was modified to ensure robustness by eliminating all households which took no trips on the survey day and all households which did not own any bicycles. Removing these households ensured that results were not biased based on the presence of ‘structural zeros’ or households that would not produce any bike trips regardless of low stress accessibility due to the lack of bicycles or they were not inclined to travel on the travel day. Additionally, because greater than 80% of the households remaining in the study produced no bicycle trips and greater than 50% produced no walk trips, the authors elected to use the zero-inflated negative binomial regression process. This process was developed for count modeling situations in which excess zeros and over dispersion of counts data require two-step models. In these situations, the probability a case is a zero is predicted and controlled.

Table 3-1 shows the summary statistics of variables included in the count models and illustrates how the vast majority of bicycle trips in the survey are limited to a few households. The demographics of the remaining 660 households that possessed a bicycle and took at least one trip on the survey day were predominantly Caucasian, home owners who live in single family homes. The variables included in the regression were identified by an exploratory analysis of the data which suggested they may correlate with bicycle trip rates.

Table 3-1 Summary Statistics

	Mean	**Min**	**Max**	**SD**
Response Variables:				
Bike Trips per Day	0.28	0	11	1.5
Bike and Walk Trips per Day	1.51	0	20	2.95
Demographic Variables				
Household Size	2.95	1	8	1.45
Household Number of Students	0.986	0	5	1.86
Single Family Unit	0.867	0	1	0.34
Household is Caucasian	0.844	0	1	0.36
Home Owned by Occupant	0.818	0	1	0.39
Island Size Measures:				
Log Island Area Square Miles	-1.39	-6	0.131	1.36
Log Island Population Per Square Miles	9.38	5.34	10.9	1.35
Alternative Measures:				
Log Block Group Housing Per Square Mile	5.69	2.03	7.99	1.29
Log Block Group Intersection Density	3.2	-0.26	4.82	0.91

The log transformed measures do not vary dramatically with the exception of the log island area square miles. Quite a few populated suburban islands encompassed only a couple blocks, while another that included downtown contained almost half the city. This measure of regional access, while basic, may produce coefficients with inflated significance due to possible heteroskedacticity. Because this report is mainly exploratory, the authors present results with caution.

3.2 LTS and ZINBR Model

3.2.1 Coding LTS to the Salem-Keizer Network

The approach used by Mekuria et al., (2012) was selected because it provides consistent criteria for network links and nodes that policy makers and the public can readily understand. Additionally, the City of Portland's four-group classification of urban bicyclists is utilized in defining their level of traffic stress system (Geller, 2013).

Upon completion of the network for the city of Salem and its adjacent suburb Keizer, the authors identified distinct 'islands' of low stress streets (LTS 1 or 2). A trip maker on any link or node within an "island" has a low stress route to any other link or node on the island, but not to links and nodes outside its island. The authors downloaded Census block files for the year 2011 onto the network and associated each census block with a low stress island if that island bisected, intersected or at all bordered that island using the select by location function in GIS. The authors identified over twenty census blocks which appeared to include the edges of two or more islands that did not connect. These blocks were flagged as connected to each island but the islands were not treated as joined.

3.2.2 Control Variable Selection and Limitations

We identified two neighborhood accessibility control variables, intersection density and population density, and calculated them for each island of low stress connectivity using Census block group shape files and the Open Streets Network (Referring to Figure 3-1). A large body of literature suggests these variables are highly important for increasing non-vehicle trips, which Ewing & Cervero, (2001) recently over-viewed in a meta-analysis.

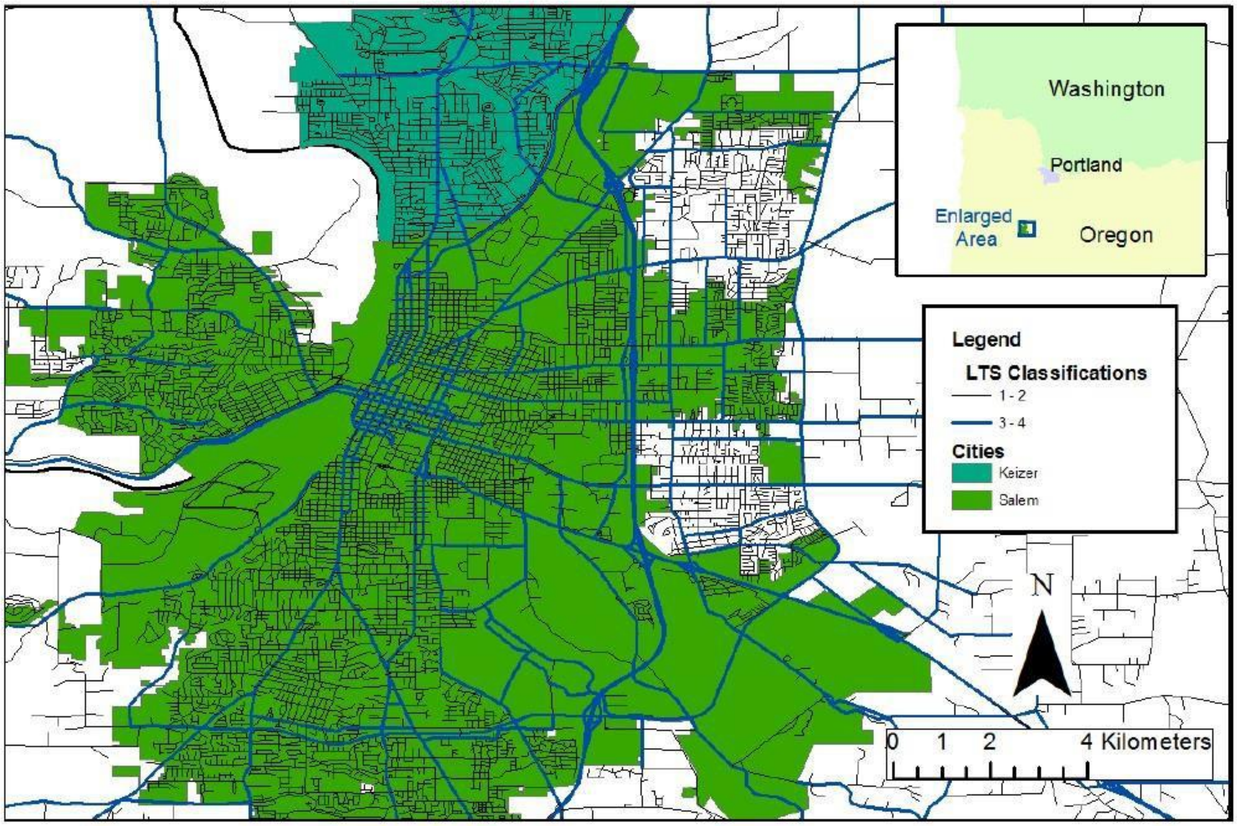

Figure 3-1 Salem Low-Stress Bicycle Traffic Network

Of the variables found to be highly significant, the authors of this report could not include land use diversity due to data limitations. This is a limitation of this study, as land use mix within low-stress islands may correlate low stress islands' size and the propensity of households with certain preferences to walk and bike to self-select into neighborhoods with broader low-stress connectivity. The authors suggest incorporating land use diversity into analysis of the effectiveness of the LTS system in explaining travel behavior in the future as land use mix and the size of low-stress islands in networks may be collinear.

3.2.3 Zero-inflated Negative Binomial Regression Model

In standard econometrics, Poisson modeling is the preferred statistical technique for predicting count models. However, the Poisson model requires that the data analyzed meet the assumption of equidispersion, where the mean of the data is equal to the variance:

$$E(Y) = V(Y) = \lambda t \quad (1.1)$$

The bicycle and walk counts used in this dataset did not conform to this assumption, requiring the authors to use the negative binomial regression. The negatively binomial model is an adaptation of Poisson wherein the equidispersion assumption is tested and estimates can be obtained by assuming a gamma distribution of the unobserved heterogeneity, ϵ, driving the non-Poisson distribution:

$$V(y_t) = \lambda t(1 + \epsilon \lambda t) \tag{1.2}$$

This randomness may be the result of omitted variable bias, but in negative binomial regression that exogenous randomness can be differentiated from randomness produced endogenously within the model:

$$\Pr[Y = y_t \mid \epsilon] = \left(\frac{\ldots}{y_t!}\right) \tag{1.3}$$

Zero-inflated negative binomial modeling builds further of this by adding a component that accounts for or controls the heterogeneity within the zero counts. This is necessary in a dataset with counts that are not negative binomially distributed due to an excess number of zeros (Jang, 2005). The zero-inflated model predicts:

$$\Pr(y_t = 0) = (\phi_t \quad) \tag{1.4}$$

This is produced by a logistic function

$$\phi_t = \frac{1}{\ldots} \tag{1.5}$$

where y_t is thus binomial negatively distributed with a probability of $1 - \phi_t$. This is integrated into the distribution and this produces a degenerate distribution whose mass is concentrated at zero, such that:

$$\Pr[Y = y_t \mid Y > 0] = 1 - \phi \quad (\quad) \left(\frac{\ldots}{y_t!}\right), y_t = 1, 2, \ldots \tag{1.6}$$

The log likelihood function of the logit model is thus:

$$l(L_{\ldots}) = \sum I(y_t = 0) \ln(\phi_t + 1 - (\phi_t e^{\ldots} + \ldots) \quad (\quad > 0) \times \ln[1 - (\phi_t \quad) - \lambda_t + y_t \ln \lambda (-) ( )] \tag{1.7}$$

This approach essentially enables us to produce systematically robust count models even in cases where observed counts are mostly or disproportionately zero.

3.3 New Hampshire Data

The crash data used in this study include all bicycle and pedestrian crashes from the State of New Hampshire between 2002 and 2013 for Concord, Manchester, Nashua, and Portsmouth as shown in Figure 3-2.

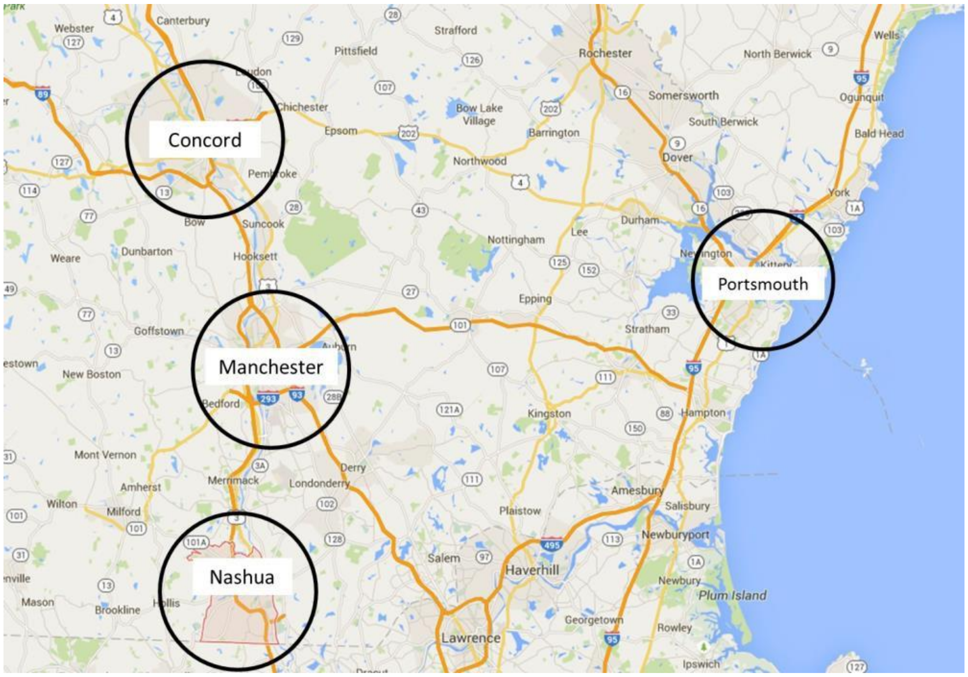

Figure 3-2 New Hampshire City Locations

The dataset includes the location of the accident, the roadway alignment, condition, and design, the lighting and weather at the time of the accident, the day and time of time the accident occurred, the total of fatalities and injuries, the traffic control if the accident occurred at an intersection, the year the accident occurred, and the level of severity including killed, incapacitating, no apparent injury, non-incapacitating, possible, and unknown. There are 602 reported cyclist crashes, on average about 50 crashes per year between the four cities with the 74 crashes in 2010 being the highest reported and 22 crashes in 2011 being the lowest reported. Table 3-2 shows the statistics for each city.

Table 3-2 New Hampshire Cities Summary Statistics

City	Crash	Population	Area (mi^2)
Concord	90	42,419	67.49
Manchester	297	110,378	34.98
Nashua	164	87,137	31.89
Portsmouth	51	21,440	16.8
TOTAL	**602**	**261,374**	

For the purposes of this study, the severity levels were broken into three levels; 'Serious', which includes killed or incapacitating injury, 'Non-Serious', which includes non-incapacitating injury and possible, and 'Property Damage Only (PDO)', which includes no apparent injury and unknown.

Of the 602 total crashes, 40 were Serious, 205 were Non-Serious, and 357 were PDO. 100 of the crashes occurred on a road classified as LTS1, 292 occurred on a LTS2 roadway, 156 occurred on a LTS3 roadway, and 54 occurred on a LTS4 roadway. Figure 3-3 shows a breakdown of the crashes based on the level of stress of the roadway and severity of the crashes. The value in parenthesis is the total for that variable.

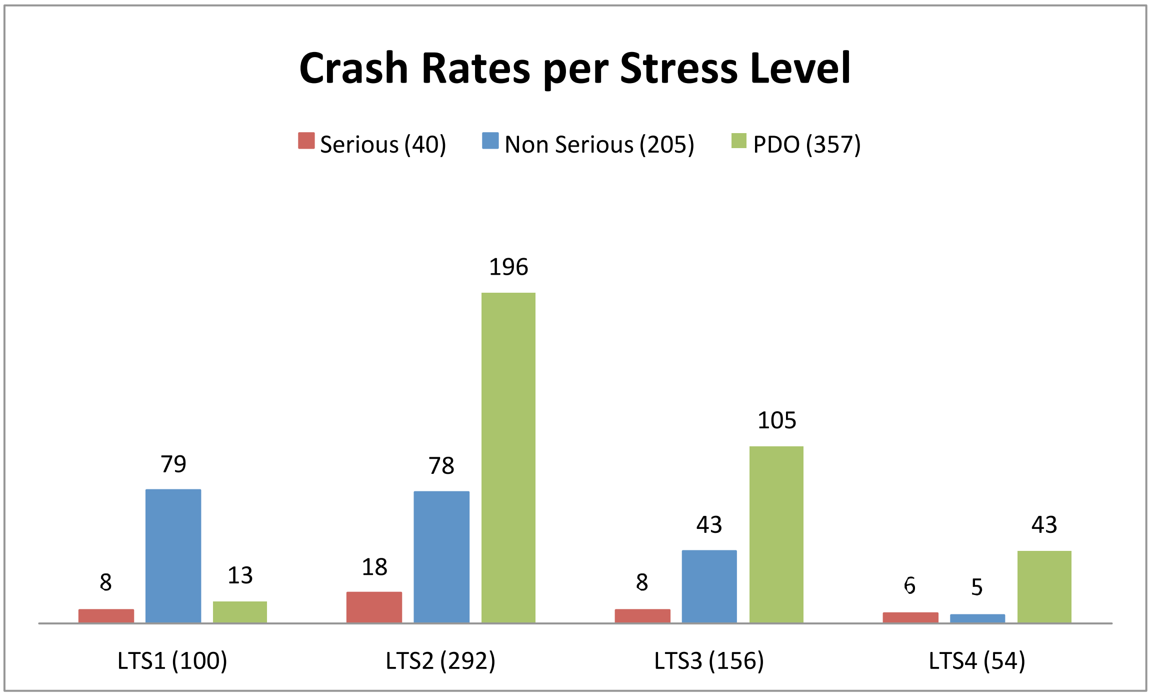

Figure 3-3 Crash Rates per LTS Level – (Total)

The LTS network was created using roadway information collected for each city on the following factors:

- Bike Lane Presence*
- Bike Lane Width*
- Speed Limit
- Parking Presence*
- Parking Width*
- Residential Indicator
- Midblock Crossing
- Number of Right Turn Lanes at Intersection Approach
- Bike Lane Configuration at Intersection Approach

The * next to some factors represent those factors which were collected for both sides of the road. It should be noted that some roads had varying LTS ratings depending on the right or left side roadway characteristics. The authors made the decision to use LTS made of the right side of the roadway due to many one way streets and the right side of the road is typically the driving side for both vehicles and cyclists.

Similar to the methodology used by Mekuria et al. (2012) and the method stated above for the Salem-Keizer area, a geocoded LTS network was created for each city in New Hampshire. For the purposes of this analysis, a visual inspection and basic statistical information was used to understand the correlation between crashes and LTS measurements.

4. Results

4.1 Salem and Keizer, Oregon Case Study

The authors used the Salem-Keizer metropolitan area as the case study. The population for Salem is 154,637 and 36,478 for Keizer. The bicycle commute mode share is 1.62% for Salem and 0.98% for Keizer respectively. The number of households from OHAS within the Salem-Keizer region which traveled on the travel day and owned bicycles is 660. This case study contains three parts: results of a demographic analysis of who has low stress connectivity to downtown, a census based analysis of LTS and mode share, and modeling household bicycle trip production with a household travel survey.

4.1.1 Who Has Low Stress Access? Implications for Bias

We find ample evidence of a demographic self-selection effect now widely seen as significant for understanding the true relationship between the built environment and travel behavior (Brownstone & Golob, 2009; Handy & Mokhtarian, 2005).

Table 4-1 Demographic Differences between Households with different LTS Access

	Access to LTS 1 & 2	No Access to LTS 1 & 2	T-test Results	P-Value
N Households	909	554		
Percent Caucasian	90.50%	83.72%	3.7	0.0075
Percent Income Above $75,000	46.70%	39.10%	2.67	0.0002
At Least 1 Walk/Bike Commuter	32.50%	17.39%	6.43	1E-0.9

Households with low-stress access to downtown, which is also a proxy for being located in the largest island of low stress connectivity, have higher rates of Caucasian and income in the OHAS data as shown in Table 4-1(this is corroborated by the Census data as well). For this reason we attempted to incorporate both variables into our analysis. However, we failed to find a significant correlation between LTS accessibility income in a numeric form (as opposed to the indicator variable format above). To best account for the issues of demographic correlation with connectivity, the models include a battery of demographic variables found to correlate with low-stress connectivity.

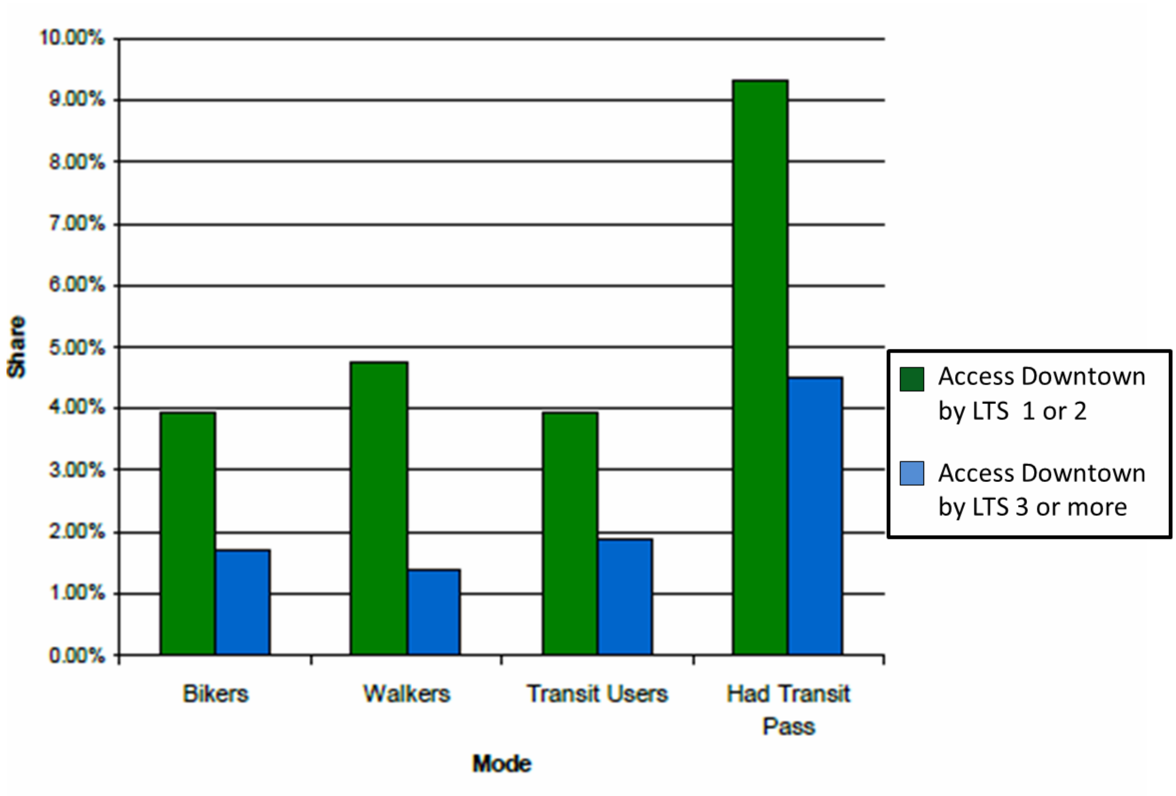

Figure 4-1 Mode share by LTS access to downtown Salem

The results in Figure 4-1 are limited to commuters living within 5 miles of employment. All differences between green and blue groups are significant at 5% level or higher. This suggests that mode choice correlates strongly with good accessibility to downtown. Future research must account for self-selection of certain demographic groups into neighborhoods of higher connectivity and accessibility.

4.1.2 Census Analysis

To utilize census data for a comparison data set, the authors used Census Block Group level mode choice from the 2007-2011 American Community Survey to the island level as shown in Figure 4-2 and Figure 4-3. Roughly five percent of block groups were spread across more than one island and in these situations, the block group's mode data was applied to the island that most inscribed it. The authors find a low stress islands job accessibility did not correlate with its bicycle mode share (aggregated from block group data). However, among survey respondents who commuted downtown, those with low stress access were more likely to bike (and walk, take transit or own a transit pass).

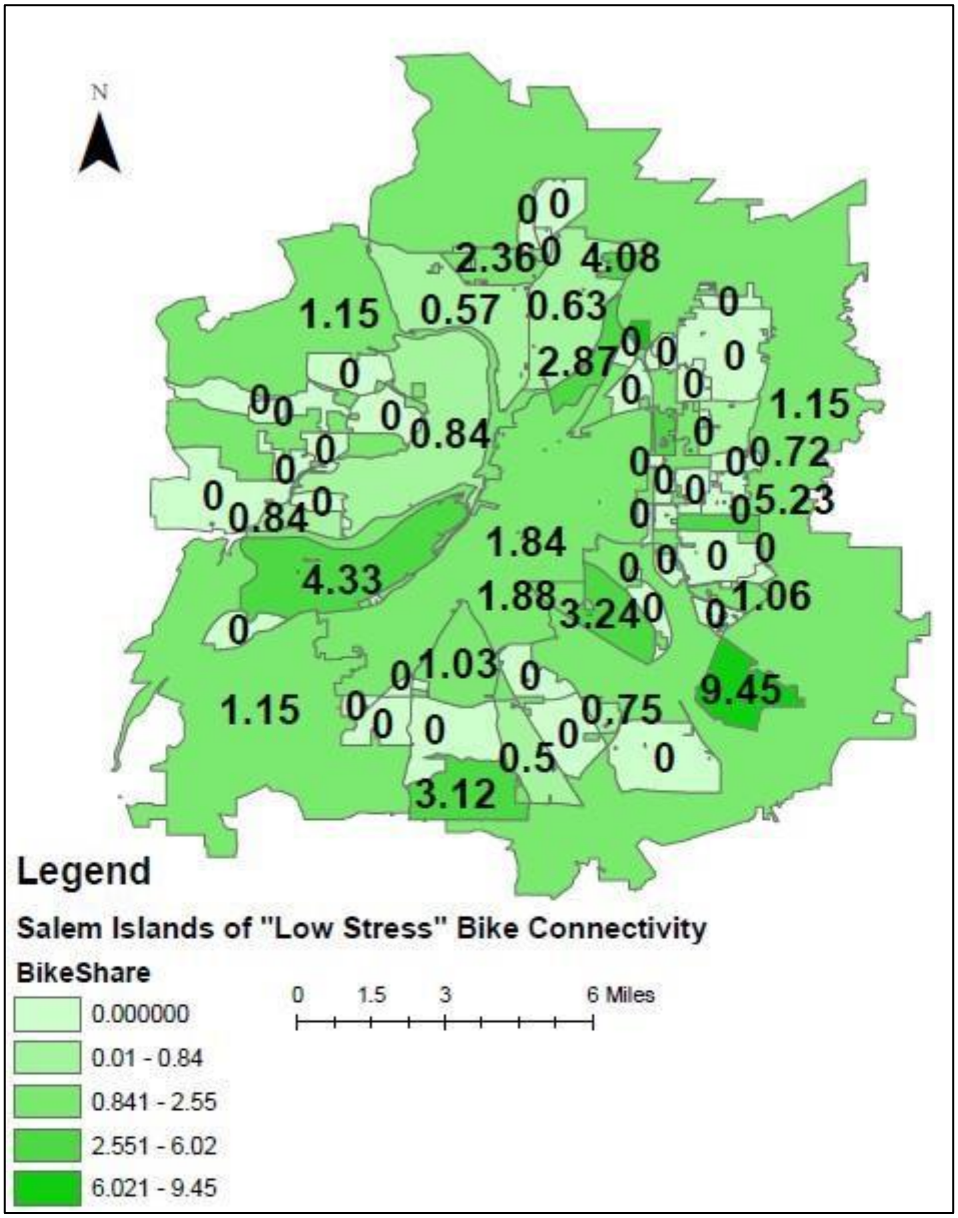

Figure 4-2 Bicycle mode share for low-stress "Islands" in Salem/Keizer (ACS 2007-2011)

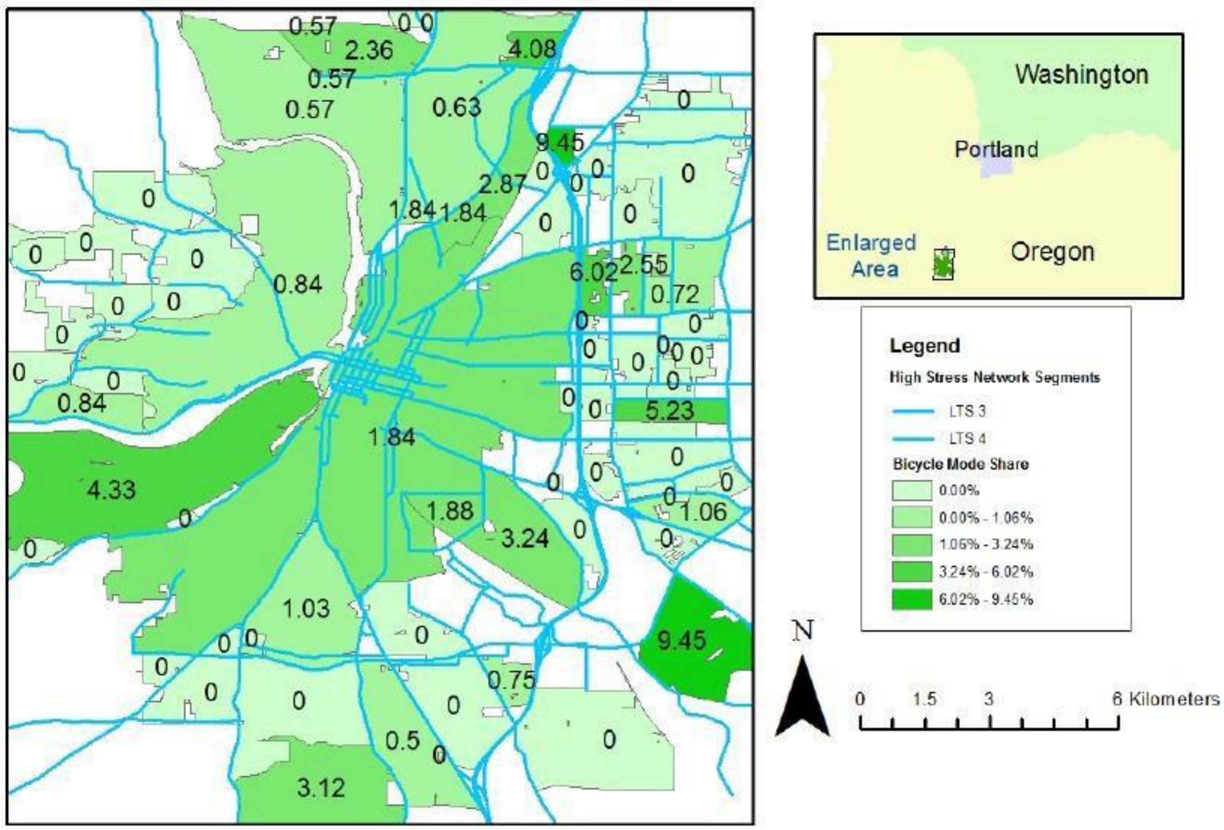

Figure 4-3 "Islands" of High Stress (LTS 3 or 4) Connectivity in Salem/Keizer (ACS 2007-2011)

While illuminating, this data source suffers its own shortfalls. Due to the small geography of a block group, the block group bicycle mode shares possess quite large margins of error. Additionally, this only covers one trip: adult workers' commutes. The difference between trip purposes captured by the Census and OHAS may best explain the divergent results, which are presented next.

4.1.3 Correlation of Low Stress Connectivity to Mode Choice

Figure 4-4 presents percentage of trips that were part of low and high stress tours by mode. Each trip in a tour that had a minimum of one high-stress trip was coded as a high stress tour. Numbers beneath the label for each mode are the values for number of trips by that mode within the scope of the analysis. Walk trips were most likely to be within the same low-stress islands and part of entirely low-stress tours, followed by bicycle and school bus trips.

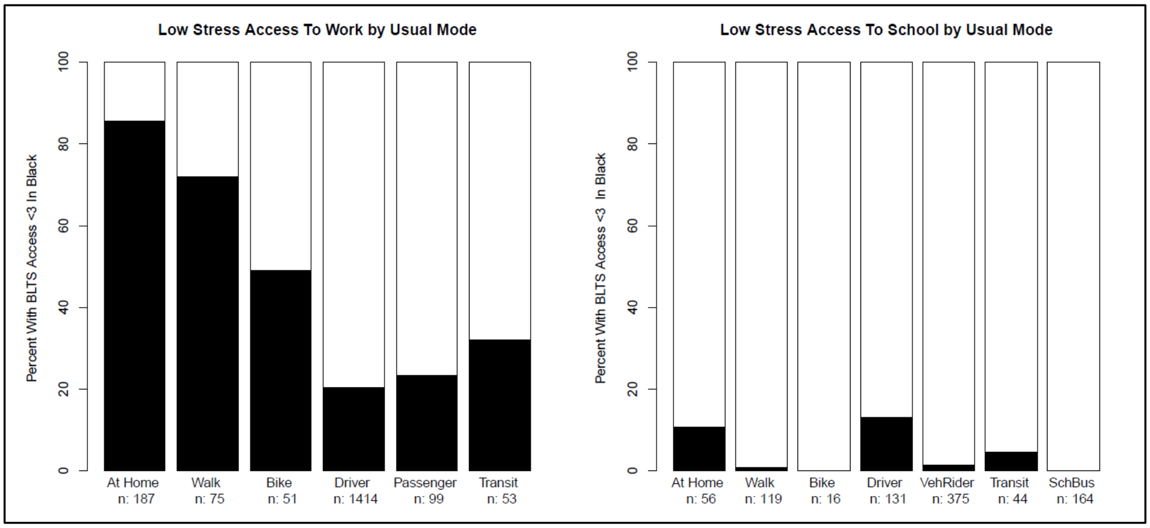

Figure 4-4 Percentage of Workers and Students with Low Stress Access by Usual Mode

Figure 4-5 presents the distribution of workers with respect to whether or not they had high stress or low stress accessibility to their place of employment, sorted by the mode they "usually" took to work as defined by the respondent.

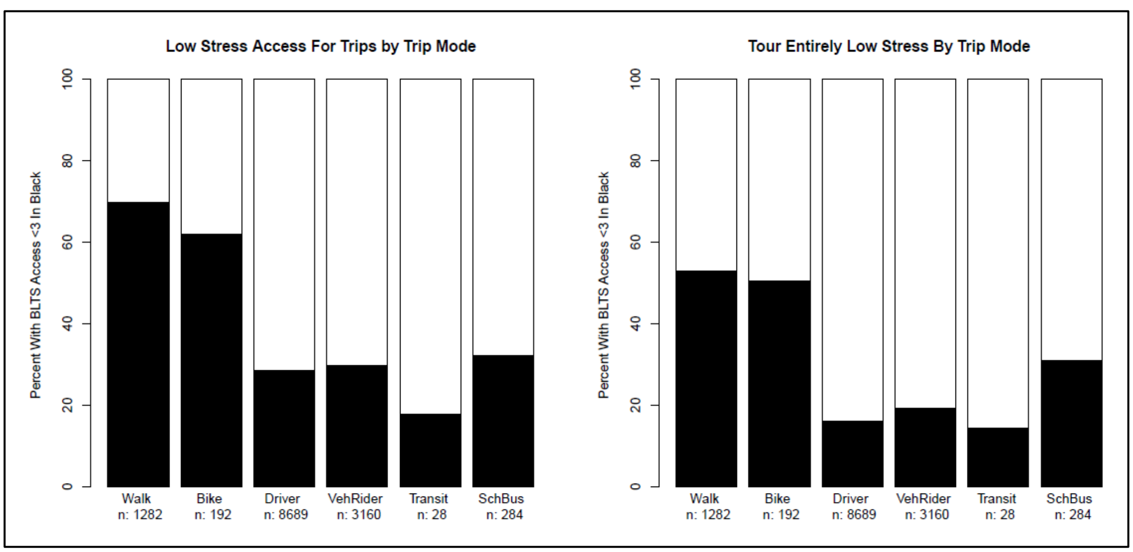

Figure 4-5 Share of Trips with Low Stress Connectivity vs Share of Trips in Low Stress Tours by Mode

Figure 4-6 shows bicycle stress levels by age of the traveler and distance of the trip. In spite of the small sample size of bicycle trips, differences by age confirm the demographic assumptions underlying LTS criteria (Mekuria et al., 2012). Individuals under the age of 18 took trips with low stress accessibility 80% of the time in the sample. This difference to the adult population was confirmed via T-test. This does not necessarily mean they opted for a low stress route, but demonstrates that their trips may be less likely to involve crossing the obstacles cutting off islands like major arterials, highways and rivers.

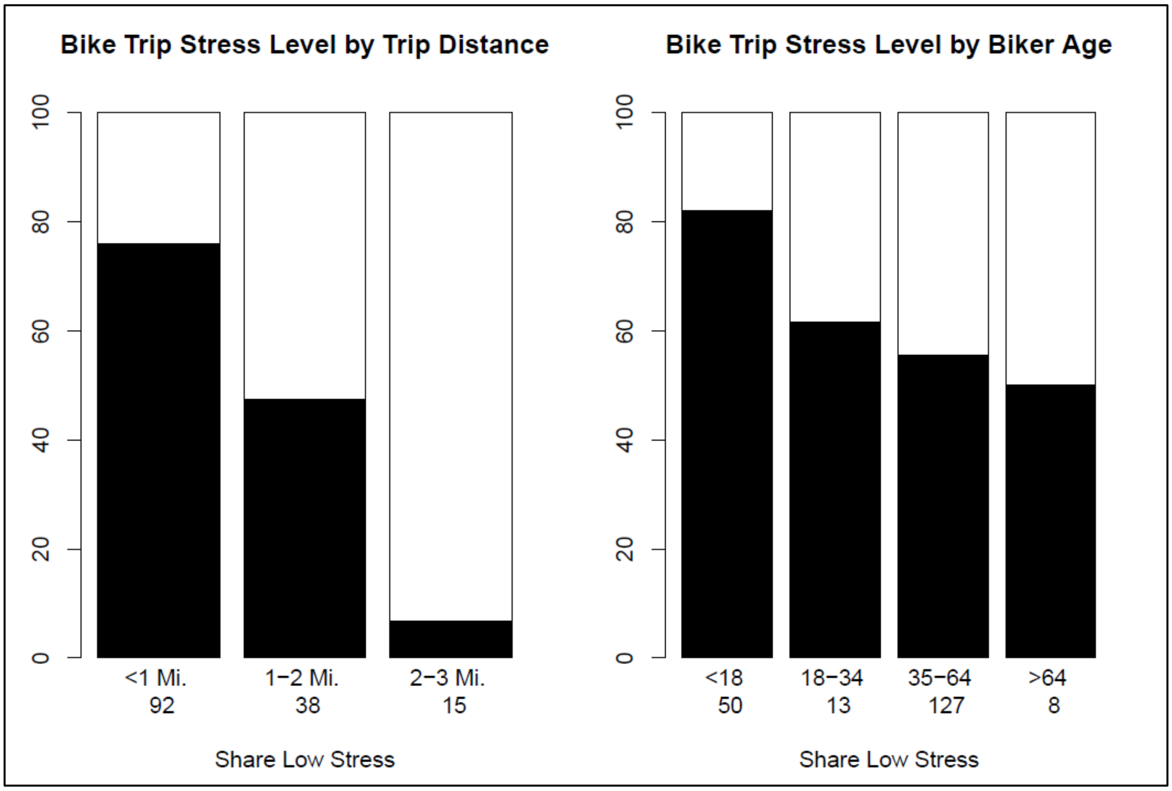

Figure 4-6 Share of Bicycle Trips within Low Stress Island by Distance and Age

Figure 4-7 shows bicycle stress levels by gender and by tour purpose. Again, bicycle trips taken as part of school tours were far more likely to remain within low-stress islands. This may be driven by school placement in suburban neighborhoods with residential streets that the LTS categorize as low stress. A gender gap is slightly visible in the bar chart in Figure 4-7. This was confirmed by T-tests to show a statistically significant difference in the percentage of low stress trips taken by men versus women, with women significantly more likely to be to destinations when a low stress route was available.

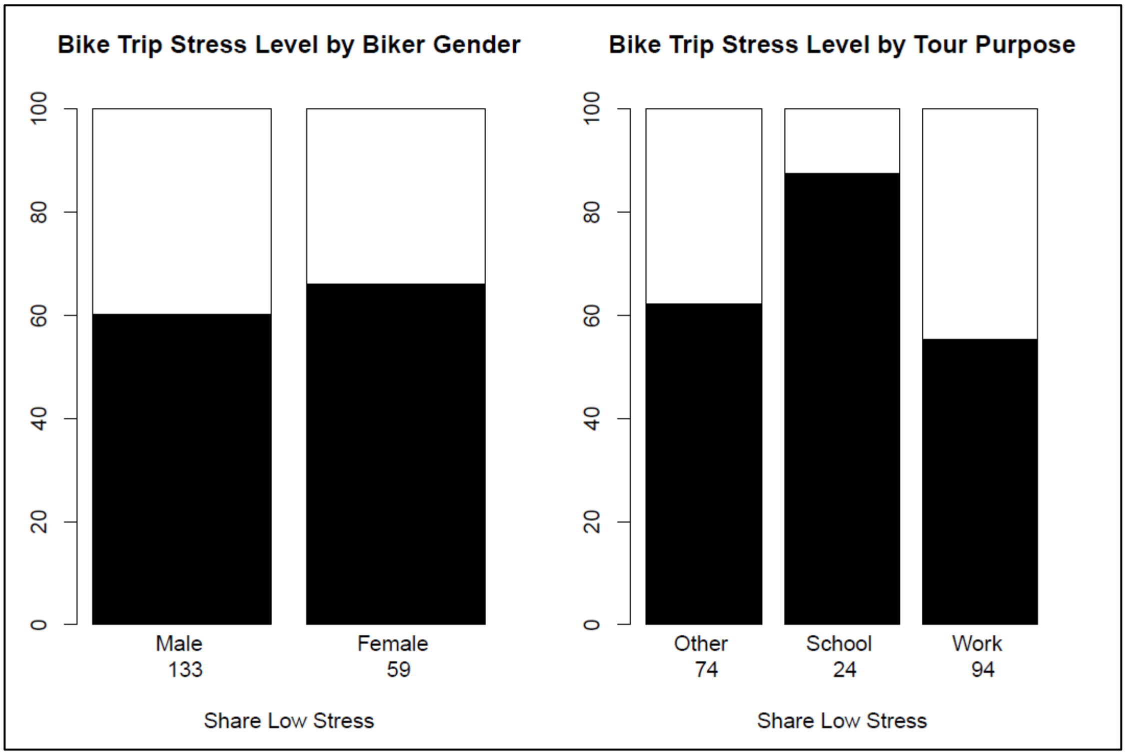

Figure 4-7 Share of Bicycle Trips within Low Stress "Island" by Gender and Purpose

The results presented in this section suggest that as availability of low stress access to destinations increases, mode shares for walking and biking may also increase. Conversely, it could just reflect that existing areas of connectivity happen to contain land uses that trip makers prefer to walk or bike to. Examples of this include trips to coffee shops from downtown work sites, or trips to schools within the same neighborhood. This explanation holds more power given our next set of results relying on census data which fail to find the same correlation when using Census Journey-To-Work commute estimates.

4.2 Correlation to Crash Data: New Hampshire Results

Using the LTS network and crash data points, several maps were created to visually inspect the correlation between crashes and LTS measurements. Figure 4-8, Figure 4-9, Figure 4-10, and Figure 4-11 show these maps and visually it appears that there is some correlation between crash frequencies along LTS 3 type roads. Referring back to Figure 3-3, roads with LTS 2 had the highest frequency of crashes at 292 followed by LTS 3 at 156.

Figure 4-8 City of Concord LTS and Crash Data Points

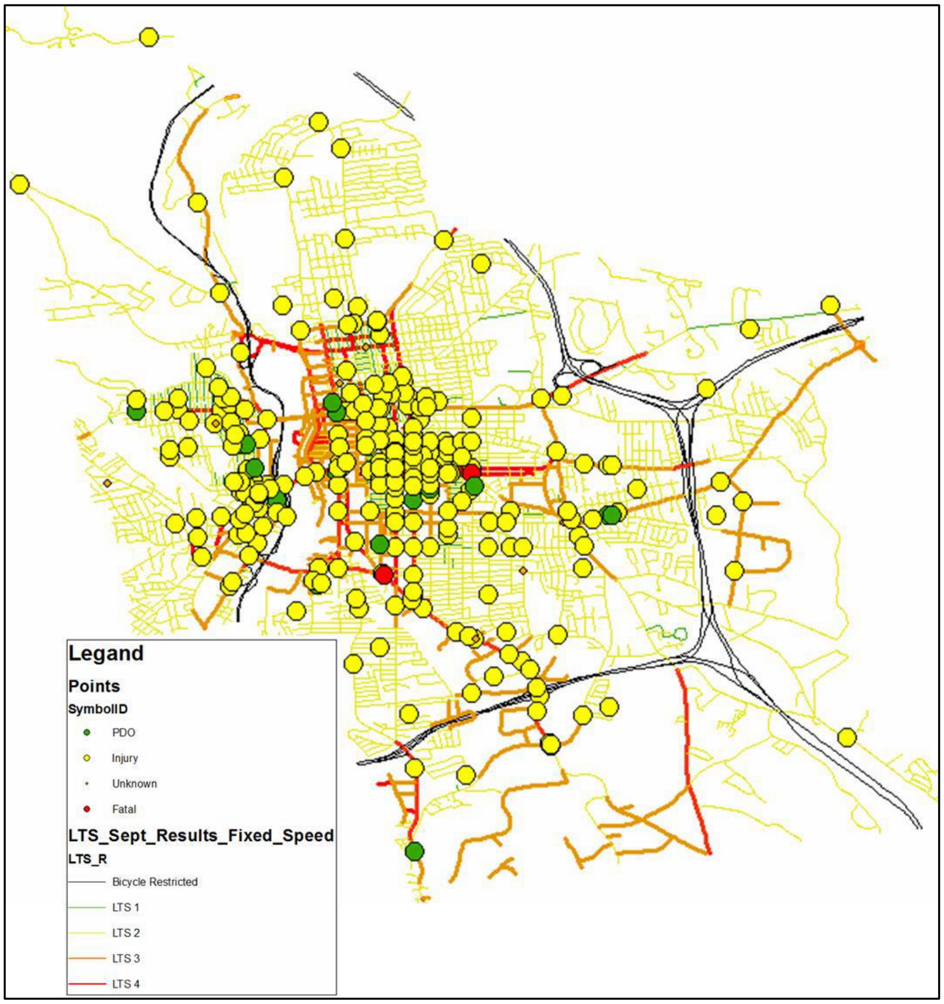

Figure 4-9 City of Manchester LTS and Crash Data Points

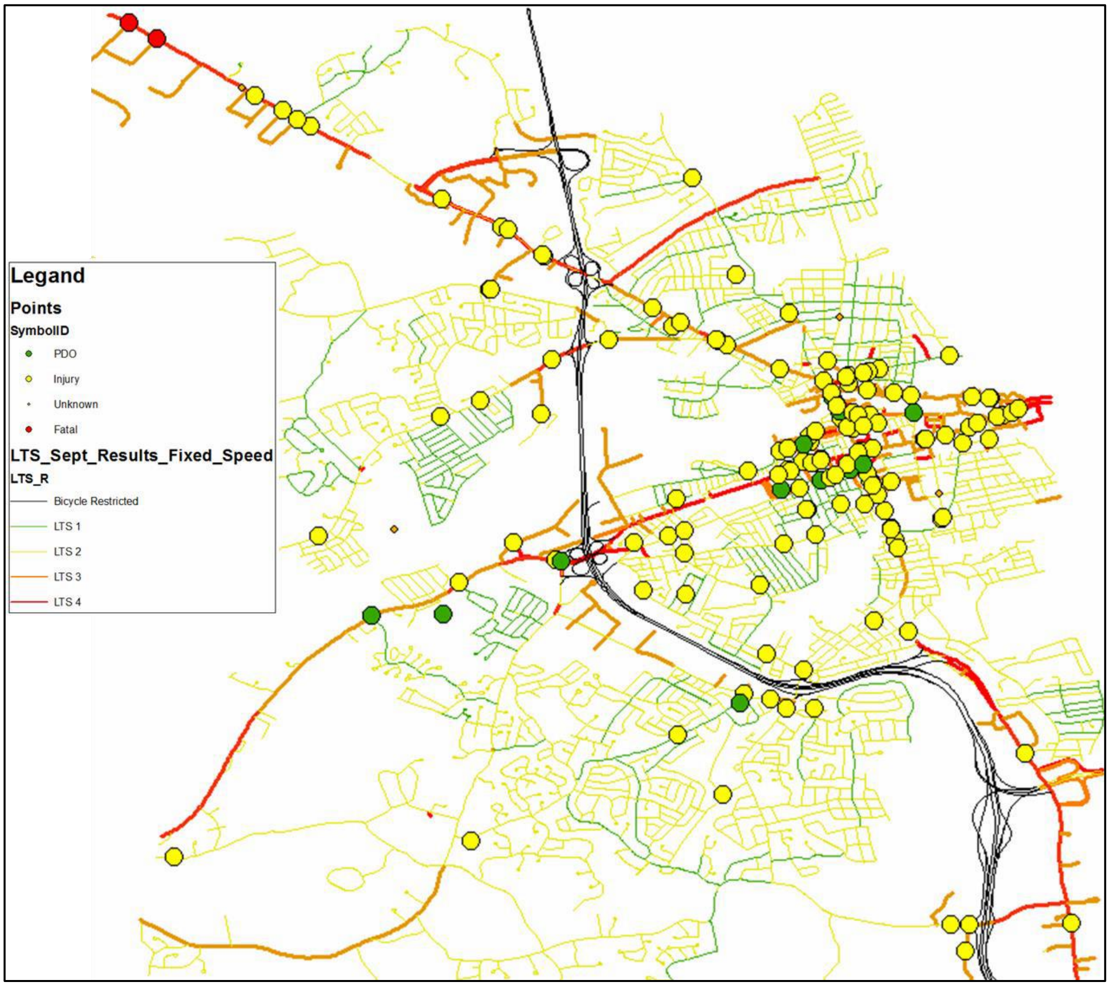

Figure 4-10 City of Nashua LTS and Crash Data Points

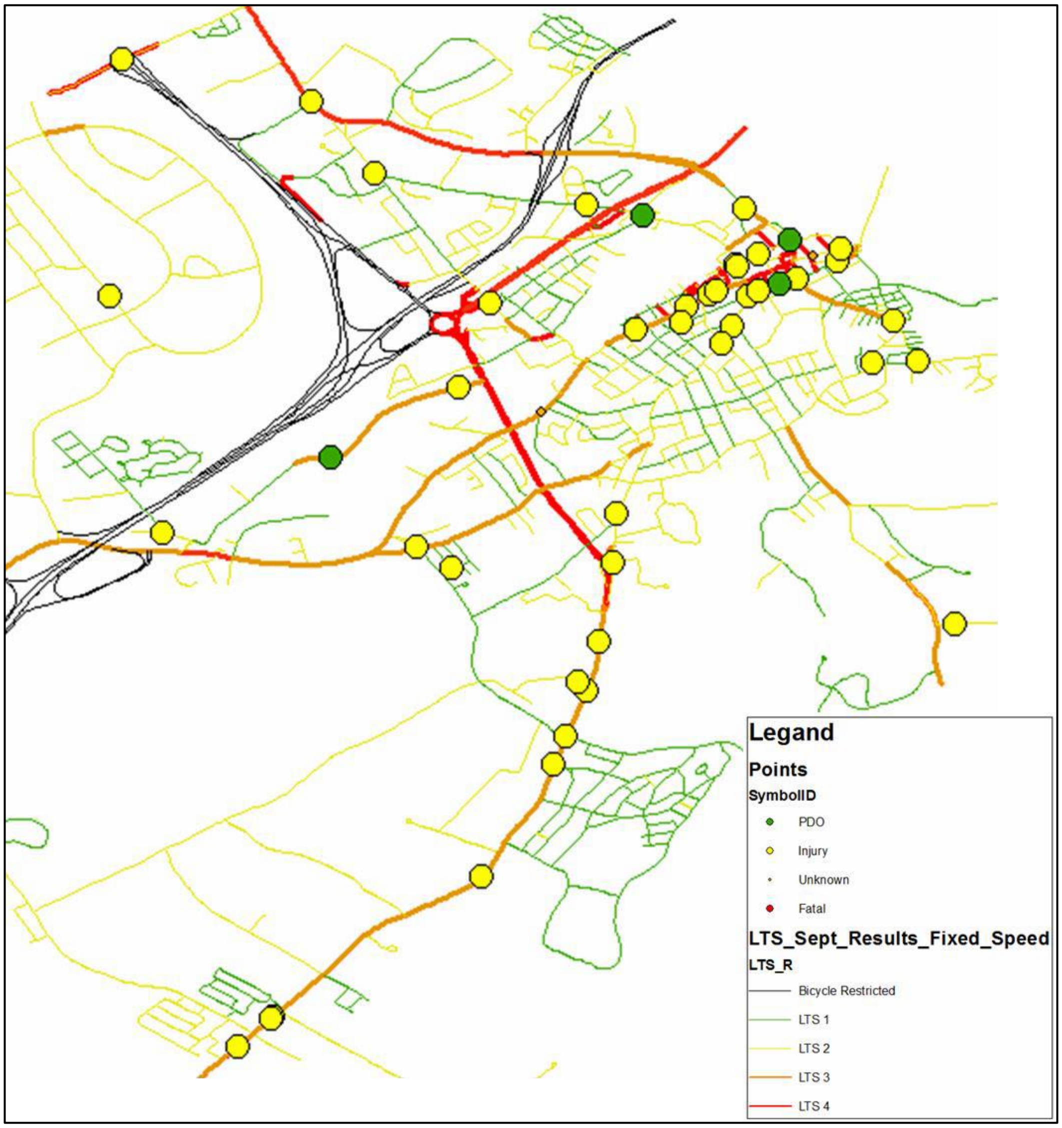

Figure 4-11 City of Portsmouth LTS and Crash Data Points

4.3 ZINBR Model Results

The ZINBR models attempting to predict bicycle trips generated by households are provided in Table 4-2. Models were run with each of the two variables of island size both with and without controls, producing four models. Theta values suggest serious violation of equidispersion in the dataset, confirming the need to use zero-inflated negative binomial regression over Poisson. Based on chi-squared tests, all models were statistically significant. In each run, variables representing low-stress island access correlated positively and significantly with bicycle trip rates. This is the case in spite of the addition of neighborhood controls of intersection density and population density.

Table 4-2 Bike Trip Model Coefficient Results

Variable--Count Model	**No Controls**	**Controls**	**No Controls**	**Controls**
Intercept	-1.6	-1.4	1.29**	1.49
Household Size	-0.02	-0.03	-0.00	-0.00
Household Number of Students	0.16	0.17	0.15	0.16
Single Family Unit	0.27	0.4	0.32	0.42
Household Is Caucasian	-0.17	-0.12	-0.19	-0.13
Home Owned By Occupant	-0.47	-0.69^	-0.54	-0.74^
Log Island Area Square Miles			0.3**	0.3*
Log Island Population Per Square Mile	0.27**	0.27*		
Log Block Group Housing Per Square Mile		0.00		-0.00
Log Block Group Intersection Density		0.00		0.00
Log Theta	2.0	2.28	2.1	2.37
Variable--Selection Model				
Intercept	3.91	3.77	1.75**	2.05**
Household Size	0.11	-0.16	0.11	0.12
Household Number of Students	-0.15	-0.17	-0.14	-0.16
Single Family Unit	0.82	0.93^	.89	.99^
Household Is Caucasian	-0.86	-0.86^	-.83^	-.85^
Home Owned By Occupant	-0.23	-.34	-.25	-.36
Log Island Area Square Miles			-.21^	-.17
Log Island Population Per Square Mile	-0.19	-.16		
Log Block Group Housing Per Square Mile		.00		.00
Log Block Group Intersection Density		-.01		-.01
Theta	7.43	9.81	8.14	10.7
Log-Likelihood	-319.7	-316.9	-318.1	-315.4
Chi-Squared P-Value	.004	0.001	0.002	0.002
AIC	669.39	671.89	666.12	668.8
Significance codes: ^.1, *.05, **.01, ***.001				

The bottom half of each column presents the results of the selection models predicting the probability that a unit would produce zero bike trips. In three of the models, a household that identified as Caucasian reduced the probability of the household producing zero bike trips and the result was significant, as we might expect given the demographic analysis indicating households that identified as Caucasian had better low-stress connectivity. In the two models that controlled for neighborhood characteristics, the single family unit indicator variable correlated positively with the probability of a household producing zero bike trips. In the home ownership models, however, household ownership correlated negatively with bicycle counts and the result was significant. The neighborhood control variables were insignificant in both the zero-selection models and the count models.

The results for the models producing walk and bike trips are presented in Table 4-3. In the selection models, the household's number of students correlated negatively and significantly with the probability of the household making no walk or bike trips. Home ownership correlated positively and significantly with households making no walk or bike trips yet living in a single family unit correlated negatively and significantly with households producing zero walk or bike trips. This suggests renters, particularly those in single family units, walk and bike more in the Salem area. This is consistent with prior research.

Table 4-3 Walk and Bike Trips Model Coefficient Results

Variable--Count Model	No Controls	Controls	No Controls	Controls
Intercept	-1.39*	-1.65***	0.89*	0.91**
Household Size	0.25**	0.28	0.26**	0.29***
Household Number of Students	-0.06	-0.01	-0.07	-0.11
Single Family Unit	-0.32	-0.41^	-0.3	-0.39
Household Is Caucasian	-0.18	-0.14	-0.21	-0.18
Home Owned By Occupant	0.11	0.2	0.08	0.16
Log Island Area Square Miles			0.2***	0.225***
Log Island Population Per Square Mile	0.21***	0.24***		
Log Block Group Housing Per Square Mile		0.00^		0.00^
Log Block Group Intersection Density		-0.02^		-0.01^
Log Theta	0.35	0.31	0.31	0.27
Variable--Selection Model				
Intercept	1.32	0.73	-0.8	0.0332
Household Size	0.064	0.13	0.06	0.14
Household Number of Students	-0.56**	-0.66**	-0.57**	-0.68**
Single Family Unit	-0.56^	-0.104*	-.85^	-1.01^
Household Is Caucasian	-0.07	-0.11	-0.08	-0.013
Home Owned By Occupant	1.25*	1.5*	1.27*	1.51**
Log Island Area Square Miles			-0.14^	-0.05
Log Island Population Per Square Mile	-0.12	-0.03		
Log Block Group Housing Per Square Mile		0.00		0.00
Log Block Group Intersection Density		-0.04^		-0.036^
Theta	1.42	1.36	1.37	1.31
Log-Likelihood	-951.9	-946.7	-952.6	-947.2
Chi-Squared P-Value	2.76E-11	2.14E-12	3.79E-11	2.74E-12
AIC	1933.804	1931.399	1935.11	1932.4
Significance codes: ^.1, *.05, **.01, ***.001				

In the count models, household size correlated positively and significantly with walk and bike trip counts. Neighborhood control variables were significant, but just barely. With or without neighborhood controls included, variables indicating low-stress island size were positive and highly significant.

The key difference between the two datasets different outcomes is that the latter results from OHAS measure all trips, whereas the census data only covers commuting. The other major difference in the models, aggregate versus disaggregate modeling, may also contribute to different results, as the latter aggregations included larger standard errors.

5. Conclusion and Future Work

This report proposed using a household travel survey as observed behavior to evaluate the effectiveness of bicycle level of traffic stress criteria proposed by Mekuria et al. (2012) in explaining bicycling trip rates, mode shares and crash incidents,. Results from the household travel survey confirmed a clear correlation between the availability of low-stress connectivity between households and employment destinations and the mode choice of workers in those households. Those results also confirmed differences in the kinds of bikers willing to take trips that required passing through a high stress link or node. Children on bicycles were far more likely to take trips by bicycle that had low stress routes available compared to adults, and women were significantly more likely to take bicycle trips with low stress options available than men. The availability of low stress routes that are correlated with various demographic attributes of cyclists confirms that the demographic research underpinning the criteria defined by Mekuria et al. (2012). This early analysis suffered drawbacks in having such a small sample of cyclists. Additionally, a regression using census data demonstrated zero correlation between bicycle commute mode share and low stress island connectivity.

Results from visually comparing LTS models and crash data suggest that LTS models can be useful in predicting where crashes are going to occur, specifically LTS 3 predicting where Injury related crashes will occur. Visual results also suggest that LTS 2 has some impact on bicycle crashes. This is an interesting results as it is understood that LTS 2 is a safe route choice and used to determine connectivity. Ultimately, these results show that more research is needed to understand how impactful LTS models are at predicting bicycle crashes.

For the relationship between trip rates and LTS, a next step in this work is examining if discrepancies in the relationship between mode choice or bicycle trip production and low-stress island size are related to the nature of an island's connectivity and its dependency on links many travelers may be unaware of. The various bicycle infrastructure classification systems identified in this report should be comparatively validated on the same set of observed travel behavior. This can enable an examination of the relative power of each criterion, enabling smaller jurisdictions to pick among those criteria relative to the cost of procuring them. This can assist smaller communities in finding the most cost-effective way to prioritize new cycling infrastructure while remaining empirically robust.

In terms of future work to analyze the geospatial correlation between bicycle crashes and LTS measurements different statistical methods could be used such as negative binomial regression model or mixed-logit model to determine what impact LTS types have on the crash severity. Additionally, more robust data could be collected for a smaller study area in order to account for the under-reporting issues that arise when working bicycle crash data. Finally, cities can be analyzed individually and then compared to determine if LTS analysis tools can be used to predict where bicycle crashes will occur. This can also assist planners in finding the most cost-effective way to prioritize bicycle infrastructure improvements.

6. References

Abdel-Aty, M., & Keller, J. (2005). Exploring the overall and specific crash severity levels at signalized intersections. *Accident; Analysis and Prevention*, *37*(3), 417–25. doi:10.1016/j.aap.2004.11.002

Arentze, T. A., & Molin, E. J. E. (2013). Travelers' preferences in multimodal networks: Design and results of a comprehensive series of choice experiments. *Transportation Research Part A: Policy and Practice*, *58*, 15–28. doi:10.1016/j.tra.2013.10.005

Broach, J., Dill, J., & Gliebe, J. (2012). Where do cyclists ride? A route choice model developed with revealed preference GPS data. *Transportation Research Part A: Policy and Practice*, *46*(10), 1730–1740. doi:10.1016/j.tra.2012.07.005

Brownstone, D., & Golob, T. F. (2009). The impact of residential density on vehicle usage and energy consumption. *Journal of Urban Economics*, *65*(1), 91–98. doi:10.1016/j.jue.2008.09.002

Campbell, M., & Lyons, G. (2008). Wayfinding in the Urban Environment. *Universities Transport Study Group Conference*, *40*(January), 13.

Caulfield, B., Brick, E., & McCarthy, O. T. (2012). Determining bicycle infrastructure preferences – A case study of Dublin. *Transportation Research Part D: Transport and Environment*, *17*(5), 413–417. doi:10.1016/j.trd.2012.04.001

Cervero, R., & Duncan, M. (2003). Walking, Bicycling, and Urban Landscapes: Evidence from the San Francisco Bay Area. *American Journal of Public Health*, *93*(9), 1478–1483. doi:10.2105/AJPH.93.9.1478

Dill, J., & Carr, T. (2003). Bicycle Commuting and Facilities in Major U.S. Cities: If You Build Them, Commuters Will Use Them. *Transportation Research Record*, *1828*(1), 116–123. doi:10.3141/1828-14

Dixon, K., Monsere, C., Xie, F., & Gladhill, K. (2012). *Calibrating The Future Highway Safety Manual Predictive Methods For Oregon State Highways*. *FHWA-OR-RD-12-07*. Salen.

Eluru, N., Bhat, C. R., & Hensher, D. a. (2008). A mixed generalized ordered response model for examining pedestrian and bicyclist injury severity level in traffic crashes. *Accident; Analysis and Prevention*, *40*(3), 1033–54. doi:10.1016/j.aap.2007.11.010

Ewing, R., & Cervero, R. (2001). Travel and the Built Environment: A Synthesis. *Transportation Research Record*, *1780*(1), 87–114. doi:10.3141/1780-10

Faghih-Imani, A., & Eluru, N. (2015). Analysing bicycle-sharing system user destination choice preferences: Chicago's Divvy system. *Journal of Transport Geography*, *44*, 53–64. doi:10.1016/j.jtrangeo.2015.03.005

Geller, R. (2013). *Four Types of Cyclists*. *Portland Office of Transportation*.

Goodman, A., & Cheshire, J. (2014). Inequalities in the London bicycle sharing system revisited: impacts of extending the scheme to poorer areas but then doubling prices. *Journal of Transport Geography*, *41*, 272–279. doi:10.1016/j.jtrangeo.2014.04.004

Greibe, P. (2003). Accident Prediction Models for Urban Roads. *Accident Analysis & Prevention*, *35*(May 2001), 273–285.

Habib, K. N., Mann, J., Mahmoud, M., & Weiss, A. (2014). Synopsis of bicycle demand in the City of Toronto: Investigating the effects of perception, consciousness and comfortability on the purpose of biking and bike ownership. *Transportation Research Part A: Policy and Practice*, *70*, 67–80. doi:10.1016/j.tra.2014.09.012

Haleem, K., & Abdel-Aty, M. (2010). Examining traffic crash injury severity at unsignalized intersections. *Journal of Safety Research*, *41*(4), 347–57. doi:10.1016/j.jsr.2010.04.006

Handy, S., & Mokhtarian, P. (2005). Which Comes First: The Neighborhood or the Walking? *Access*, *26*, 16–21. Retrieved from http://www.des.ucdavis.edu/faculty/handy/walking_or_neighborhood.pdf

Hood, J., Sall, E., & Charlton, B. (2011). A GPS-based bicycle route choice model for San Francisco, California. *Transportation Letters: The International Journal of Transportation Research*, *3*(1), 63–75. doi:10.3328/TL.2011.03.01.63-75

Jang, T. Y. (2005). Count Data Models for Trip Generation. *Journal of Transportation Engineering*, *131*(6), 444–450. doi:10.1061/(ASCE)0733-947X(2005)131:6(444)

Kang, K., & Lee, K. (2011). Development of a Bicycle Level of Service Model from the User's Perspective. *KSCE Journal of Civil Engineering*, *16*(6), 1032–1039. doi:10.1007/s12205-012-1146-z

Kim, J.-K., Kim, S., Ulfarsson, G. F., & Porrello, L. a. (2007). Bicyclist Injury Severities in Bicycle-Motor Vehicle Accidents. *Accident; Analysis and Prevention*, *39*(2), 238–51. doi:10.1016/j.aap.2006.07.002

Landis, B., Vattikuti, V., & Brannick, M. (1997). Real-Time Human Perceptions: Toward a Bicycle Level of Service. *Transportation Research Record: Journal of the Transportation Research Board*, *1578*, 119–126. doi:http://dx.doi.org/10.3141/1578-15

Larsen, J., Patterson, Z., & El-Geneidy, A. (2013). Build It. But Where? The Use of Geographic Information Systems in Identifying Locations for New Cycling Infrastructure. *International Journal of Sustainable Transportation*, *7*(4), 299–317. doi:10.1080/15568318.2011.631098

Lee, C., & Abdel-Aty, M. (2005). Comprehensive analysis of vehicle-pedestrian crashes at intersections in Florida. *Accident; Analysis and Prevention*, *37*(4), 775–86. doi:10.1016/j.aap.2005.03.019

Li, Z., Wang, W., Liu, P., & Ragland, D. R. (2012). Physical environments influencing bicyclists' perception of comfort on separated and on-street bicycle facilities. *Transportation Research Part D: Transport and Environment*, *17*(3), 256–261. doi:10.1016/j.trd.2011.12.001

Lundberg, B., & Weber, J. (2014). Non-motorized transport and university populations: an analysis of connectivity and network perceptions. *Journal of Transport Geography*, *39*, 165–178. doi:10.1016/j.jtrangeo.2014.07.002

Martínez-Ruiz, V., Lardelli-Claret, P., Jiménez-Mejías, E., Amezcua-Prieto, C., Jiménez-Moleón, J. J., & Luna del Castillo, J. D. D. (2013). Risk factors for causing road crashes involving cyclists: An application of a quasi-induced exposure method. *Accident; Analysis and Prevention*, *51*, 228–37. doi:10.1016/j.aap.2012.11.023

Mekuria, M. C., Furth, P. G., & Nixon, H. (2012). *Low-Stress Bicycling and Network Connectivity*. San Jose. Retrieved from http://transweb.sjsu.edu/PDFs/research/1005-low-stress-bicycling-network-connectivity.pdf

Milakis, D., & Athanasopoulos, K. (2014). What about people in cycle network planning? applying participative multicriteria GIS analysis in the case of the Athens metropolitan cycle network. *Journal of Transport Geography*, *35*, 120–129. doi:10.1016/j.jtrangeo.2014.01.009

Moahn, D., Tiwari, G., Khayesi, M., & Nafukho, F. M. (2006). Risk Factors for Road Traffic Injuries. In *Road Traffic Injury Prevention: Training Manual* (pp. 21–40). Geneva: World Health Organization.

Monsere, C., Dill, J., McNeil, N., Clifton, K., Foster, N., & Goddard, T. (2014). *Lessons from the Green Lanes: Evaluating Protected Bike Lanes in the U . S* . doi:NITC-RR-583

Mountain, L., & Jarrett, D. (1996). Accident Prediction Models for Roads with Minor Junctions. *Accident Analysis & Prevention*, *28*(6), 695–707.

Oh, J., Jun, J., Kim, E., & Kim, M. (2008). Assessing Critical Factors Associated with Bicycle Collisions at Urban Signalized Intersections. *Transportation Reserach Board*, 1–17.

Pai, C.-W. (2011). Overtaking, rear-end, and door crashes involving bicycles: an empirical investigation. *Accident; Analysis and Prevention*, *43*(3), 1228–35. doi:10.1016/j.aap.2011.01.004

Petritsch, T., Landis, B., Huang, H., & Challa, S. (2006). Sidepath Safety Model: Bicycle Sidepath Design Factors Affecting Crash Rates. *Transportation Research Record*. doi:10.3141/1982-25

Providelo, J. K., & da Penha Sanches, S. (2011). Roadway and traffic characteristics for bicycling. *Transportation, 38*(5), 765–777. doi:10.1007/s11116-011-9353-x

Rybarczyk, G., & Wu, C. (2010). Bicycle Facility Planning Using GIS and Multi-Criteria Decision Analysis. *Applied Geography*, *30*(2), 282–293. doi:10.1016/j.apgeog.2009.08.005

Schepers, J. P., Kroeze, P. a, Sweers, W., & Wüst, J. C. (2011). Road factors and bicycle-motor vehicle crashes at unsignalized priority intersections. *Accident; Analysis and Prevention*, *43*(3), 853–61. doi:10.1016/j.aap.2010.11.005

Schepers, P., & den Brinker, B. (2011). What do cyclists need to see to avoid single-bicycle crashes? *Ergonomics*, *54*(4), 315–27. doi:10.1080/00140139.2011.558633

Sener, I. N., Eluru, N., & Bhat, C. R. (2009). An analysis of bicycle route choice preferences in Texas, US. *Transportation*, *36*(5), 511–539. doi:10.1007/s11116-009-9201-4

Sherwin, H., & Melia, S. (2012). Cycle Mapping in the UK and the “London Cycle Map,” 1–49. Retrieved from http://eprints.uwe.ac.uk/17899/

Stone, M., & Broughton, J. (2003). Getting off your bike: cycling accidents in Great Britain in 1990–1999. *Accident Analysis & Prevention*, *35*(4), 549–556. doi:10.1016/S0001-4575(02)00032-5

Tilahun, N. Y., Levinson, D. M., & Krizek, K. J. (2007). Trails, lanes, or traffic: Valuing bicycle facilities with an adaptive stated preference survey. *Transportation Research Part A: Policy and Practice*, *41*(4), 287–301. doi:10.1016/j.tra.2006.09.007

Titze, S., Stronegger, W. J., Janschitz, S., & Oja, P. (2008). Association of built-environment, social-environment and personal factors with bicycling as a mode of transportation among Austrian city dwellers. *Preventive Medicine*, *47*(3), 252–9. doi:10.1016/j.ypmed.2008.02.019

Vandenbulcke, G., Thomas, I., & Int Panis, L. (2014). Predicting cycling accident risk in Brussels: a spatial case-control approach. *Accident; Analysis and Prevention*, *62*, 341–57. doi:10.1016/j.aap.2013.07.001

Walker, I. (2007). Drivers overtaking bicyclists: objective data on the effects of riding position, helmet use, vehicle type and apparent gender. *Accident; Analysis and Prevention*, *39*(2), 417–25. doi:10.1016/j.aap.2006.08.010

Wang, Y., & Nihan, N. L. (2004). Estimating the Risk of Collisions between Bicycles and Motor Vehicles at Signalized Intersections. *Accident Analysis & Prevention, 36*(3), 313–321.

Wierda, M., & Brookhuis, K. A. (1991). Analysis of cycling skill: A cognitive approach. *Applied Cognitive Psychology*, *5*(2), 113–122. doi:10.1002/acp.2350050205

Winters, M., Davidson, G., Kao, D., & Teschke, K. (2011). Motivators and deterrents of bicycling: Comparing influences on decisions to ride. *Transportation*, *38*(1), 153–168. doi:10.1007/s11116-010-9284-y