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The Impacts of the Bicycle Network on Bicycling Activity: a Longitudinal Multi-City Approach

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The Impacts of the Bicycle Network on Bicycling Activity:

A Longitudinal Multi-City Approach

by

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A dissertation submitted in partial fulfillment of the
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in
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Abstract

Bicycling is a promising approach to improve health, environment, and economic development of urban places. Theoretically, a bicycle network's component goes beyond lanes and paths, and would generate greater impacts than the sum of its parts. However, most previous research focused on how individual types of bicycle-related infrastructure could promote bicycling. Few empirical studies investigated how bicycle networks impact bicycling activity. This project attempts to address this question. Specifically, how to properly measure bicycle networks, and what impacts bicycle networks have on bicycling activity, e.g. bike ridership and bike mode choice, across different cities and longitudinally.

To address the first question, I constructed two types of bicycle network measures – the regional level measures and the route level measures – based on the definition of Level of Traffic Stress from Mekuria et al. (2012). Then I adjusted these measures to better account for the bike networks in the two US case cities, Portland, OR and Minneapolis, MN. To address the second question, I first used regression approaches to examine the correlational relationship between bicycle networks and bicycling ridership in both case cities. Then, I studied the causal relationship between bicycle networks and bike ridership using the Difference-In-Difference (DID) approach. Finally, I evaluated the robustness of the relationship between bike networks and bicycling activity using a different output measure, bike mode choice, and a different dataset.

The results suggested the bicycle network measures that incorporated the morphology, connectivity and comfort characteristics provided a more complete view of the network

property. The low stress bicycle network was associated with high bicycle ridership and high probability of choosing bikes among other travel modes. In addition, the results also indicated that improvements in bicycle networks would disproportionally benefit disadvantaged populations, such as female and low-income groups, more by increasing their possibilities of riding bikes. However, no causal relationship could be inferred between bike networks and bicycling ridership, which is potentially explained by some limitations of applying DID approach to my datasets. Future research is needed to further explore the causal relationship between bicycle networks and bicycling activity using other approaches.

Acknowledgements

This project would not be possible without the help and support from many people. First and foremost, I would like to express my deepest gratitude to my advisor Dr. Jenny Liu. During the past five and a half years, she offered me many opportunities to conduct different types of cutting-edge research, and guided me to form my own research framework. She spent tons of time to discuss the details of my research with me, and provided constructive suggestions on my work. I would like to express my gratitude to Dr. Jennifer Dill. The idea of this dissertation was inspired by her work, and the research design was also guided by her expertise. She always gave me very insightful comments on how to improve the work along the way. I would like to thank Dr. Liming Wang. The idea and method of the mode choice part of this project was developed from his discrete choice modeling class. He is always very patient when answering my questions, and he offered me guidance on broadening the research approach. I also want to thank Dr. Jong Sung Kim. Under his supervision, I received very comprehensive statistical training, which provided me the necessary skills to complete this work.

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Finally, I owe my sincere gratitude to my family. Coming abroad to pursue this degree is an adventure in my life. Their understanding and support were critical for me to get through many challenges. In particular, I would like to thank my husband Foen, who always stands by me and gives me full support. My three-month old son Easton deserves a special mention. His arrival gives me new insights to the world, and new inspiration of what I should pursue in the future!

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Introduction

Bicycling is a promising approach to improve health, environment, and economic development of urban places. While most previous research focuses on how individual types of bicycle-related infrastructure can promote bicycling, emerging studies are directing effort towards bicycle network analysis. Bicycle network forms connected paths to enable bicyclists to travel smoothly and safely between origins and destinations. A bicycle network goes beyond the individual components, such as lanes and intersections, and it focuses on the overall connection of nodes (intersections) and links (lanes). Theoretically, bicycle network would generate greater impacts than the sum of its parts (Buehler & Dill, 2016). The current bicycle network research examined many perspectives of a network, such as graphical design, quality of service (e.g. level of traffic street (LTS), level of service (LOS)), and access to destinations, etc. However, few empirical studies looked at how bicycle network influenced bicycling activity. Moreover, no studies have utilized a longitudinal design, which is necessary to establish the causal relationship between the bicycle network and bicycle outcomes.

This project will address the following research question – how do bicycle networks, instead of individual bicycle facilities, impact bicycle activities? In particular, this project will tackle the following sub-questions:

- Q 1: How to measure bicycle networks? The network measures are often sensitive to geographical scales (i.e. neighborhood, corridor, etc.), so what are the proper measures to define bicycle networks at different scales?

- Q 2: The improvement of bicycle network tends to provide more bike-able environment to promote bicycling. What impacts bicycle networks have on bicycling activity? In particular,
    - Q 2.1: How do bicycle networks influence bike ridership?
    - Q 2.2: Is there any cause relationship between bicycle networks and bicycle ridership?
    - Q 2.3: How do bicycle networks influence bike mode choice?

Literature Review

Bicycle Network

As defined by a FHWA report (2016), an active transportation network "consists of a series of interconnected facilities that allow non-motorized road users of all ages and abilities to safely and conveniently get where they need to go". Six principles, which are Cohesion, Directness, Accessibility, Alternative, Safety and Security, and Comfort, are identified to form a complete active transportation network (Louch et al., 2016):

- Cohesion: a connected and cohesive active transportation facilities between destinations;
- Directness: minimize distance that pedestrians and bicyclists reach destinations;
- Accessibility: designed for all users, regardless of age and ability;
- Alternatives: route options for different types of users;
- Safety and security: minimize risk of injury, danger and crime;
- Comfort: create more welcoming amenities and environment.

A recent FHWA report (2018) also defines five key components of bicycle network connectivity: network completeness, network density, route directness, access to destinations, and network quality.

As described in the definitions above, the bicycle network goes beyond individual active transportation infrastructure links or nodes; it emphasizes the connectivity of the infrastructures, the comfort and safety of riding, and access to destinations by different groups of population. It accounts for the route characteristics, the most important bicycle travel attribute. In practice, three types of measures are commonly used to evaluate the bicycle network: network topology measures, level of stress measures, and route quality measures. Access to destinations can also be overlaid on each of these measures using land use or parcel data.

Network Topology

The network topology examines the arrangement of nodes and links, especially their location and nature of their connectivity; in other words, network topology describes the transportation structure and flow, which determines the efficiency of the network. One of the common methods to measure network topology is graph theory. Graph theory was introduced to the transportation geography field since Garrison and Marble (1962), and this method is now commonly applied in transportation research (Dill, 2004; Rodriguez, Comtois, & Slack, 2009; Schoner & Levinson, 2014). Simple graph theory measures included network density, cul-de-sac density, alpha index (α), gamma index (γ) and so on. Some studies used factor analysis to categorize these graphic measures to transportation network terminology, such as connectivity, fragmentation and directness, etc. (Schoner & Levinson, 2014). The unit of analysis can be adjusted to different geographical scales for these measures based on different research objectives.

Beyond the pure graph typology measures, additional measures are designed to account for both typology characteristics and travel attributes. For example, effective walking area measures the ratio of number of parcels within a quarter mile walking distance of a node to the total number of parcels within a one-quarter mile radius of that node; Route directness measures the ratio of route distance to straight-line distance. These measures include OD (origins and destinations) and land parcel components to typology measures. (Dill, 2004; Rodrigue et al., 2009)

Quality of the Network

Bicycle is a travel mode for which the quality of the route network truly affects the comfort and safety of the travelers. The network quality determines the attractiveness of this mode. Therefore, recent studies have designed multiple measures to evaluate the quality of the bicycle infrastructure and network.

Initially developed by Landis et al. (1997), bicycle level-of-service models were calibrated to estimate bicycle quality. Highway Capacity Manual (HCM) (Huff & Liggett, 2014) defines bike level-of-service (BLOS) such that the quality of the each network link is a function of bicycle infrastructure attributes (i.e. bike lane type, width, etc.) as well as roadway attributes (i.e. motorized traffic speed, volume, number of lanes, share of heavy vehicles, etc.).

An alternative network quality measure is the Bicycle Level of Traffic Stress (LTS) developed by Mekuria et al. (2012). It is based on the concept of minimizing cyclist stress during a trip. Each road segment is classified on a four-point scale metric, based on separation from motor vehicle traffic, number of lanes, width of bike lane, vehicle speed limit, bike lane blockage and mix traffic, all of which contribute to cyclist stress. The characteristics of intersections, such as pocket bike lanes, presence of right turn lane, and signal timing, are also incorporated in the LTS metric. The LTS approach has been favored by practitioners and researchers because it does not require as intensive datasets as the BLOS measures, such as share of heavy vehicles and vehicle volumes. It allows agencies to create a complete bicycle network classification using readily available datasets (H. Wang et al., 2016).

Bike-ability is an additional approach to evaluate quality of the network. One example is the bike-ability index developed in Winters et al.'s (2013) article, which composited of five factors: bike facility availability, bike route separation, street connectivity, topography and land use. The combination of the weights of five factors was derived from a focus group survey that examined the importance of each bike-ability component.

Route Quality

Bicycle network can be evaluated through individual route quality that is derived from the results of route choice models (2013). Lowry et al. (2016) assessed the bicycle network connectivity by calculating access to important destinations via the shortest paths, which is derived from bicycling route choice behavior research results (J. Broach et al., 2012; Hood et al., 2011). In particular, they applied the concept of marginal rate of substitution[1] (MRS) to determine the stress of links and nodes in each route, and calculated the accessibility of residents to important destinations in the city.

Broach and Dill (2017) firstly tested a route quality measure - quality-weighted distance, taking into account the perceived travel cost based on route preference and willingness to detour. A route with more negative factors such as steep grades or heavy mixed traffic

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[1] The marginal rate of substitution (MRS) is the rate at which a consumer can give up of one good in exchange for another good while maintaining the same level of utility.

would have a higher weighted distance than its actual length; while a route with more positive factors, such as off-street trails, might have a lower weighted distance than its actual length.

Bicycle Network and Travel Behavior

Existing studies explored the relationship between individual infrastructures and bicycling behavior. There is consensus that cyclists who ride on roadways prefer fewer travel lanes, lower motorized travel volume, slower speed and no on-street parking (J. Broach et al., 2012; Dill, 2009; I. Sener et al., 2009). In terms of different bicycle infrastructures, studies in various locations around the world consistently found that installing cycle tracks, or increasing the percentage of cycle tracks along the route, increased cycling levels (Goodno et al., 2013; Lusk et al., 2011; Monsere et al., 2014; Snizek et al., 2013; Wardman et al., 2007). Aggregate studies (Nelson & Allen, 1997; Parkin et al., 2007) and individual-based studies (Beenackers et al., 2012; Moudon et al., 2005) also showed similar outcomes with the installation of bike paths. Some studies also compared the impact hierarchy of different types of facilities on bicycle mode choice. Disaggregated studies based on individual stated preference or revealed preference methods revealed that separated bike lanes and off-street bike paths are more desired than bike lanes (which are simply striping on the road) or roads with no facilities, and people were willing to detour to switch from less desirable facilities to advanced facilities with lower volumes of traffic and slower speeds (J. Broach et al., 2012; Krizek et al., 2007; Tilahun et al., 2007).

Other than street link of bikeway facilities, studies also showed the importance of street intersection characteristics and treatments on cycling behavior. Several studies showed that cyclists prefer to avoid intersections with stop sign or traffic lights (Menghini et al., 2010; Rietveld & Daniel, 2004; I. N. Sener et al., 2009). However, a study found when travel volumes at the intersection increased to over 5000 or 10000 vehicles per day, the high travel volumes overcame the negative effect of traffic signal (J. Broach et al., 2012). In addition, one study found cyclists preference on cyclist-activated traffic signal crossing (Winters et al., 2010). The bike-box at intersections improved the perception of safety as well (Dill et al., 2012).

The network component goes beyond the lanes and paths, which focuses on overall network analysis of nodes (intersections) and links (lanes). Theoretically, bicycle network would generate greater impact than sum of its parts, but generally there were few empirical studies that link bicycle ridership with nodes-link network as whole (Buehler & Dill, 2016a).

Stinson et al. (2014) considered the network of bike lanes and found that people who live near more than one bike trail have greater propensity of bicycle to work and to recreation. Another study developed several different bike network measures that represent the size, connectivity, design, fragmentation, and directness of network (Schoner & Levinson, 2014). The density factor of all types of bike facilities had the largest elasticity on bicycle commuting, followed by fragmentation, directness, and connectivity, while the size factor did not show significant results. Therefore, these research results emphasized the importance of densifying a city's bicycle network with improvement in continuity and directness, while simply enlarging the breadth of the facility may not achieve the goal of promoting bicycle activity. Some other studies developed network-based measures to evaluate bike-ability of a region (M. B. Lowry, Furth, & Hadden-Loh, 2016; M. Lowry, Callister, Gresham, & Moore, 2012). Usually they considered multiple level-of-service or low-stress factors into the network measure to allow planners to estimate the effect of making change to the network on overall bike-ability.

Recent studies applied LTS measures to evaluate the impacts of bicycle network qualities on bicycle activities across different cities. A recent study implied LTS measures to evaluate the impacts of bicycle network design on bicycle mode share in UK cities (Cervero et al., 2018). They utilized the open source OpenStreetMap dataset to measure the bicycle network LTS and travel path stress between each census zone centroid pairs of 36 cities in UK. They found reducing route circuity and on-road stress contributed to higher bicycling commuting level.

In terms of causal relationship between bicycle network and bicycle activity, a study applied quasi-experimental design of control and treatment group of bike boulevards installation in Portland found that there was no correlation between living near new bike boulevards and bike usage level after controlling time and exposure effects (Dill et al., 2014). However, they indicated the time length of behavior change after infrastructure installation might be longer than the time range of their study had capture, which called for further pre/post studies.

Bicycle Data

There are two basic approaches to collect cycling data: place-based and person based. The place-based approach manually or automatically counts cyclists at selected locations. It can be easily implemented, and is practical for measuring the total number and location distribution of cycling trips. However, it provides very limited information about the demographic characteristics of the cyclists and the trip attributes (Krizek et al., 2009). In addition, the bicycle counts data also has severe spatial autocorrelation issues that need to be addressed in analysis.

The person-based approach usually involves person or household surveys asking about specific travel pattern. It provides more detailed demographic information such as who is cycling, how, and why they cycle, but it is difficult to measure the total amount of cyclists. There is another hybrid approach that uses intercept surveys in conjunction with counts at selected locations. This approach provides information about both the total number and the personal characteristics of cyclists, but it may neglect the population group who do not cycle. (Handy et al., 2014)

In terms of person-based survey, there are generally two kinds: stated preference and revealed preference. State preference (SP) surveys ask respondents to evaluate or rank their preferences for different travel modes or route choices given several scenarios. In contrast, the reveal preference (RP) surveys records the actual travel mode and route choice decisions of people. The SP survey is easy and inexpensive to implement compared to the RP survey. It also allows the researcher to test rare or nonexistent options, which is an advantage to study low percentage travel mode such as bicycling.

However, the main drawback of the SP survey is that it might not be consistent to respondents' actual behavior choice due to systematic biases in SP situations (Wardman, 1988). This is particular problematic for route choice studies, because it is difficult for cyclists to evaluate an unknown route compared to a familiar one (J. Broach et al., 2012).

Literature Gaps Identified from Previous Studies

Currently, there are several types of bicycle network measures. However, each one has its own drawbacks. The scales of four LTS stress levels are arbitrary. BLOS requires a large amount of roadway data input, which is hard to collect in actual research and planning practice. Route quality measures derived from route choice models are built on empirical studies of a few cities which the parameters might not applicable to other cities. In general, these measures lack of wide empirical examination about their sensitivity and applicability.

There were limited empirical studies providing evidence on the effects on bicycling activities. In particular, current studies on effect of bicycle network on bicycle activity mostly used cross-sectional data, which analyzed the correlation between bicycle network supply and cycling level at one point in time. Longitudinal analysis, which tracks the relationship between bicycle network supplies and cycling levels over time, would provide causal inference on this topic.

Conceptual Framework

A complete network assessment involves the assessment of multiple aspects, such as morphology, connectivity, stress and comfort, and access to destination for bicyclists (Figure 1). The changes to bicycle networks can affect bicycling activities. The bicycling activities can be represented by the regional level bicycle ridership and the individual corridor level bike mode choice. In addition to the impacts of network effects of the bicycle infrastructure, other factors including social-demographic, built environment, roadway characteristics, and city context, could also contribute to the variation in bicycling activities.

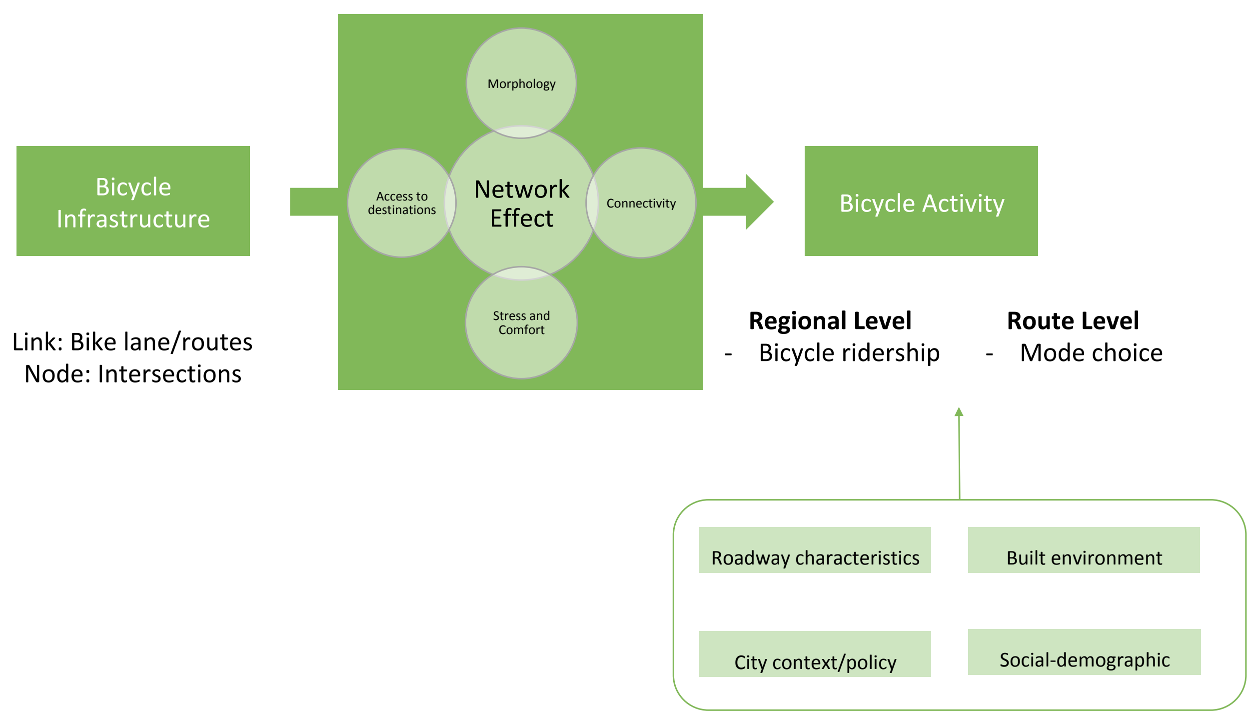

Figure 1. Conceptual Framework

Based on this framework, I first developed some metrics to assess the quality of the bike network. Bicycle networks are often assessed from multiple aspects, which consist of morphology, connectivity, comfort, and access to destinations. I used these guiding principles in developing my metrics.

Then, I used these metrics to test the following two hypotheses:

- I hypothesize that the bicycle network characteristics positively affect bicycling activity, which means a better bicycle network will bring more bicycle ridership and higher bicycle mode choice.
- I hypothesize that, given sufficient time for behavior change to occur in response to bicycle network changes, a causal relationship can be inferred between bicycle network and bicycle activity.

Methodology & Data Overview

This section describes the methodology and data used to answer my research questions. First, I will cover the methodology and data in measuring bicycle networks. Then, I will describe the criteria used to select the case cities, Portland, OR and Minneapolis, MN. Lastly, I will describe the specific modeling methods and data used to evaluate the impact of bicycle network on bike counts, bike mode choice, and the causal inference.

Methods and Data to Measure Bicycle Network

The Level of Traffic Stress (LTS) was used to measure bike networks in this project. The Level of Traffic Stress is a rating given to a road segment or intersection that measures how "stressful" a particular segment or intersection is for cyclists (Mekuria et al., 2012). LTS scores range from 1 to 4 with higher scores indicating more stressful environments. An LTS score of 1 refers to separated infrastructure with low travel volume and low speed; LTS 2 refers to segments where cyclists have limited interaction with traffic such that they are protected or separated from higher speeds or multilane traffic corridors; LTS 3 refers to cyclist interaction with moderate speed and traffic volume; and LTS 4 involves interactions with higher speeds and traffic volumes.

There are a number of reasons to choose LTS in this project. First, this measure has been widely used by researchers and practitioners (Cervero et al., 2018; H. Wang et al., 2016; Wasserman et al., 2019). Therefore, choosing this approach facilitates the comparison of results among different studies. Second, the concept of LTS closely embodies the principles defining an effective, and safe bicycle network (Louch et al., 2016). The LTS incorporates the comfort and safety principles that dictate that cyclists should not face undue stress or risks while traveling. It also incorporates the principle of accessibility to all groups of users because the four levels of traffic stress are linked to four types of cyclists classification (Dill & McNeil, 2013, 2016; Geller, 2009). Within this classification scheme, the “interested but concerned” group, which includes the majority of the population, represents the network suitable for children (LTS1) and most adults (LTS2). Therefore, using the LTS bicycle network within the context of this research provides planners with a straightforward way to evaluate whether improving bicycle networks may accomplish the goal of increasing ridership for what types of cyclists. Lastly, the data requirements are less onerous than other methods, such as BLOS. It allows researchers and planning agencies to collect necessary data for bicycle network measure using readily available datasets.

In order to estimate an LTS score, the analyst requires roadway characteristics including separation from motor vehicle traffic, width of bike lane, bike lane blockage, number of travel lanes, vehicle speed limit, and travel volume. Previous city-based street network analyses utilized data from local data archives, such as the Regional Land Information System at Metro, to evaluate the street network. Recently, the growing availability of universal crowdsourced data sources, such as OpenStreetMap (OSM), have made collecting street network information a more straightforward process. Because it does not rely on individual cities to share their data. OSM is a free online volunteer-driven geographic information (VGI) service, which provides up-to-date data at fine geographical and temporal level of street segment characteristics with global coverage (Mocnik et al., 2018). This data set includes thousands of cities around the world, which made research consistent, replicable, and scalable. OSM data has been utilized to bicycling research related to route choice (Yeboah & Alvanides, 2015), cycling behavior (Cervero et al., 2018), and to assess health impacts of cycling (Mueller et al., 2018).

Previous research on the completeness and accuracy of OSM tags related to bicycle infrastructure found that it was more accurate than Google Maps when comparing the central cities of Portland, Oregon and Miami, Florida (Hochmair et al., 2015; Wasserman et al., 2019). Additionally, Hochmair et al. (2015) noted that the OSM data for bicycle facilities have had continued growth and refinement. A more recent study compared the OSM-derived LTS with ground-truth LTS in Montgomery County in California. They found OSM-derived LTS scores correctly identified 89.9% of the ground-truth LTS levels. In general, OSM provides reliable and consistent road network data across cities.(Wasserman et al., 2019).

To ensure a consistent methodology across different city cases, OpenStreetMap (OSM) was used as the main data source for measuring street networks. In the scenarios when the OSM data is inadequate, I supplemented it with local network data. For example, I used local data when there was a large discrepancy between the OSM and local data or if the OSM data had a lot of missing values. With guidance from the OSM wiki (https://wiki.openstreetmap.org) and historic OSM data from the Overpass API, any link that has cycleway facilities, such as separated paths, cycle track and shared road space, can be flagged.

In addition to bicycle infrastructure types, other street network attributes were collected through OSM, including speed limit, number of travel lanes, and elevation. There were missing values for speed limit and number of travel lanes in OSM data, especially in suburban residential areas. Previous studies (PeopleForBikes, 2019; Wasserman et al., 2019) utilized roadway functional classification to impute the missing values. Similar criteria were applied here, as shown in Table 1. For example, if a residential street has no information for the speed limit or the number of lanes, it is assumed to have two lanes and a speed limit of 25 miles per hours.

Table 1. Imputation of Roadway Characteristics

Highway tag (functional class)	**# of lanes assumed**	**Speed assumed (miles per hours)**
Residential	2	25
Unclassified	2	25
Tertiary	3	30
Track	2	30
Secondary	4	35
Primary	4	45
Trunk	6	65
Other	2	25

Notes:

1. These assumptions only apply if there is no tag provided for speed limit or number of lanes.
2. Lane assumptions for one-way streets are halved to reflect an accurate per segment assumption.

In addition, although travel volume was critical information to determine LTS, it is not available through OSM, and not available through any systematic collection fashion across different cities in the US (Wasserman et al., 2019).

Given data availability issues, the traffic stress of all the road segments in this project was evaluated on whether a street segment has bike facilities, its speed limit and the number of lanes per direction (Table 2). Road segments with a bike facility, lower speed limits and fewer number of lanes have lower stress values.

Table 2. LTS Calculation Logic

Bicycle facility	**Variable threshold**	**LTS1**	**LTS2**	**LTS3**		**LTS4**
Separated paths /cycle tracks	NA	LTS1				
With bike lane	Speed limit	<25	25-35	40-45	<=35	>=40
	# of lanes per direction	<=1	<=2	<=2	>2	>2
Mix traffic	Speed limit	<=25	20-30	35-40	20-30	>=35
	# of lanes per direction	unlaned	<=1	<=1	2-3	>2

The development of the original LTS criteria largely referenced Dutch bicycle planning and design standards (Mekuria et al., 2012), where the topology was mostly flat across the cities. In addition, it only differentiated the stress level for separated paths and cycle tracts from regular bike lanes, and treated other bike facilities, such as buffered bike lane, bike boulevards among others, the same as bike lanes. As a result, it is preferred to calibrate these criteria to better reflect the network in the case cities in the US.

Firstly, I calibrated my LTS metric by bicycle infrastructure type. Previous literature found buffered bike lanes, which provided greater separation of cyclists from traffic, increase travel comfort (Monsere et al., 2012). In addition, bike boulevard is a unique type of bicycle infrastructure in the US, featuring with low motorized traffic speed and volume to prioritize bicycle travel. Previous route choice analysis found bicyclists had a strong preference for bike boulevards over striped bike lanes (J. Broach et al., 2012). Therefore, I rated segments of bike boulevards and buffered bike lanes as low stress segments, defined as level 1 or level 2. Additionally, road segments that may have high original LTS scores, such as 3 or 4, would have their scores lowered if they had a buffered bike lane or a bike boulevard.

The terrain for many cities in the US is not all as flat as in the Netherlands in general. Previous studies showed different slope levels significantly affected bicycle route choice, and bicyclists' preference of riding (J. Broach et al., 2012). Therefore, I added an additional measure to my LTS score system, the slope of the street segment, which is expected to better capture the comfort level of cycling. Segments with a slope of 0-2% are rated as stress level 1; between 2-4% are rated as stress level 2, between 4-6% are rated as stress level 3, and above 6% are rated as stress level 4. In addition, I adjusted the original LTS scores by the slope. A segment's final LTS score is assigned with the higher one of the original score and the score of slope. For example, if a road segment is rated as stress level 1, but it has a slope of 3%, the stress level is relabeled as stress level 2.

Table 3. Updated LTS Calculation Logic

Bicycle facility	**Variable threshold**	**LTS1**	**LTS2**	**LTS3**		**LTS4**
Separated paths	NA	LTS1				
Cycle tracks	NA	LTS1				
Buffered bike lane	NA	LTS1/LTS2				
Bike boulevards	NA	LTS1/LTS2				
With bike lane	Speed limit	<25	25-35	40-45	<=35	>=40
	# of lanes per direction	<=1	<=2	<=2	>2	>2

Mix traffic	Speed limit	<=25	20-30	35-40	20-30	>=35
	# of lanes per direction	unlaned	<=1	<=1	2-3	>2

Note: The lowest LTS for slope 0-2% is 1, 2-4% is 2, 4-6% is 3, and 6% above is 4.

Case City Selection

The cities in the United State generally have limited bicycle infrastructure and low bicycle travel share. Only the cities with relatively high bicycle activities can provide a large enough sample size for statistical analysis. Also, only the cities with substantial bicycle network construction in the most recent decade can be used to infer relationship between bike networks and bike activity.

Beyond the popularity of bicycling, I also chose cities based on the availability of bicycling activity data, such as bike counts and travel survey data. Based on the information from BikePed Portal, Portland, OR, Boulder, CO, San Diego, CA, and Arlington, VA are the most popular bike cities, each of which had more than 20 bike counters in 2018. Some cities, such as Portland, OR and Minneapolis, MN, also host annual peak-hour bike counts data, which offers another data source to track bicycle ridership.

In terms of individual-based travel survey data, statewide and regional travel surveys usually recruit a large number of participants. Only cities with individual travel survey data that had a sufficient number of bike trips and precise spatial origin-destination data can be included for route level analysis.

As described above, the selection of the case cities in this project was based on: 1) whether the city has substantial bicycle activity; 2) whether the there are significant change of bicycle network during the past decades; 3) data availability of bike counts and travel survey. Based on these criteria, two cities were selected for the analysis: Portland, OR and Minneapolis, MN.

The City of Portland, OR is well known for its well-developed bikeway network and long history of bicycling culture. Since 2000, bicycle boulevards projects and off-street trails such as the Springwater Corridor have provided bicycle facilities that are comfortable for people of all skill levels to use. Striped bike lanes on major streets and traffic calming facilities were installed around the same time. With the improvement of infrastructure, bicycling became more and more popular in Portland, which is reflected by the highest (6.3%) among all largest cities in the United States as of 2017. Longitudinally, bicycle commuting mode share in Portland in 2017 is 374% of the mode share in 2000[2]. Therefore, Portland is selected as one city case, given the popularity of bicycling, and the significant improvement of bikeway facilities.

The City of Minneapolis, MN is another popular biking city in US. It ranks as the #3 highest bicycle commuting mode share among all largest cities in US in 2017[3]. It shares many similarities with Portland, such as well-constructed bicycle infrastructure, and relatively high bicycling population. However, the two cities are different in some aspects,

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[2] Retrieved from webpage "Bicycles in Portland Fact Sheet" at https://www.portlandoregon.gov/transportation/article/407660

[3] Retrieved from webpage "US Cities with the Most Bicycle Commuters" at https://www.move.org/cities-most-bicycle-commuters/

such as climate, city size, and terrain character, etc. Therefore, it provides a good contrast for a comparative analysis. The Minneapolis Bicycle Master Plan adopted in 2011 listed all the bikeway improvement projects across the city, which includes off-street trails, bike boulevards, bike lanes, and shared lanes. In addition, the Climate Action Plan in 2013 recommended the construction of 30 miles of on-street protected bike facility by 2020[4]. The city has had appreciable investment to improve bicycle infrastructure, such as protect bike lanes, bikeway constructions, over the past decade.

In terms of the longitudinal time selection, data from two time points were selected. The selection of time points is mostly based on the data availability of the street network, bike counts, travel survey, and other covariates mentioned in the conceptual framework. I used the data of 2011 and 2017, because 2017 is the most recent year in terms of data availability across different data sources, such as bike counts and socio-demographics, while 2011 was the last year of Oregon's statewide travel survey. To be consistent in comparing the results between the two city cases, the same pair of time points was used for the two cities.

Methods and Data to Model the Impacts of Bicycle Network on Bicycling Activities

Various quantitative modeling approaches were applied in this project to investigate the impacts of bicycle network on bicycling activities. The modeling approaches were chosen based on the property of the bicycling activity outcome variables, and the specific

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[4] Retrieved from webpage "Bicycling in Minneapolis" at http://www.ci.minneapolis.mn.us/bicycles/index.htm

question this project aims to address. In particular, negative binomial model was used to model the impacts on bike counts, multinomial model was used to model bike mode choice, and difference-in-difference (DID) was used to address the causal relationship between bicycle network and bike counts. The detailed modeling approaches are described as below.

Bike Count – Negative Binomial Regression

First, how the bicycle network impacts bicycle ridership was evaluated using a negative binomial regression model. The dependent variable, bicycle counts, is non-negative and not normally distributed. In such cases, Poisson or negative binomial regression, instead of ordinary least square (OLS), would be a more appropriate approach to estimate bike counts (Hankey et al., 2012). Poisson distribution assumes the means and variance are equal to λ. However, for most of the count data, there is an over-dispersion issue, which means the variance is larger than the mean. In comparison, negative binomial distribution introduces an over-dispersion parameter α to account for this issue. In the negative binomial distribution, the probability of y equals m conditioning on the linear combination of X vector and parameter λ and α:

$$P(y = m|\lambda, \alpha) = \frac{\Gamma\,(m + \alpha^{-1})}{m!\,\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1} + \lambda}\right)^{\alpha^{-1}}\left(\frac{\lambda}{\alpha^{-1} + \lambda}\right)^{m}$$

In the estimation of negative binomial models, one common assumption is the mean and variance of y are λ and $\lambda+\alpha\,\lambda^2$ respectively (X. Wang et al., 2013). α is the over-dispersion parameter, and when α =0 the negative binomial distribution is the same as Poisson distribution. As a result, negative binomial regression is the most appropriate regression model for count data estimation. The expected value of dependent variable y can be predicted as

$$E(y|X) = \hat{\lambda} = \exp\,(\widehat{\beta_0} + \widehat{\beta_1}x_1 + \widehat{\beta_2}x_2 + \cdots + \widehat{\beta_n}x_n\,)$$

Because negative binomial model uses a non-linear link function, the coefficients should be interpreted as one unit increase in variable associated with the expected bike count by $\exp(\beta)$ times.

Mode Choice – Multinomial Logit Regression

In order to model the effects of the bicycle network attributes on bicycle mode choice, it is not appropriate to utilize the commonly used Ordinary Least Square (OLS) regression method. Because the dependent variable, mode choice, is discrete, which violate the assumption of OLS.

The mode choice is often modeled under the framework of maximization utility theory. In this framework, each possible choice in the "choice set" endows a certain utility. Travelers make rational choice among competing alternative modes based on attributes and context of the modes and characteristics of the decision makers to maximize their personal utility. The model estimates the probability of a particular choice based on the utility of that choice relative to all other choices (Ben-Akiva & Lerman, 1985; McFadden, 1973)

Utility for a certain mode is specified as a function of the attributes of that mode, either observed or random:

$$U_i = f\,(V_i, e_i)$$

Subject to, $V_i = f(T_i, B_i, BE_i, D_i)$

Where U_i is the utility of alternative modes; V_i is the observed component, which refers to mode alternative attributes, and individual characteristics; e_i is the random component. In terms of specification, the utility of each mode V_i, is determined by vector of attribute of the trip T_i (i.e., travel time, travel distance, trip purpose, etc.), vector of bicycle network B_i, vector of built environment BE_i (i.e., population density), and vector of demographic characteristics D_i (gender, age, income, life stage related to family status, etc).

The random utility maximization (RUM) hypotheses the probability of choosing certain mode is determined by the utility of that mode exceeds all other alternative modes, leads to multinomial logit (MNL):

$$P_i = \frac{e^{V_i}}{\sum_i e^{V_i}}$$

Where Pi is the probability of choosing each mode, and V_i is the observed utility of each mode, given the assumption of random component are independent and identical (IID).

Causal Inference – Difference-in-Difference Model

As identified in the literature section, there is no study exploring the causal relationship between the bicycle network and bicycling behavior. A before and after comparison study was designed to examine the causal impact of bicycle network on outcome variables. In particular, difference-in-differences (DID) approach (Angrist et al., 2009) was applied. This approach studies the effect of a treatment, in our case bicycle network improvement, on a “treatment group” versus a “control group” by comparing the average over time in outcome variables in each group. The approach looks at the change in the variable of interest in the treatment group before and after it is treated. In this case, this means looking at some time period before and after a bicycle network improvement, and comparing the cycling behavior outcome indicators to the control group, which has not received the bicycle network improvement. The difference in growth trajectories between the two periods will give an unbiased estimate of the effect of the treatment.

DID is a linear modeling approach and its basic formula is expressed as:

$$Y_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 A_{it} + \beta_3 T_{it} A_{it} + \beta_4 Cov_{it} + \varepsilon_{it}$$

Y_{it} is the observed outcome in group i and t (in this case change in bicycling behavior); T_{it} is a dummy variable set to 1 if the observation is from the treatment group, or 0 if the observation is from the control group; A_{it} is a dummy variable set to 1 if the observation is from the post-treatment period; β_3 is the DID estimator of the treatment effect; Cov_{it} is an array of control covariates for treatment group and control group in either time period, such as physical, demographic and built environment dynamics, and β_4 is the corresponding estimator. Typically, the DID estimator of interest is β_3. If it is statistically significant and positive, it suggests a positive causal effect of the bicycle network improvement on the bicycling behavior. Conversely, if the estimate is significant and negative, it indicates a negative effect of the improvement. Finally, a non-significant result indicates the improvement had no statistically discernible effect.

In this project, bicycle network characteristics at two points in time have been measured. At the regional level, the areas with no or minimal network changes are considered as the control group, while the areas with many bicycle network changes are considered as the treatment group. Given that previous research found that two to three years is too short for behavior change (Dill et al., 2014), two time points at least five years apart with substantial bicycle network change were selected in this study. The potential causal inferences between bicycle network and activity were investigated.

Data Collection

Data for Bike Counts Models

Bike Counts Data

Bicycle counts are the most straightforward measure to track bicycle travel volume and bicycle activity at the aggregated level. They can also be used to estimate the total number and the spatial distribution of cycling trips. From the practical perspective, bike counters are relatively easy to implement. In general, there are two types of bike counts data: one is all-day automatic counter and the other is peak hour only manual counts. Both types of data have their advantages and drawbacks. For example, manual peak-hour bike counts are only collected at peak hours, when most bike traffic occurs, it may not well represent full day bicycle activities. As for automatic counters, they were not used to collect bike counts until recent years, which means that the bike counts data collected by automatic counters may not exist in many locations. In this project, I used manually collected bike counts data to evaluate the bicycling behavior in both cities.

It is worth noting that there are some limitations of using bike counts to represent bicycling activities. First, it provides no information about the demographic characteristics of the cyclists and the trip attributes (Krizek et al., 2009). In addition, bike counters are often spatially auto-correlated, which means the bike counter in one intersection is likely to be impacted by the surrounding intersections. Given these caveats, bike count is still a popular practical indicator to evaluate bike activities.

The City of Portland has a good historic record of manually collected peak-hour bike counts data, which goes back to as early as 2000. One drawback of this dataset is that many counter locations have changed over time, thus it poses some difficulties to compare data collected between different years. As a result, I used only the bike counters, the locations of which remain the same in 2011 and 2017, from the Portland manual bike counts data for my analysis. The total bike counters included is 141.

Similarly, the Department of Public Works in the City of Minneapolis collected peak-hour pedestrian and bicyclist counts at a variety of locations from 2007-2018. There are only 64 bike count locations where bike counts information is available in both 2011 and 2017. To include enough bike counters for the analysis, for each location, I filled the years with missing data with the mean of bike counts one year before and one year after the missing year. For example, if the bike counts for a location is missing in 2017, it is filled with the mean value of the bike counts of 2016 and 2018, if both are available. After this operation, 150 bike counter locations were included in the analysis.

Other Control Variables

According to the conceptual framework of this project, multiple control variables were selected to examine other factors that might influence bike counts, which include street design and land use characteristics, demographic, and geographical relationship characteristics.

Previous research suggests that bicycle travel behavior could be affected by "5Ds" – Density, street Design, Diversity, Destination accessibility and Distance to transit. Among them, density and street design had stronger influences on bicycle behavior than others (Cervero & Kockelman, 1997; Ewing & Cervero, 2010). Therefore, I included many density and street design related variables in the street design and land use data category, such as population density, intersection density, and network density by auto, multi-model, and pedestrian. In addition, job-housing balance and transit accessibility were selected to capture the impacts of diversity and distance to transit features of the built environment. The population density variable was calculated based on the American Community Survey (ACS, five-year rolling) dataset, and the intersection density was directly calculated from the street network constructed using the OSM data. The rest variables were retrieved from EPA Smart Location dataset.

In addition, previous literatures suggest that socio-demographic characteristics, such as gender, income, and age, also influences bike activities. For example, many studies found that the individuals who are male, young, well-educated, student, or from zero-car households were more likely to choose bicycling (Heinen et al., 2010; Plaut, 2005; Schneider, 2011; Xing et al., 2010). Therefore, I also selected some socio-demographic variables in my analysis, which include age, race, education level, income, vehicle ownership and crime feature. The social-demographic information was gathered from the ACS dataset as well. The data was gathered from the Police Department of each city. Lastly, bike count is also impacted by the traffic flow, which means the counts at one location are likely to be affected by nearby locations and the overall network. I used an ArcGIS toolbox, "Urban Network Analysis"[5], to generate the network indexes for each bike counter. Two variables, betweenness and closeness, were calculated based on the network toolbox.

A buffer area for each bike counter was computed using bicycle street network. The data retrieved from ACS and EPA is at census tract level. The buffer area may overlay one or more census tracts. To be more precise in estimation, the census tract level information were proportionally aggregated to the buffer area to represent the property of that bike counter.

[5] "Urban Network Analysis Tool" is retrieved from http://cityform.mit.edu/projects/urban-network-analysis

Table 4. Variable Description in Bike Count Models

Category	Variable name	Description	Sources	Longitudinal?
Demographic	% of households with 0 vehicles	Percentage of households with no vehicles in the catchment zone where the intersection locates	ACS (five-year rolling)	Yes, 2011/2017
	% of white population	Percentage of white population in the catchment zone where the intersection locates		
	% of elder population	Percentage of population over 65 in the catchment zone where the intersection locates		
	% of population with college degree or above	Percentage of population with college degree or above in the catchment zone where the intersection locates		
	Median household income	Median household income in the catchment zone where the intersection locates		
	Crime	Number of crimes in the catchment zone where the intersection locates	City Police Bureau	No, 2017
Street Design & Land use	# of intersections	Number of intersections in the half-mile buffer zone of each bike counter	Open Street Map	Yes, 2011/2017
	Population density	Population density of the catchment zone where the intersection locates	ACS (five-year rolling)	Yes, 2011/2017
	Transit accessibility	Proportional accessibility to region destinations by transit	EPA Smart Location Database	No
	Job housing balance	Jobs per household		
	Auto network density	Facility miles of auto-oriented links per square mile		
	Multi-modal network density	Facility miles of multi-modal links per square mile		
	Pedestrian network density	Facility miles of pedestrian-oriented links per square mile		
Geographical relationship	Betweenness	The number of shortest paths between pairs of other bike counters in the network that pass by the focal bike counter	Derived from ArcGIS network analysis	No
	Closeness	Inverse of cumulative distance from the focal bike counter to all other bike counters		

Data for Mode Choice Models

The main data source used for bike mode choice models was the Oregon House Activity Survey Dataset (Oregon Modeling Steering Committee, 2011). This survey collected detailed individual trip information, such as travel mode, O-D route, trip chain, and trip purpose, and socio-economic information, like demographics, household income levels, and vehicle ownerships, etc. In addition, I added a variable, population within 2 miles of home address, to evaluate the built environment for each individual trip, because the average trip length in my dataset is about 2 miles. This variable is retrieved from the ACS dataset (Table 5).

The travel survey data was re-organized by ordering each individual's trip chain. The X and Y coordinates for the origin and destination (OD) of each trip were extracted. Each trip was geocoded on a map, so that trip distances and specific geographical characteristics could be computed. The total number of trips occurred in Portland before clean up is 15,054. Bicycle mode was the major mode of interests for this project, so only two additional main travel modes, auto (including car/vanpool, and passenger) and walk (which covered 98.7% of all trips), were considered.

To further clean up the dataset, the individuals without driver's licenses were excluded to make sure that each individual in the analysis have the same set of options in their mode choice. In addition, the routes that could not be calculated in the GIS network analysis or extended beyond the Portland city boundary were excluded. The trips with lengths under 30 meters were likely caused by errors, thus were excluded as well. The cleaned dataset ended up with a total of 12,637 trips.

Bicycle mode choices are more likely to be affected by route impedances than other travel modes (J. P. Broach, 2016), so mode-specific trip network distances were computed for auto, bicycle, and walk, respectively, to take into account of the fact that different travel modes differ in their sensitivities to route impedance. Street network, retrieved from both the OSM and the RLIS archives, was combined with bicycle route file. Mode-specific street networks were constructed, and trip distances for each alternative mode were computed based on the assumption that travelers would choose the shortest path for their trips.

- Auto routes: automobile routes were calculated solely based on the shortest paths between origins and destinations.
- Bicycle routes: bicycle routes were generated by finding the shortest weighted route between origins and destinations in bicycle street network. The bicycle street network excludes freeways from the street layer. Following previous research (Cervero et al., 2018), a linear scale of weight were chosen for the four levels of stresses: LTS 1 – 0.9, LTS2 – 1.0, LTS3 – 1.1, and LTS4 – 1.2. The weighted segment lengths were computed as the actual length of the segment multiplied by the weight of that segment.
- Pedestrian routes: similar to bicycle routes, the pedestrian routes were generated by calculating the weighted trip length from origin to destination in the pedestrian street network. The pedestrian street network also excluded freeways and highways. Each major street (classified in the Transportation System Planning (TSP) street classification as primary arterial, arterial and tertiary) was given a

weight of 1.1, while all other segments had a weight of 1. The weighted segment lengths were computed as the actual length of the segment multiplied by the weight of that segment.

Table 5. Variable Description in Mode Choice Models

Category	**Variables**	**Variables/Indicators**	**Data Source**
Dependent variable	Mode choice	Mode choice (Auto, bike and walk)	OHAS
Independent variable	Trip attributes	Travel distance (based on mode-specific network distance)	OD information from OHAS spatial confidential data; Network data from OSM
		Trip purpose (percentage of work related trips)	OHAS
	Built environment	Population within 2 miles of home address	ACS
	Socio-demographic characteristics	Age	OHAS
		Gender	
		Race	
		Education	
		Household size	
		Household income (median)	
		# of vehicles household owns	
		# of bikes household owns	

How to Measure Bicycle Network?

As mentioned in the FHWA report (2018), six principles – cohesion, directness, accessibility, alternatives, safety and security, and comfort - were incorporated to define an active transportation network. These principles guide the measurement of bicycle network in this project. The bicycle network emphasizes the connectivity of the infrastructures, the comfort and safety of riding, and access to destinations by different groups of population.

I measured particular networks at two scales: the regional and route level. The regional level network measure assesses the network characteristic of a specific region/location, such as city, neighborhood, or intersection; while the route level network measure assesses the network characteristics for particular route.

Regional Level

The level of the bicycle network around each intersection is determined by both how connected are the bicycle facilities in nearby regions and how easily bicyclists can get around the region from that intersection. To incorporate different principles of the network, I designed four measures in particular. Each individual measure incorporates different principles as described below, such that the combination of the four measures may provide a more complete view of the bicycle network of the region.

a. Size of catchment area at varying buffer distances from the intersection

   This measure calculates the square mile of land area that can be reached from the intersection using the network distance (the street network only includes the roadway that are legal for bikes). It only takes into account the connectivity of the surrounding area of each intersection, and does not take segment quality into account. Different buffer distance, 0.25 mile, 0.5 mile, and 1 mile, were tested to evaluate the best distance range for this measure. The selection of those buffer distances is because those buffered distances were common used distance in bicycle research. Figure 2a shows an example of the catchment area of half-mile buffer distance from the intersection.

This measure incorporates the network principle of cohesion and directness. Regions with well-connected street designs would have larger catchment area than the regions with irregular and cul-de-sac street designs. The larger the value is, the more favorable the region is for bicyclists.

b. Percentage of length of low stress segments (LTS1 and LTS2) in catchment area

This measure calculates the share of the total length of all street segments in a catchment area that are low stress (LTS 1 and LTS2). The catchment area refers to the half-mile buffer catchment area calculated in the previous measure. For example in Figure 2b, the street segments within the half-mile catchment area are rated from 1-4. Of those segments, 70%, in terms of length, are rated as LTS1 and LTS2.

This measure incorporates the comfort and safety principle of the network. It evaluates the quality of the surrounding bicycle network in terms of how stressful it is. The higher the percentage of low stress segments lengths, the better quality the bicycle network has.

c. Average LTS of street segments adjacent to the intersection

The previous measure (b) evaluates the general bicycle network quality in the surrounding region. However, the counts at a given intersection are likely to be more heavily affected by the street segments adjacent to the intersection than further areas. Therefore, this metric provides the information of the stress level at a finer scale to supplement measure (b). For example, as shown in Figure 2c, there are four street segments adjacent to the intersection of interest. Two of them are rated as stress level 1, and the rest two are rated as stress level 3. Therefore, the average LTS is 2 to represent the network characteristics of that intersection. The larger this value is, the less comfort the bicyclist would feel when passing by the intersection.

d. Area can be reached from the intersection through only low stress segments

This measure calculates the square mile of land area that can be reached from the intersection through only low stress street segments. It evaluates the extensiveness of the bicycle network. Wherever a traveler encounters a high stress segment, a detour is needed. In certain occasions, a traveler can travel a very large area through low stress segments if the route extends on a long series of connected low stress segments. To account for this, 2 miles is set as the maximum distance one would travel along the low stress segments. 2 mile was chosen because the average travel distance for bike trips is around 2 miles in the case city of Portland (OHAS, 2011).

This measure incorporates the network principles of cohesion, comfort and safety. It evaluates the network through both connectivity of the facilities and the comfort level of travel. The larger this value is, the more connected the bicycle network is and the more comfortable the region is for bicyclists to travel around.

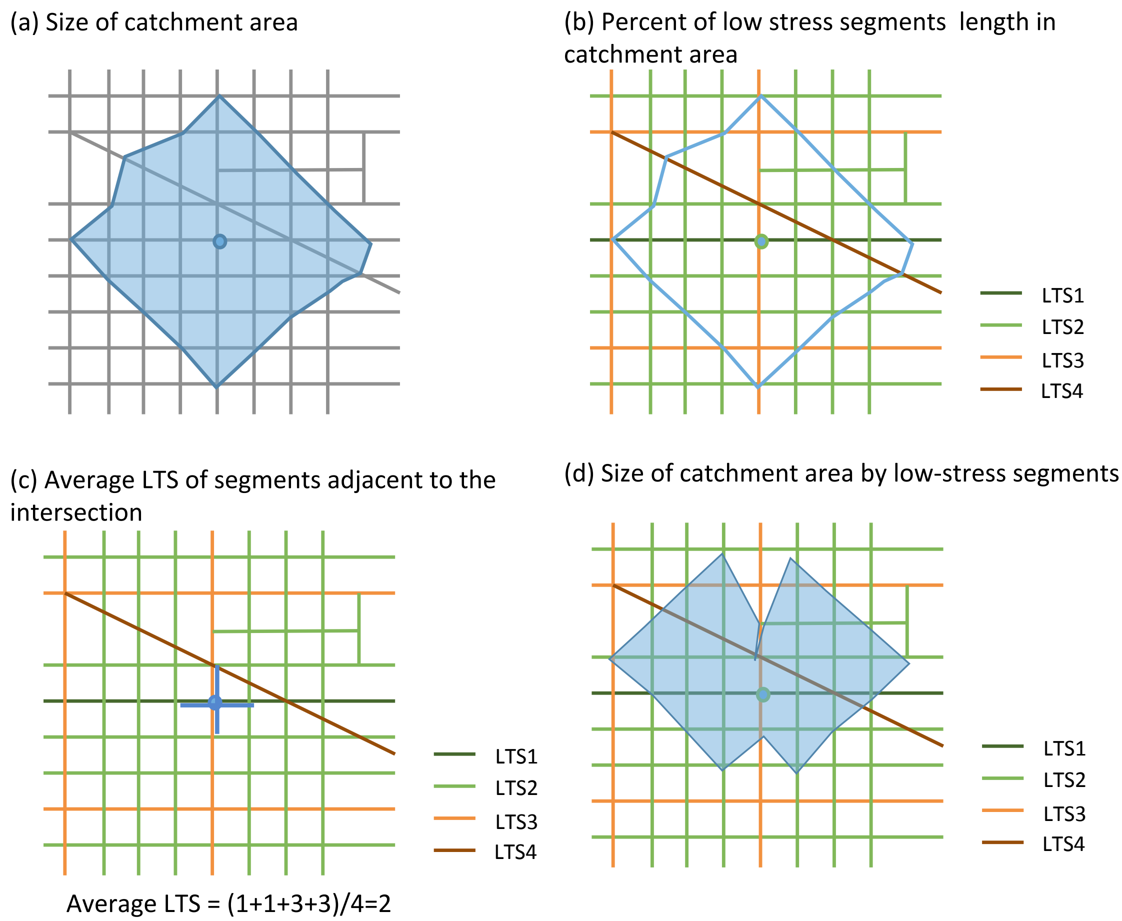


Figure 2. Bicycle Network Measures Illustration (for specific location/region)

The four regional measures complement each other in the sense that they incorporate different network principles. The first measure, the size of catchment area, focuses on the cohesion and directness principles of the network. It reflects how well-connected the street network is and how to minimize the travel distance through the street layout. The other three measures incorporate the comfort and safety principles of the network. They take into account of the stress feature of each street segment. In particular, measure (b) evaluates the general comfort level of the region, and measure (d) evaluates the connectivity and extensiveness of the network by comfortable and safe travel route. The combination of the four measures provides a more complete view of the bicycle network of the region than each individual measure. However, the accessibility and alternatives principle have not been incorporated into the regional level measures due to data limitations and for computation simplicity.

Route Level

The ultimate goal of constructing the bicycle network is to provide "low-cost" routes that connect origins and destinations (OD) to compete with other travel modes. Travel survey data was utilized to examine how the actual bike mode choice between OD pairs were affected by bicycle network attributes. While regional level bicycle network measures focuses on evaluating the network characteristics of certain locations, route level measures evaluate the bicycle network characteristics for each travel route. It aims to incorporate the principle of directness and comfort in the measures. The measures utilize travel survey data to figure out the travel route of Origin-Destination pairs, and evaluate the route comfort and stress level for bicyclists in the network.

Following previous studies (J. Broach & Dill, 2017; Cervero et al., 2018), two measures were developed. The measures evaluate how direct the route is from origins to destinations, and how comfortable and safe the route is.

a. The ratio of the travel route length weighted by the stress level to the actual route length

   This measure assigns a weight to each segment based on its stress level. The bicycle street network excludes freeways from the street layer. Following previous research (Cervero et al., 2018), a linear scale of weight were chosen for the four levels of stresses: LTS 1 – 0.9, LTS2 – 1.0, LTS3 – 1.1, and LTS4 – 1.2. The weighted segment lengths were computed as the actual length of the segment multiplied by the weight of that segment. As the example shown in Figure 3, the actual route from origin to destination is 2400. Among the 12 street segments along this route, 7 of them are LTS1, 2 of them are LTS2, and 3 of them are LTS3. Applying the weights to those segments leads to a weighted travel route length of 2320, and the value of this measure is 0.967. In general, The larger the value of this measure, the higher the stress of this route.

b. The percentage of the length of low stress segments along the shortest travel paths

   This measure supplements the first measure by focusing on measuring the percentage of the length of low stress street segments along a route. Compared to the first measure, this measure is simpler to implement and it is more generalizable when comparing the results from different studies.

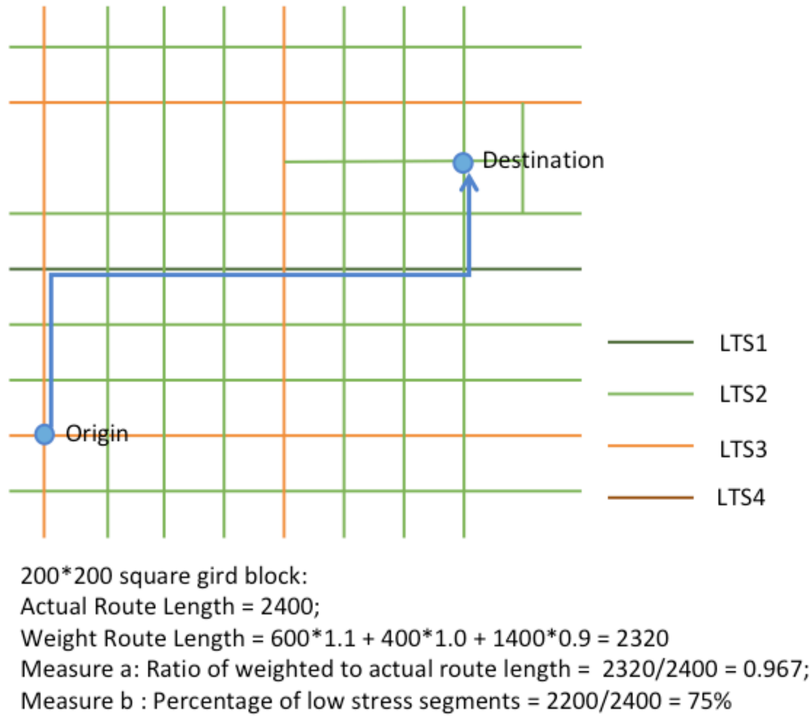


Figure 3. Bicycle Network Measures Illustration (for travel route)

Case Study

The following sections present how to apply the regional level bicycle network measures to evaluate the network characteristics of the bike counters at the two case cities.

Case 1: Portland, OR

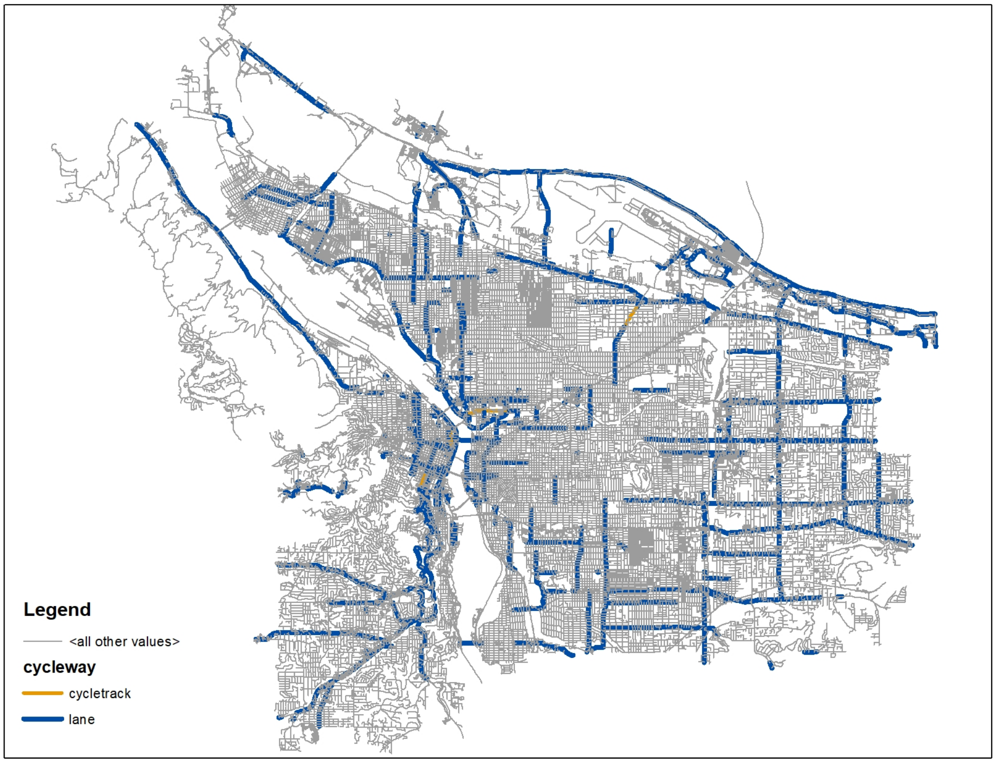
Comparison Between Crowdsourced Data and Local Archives

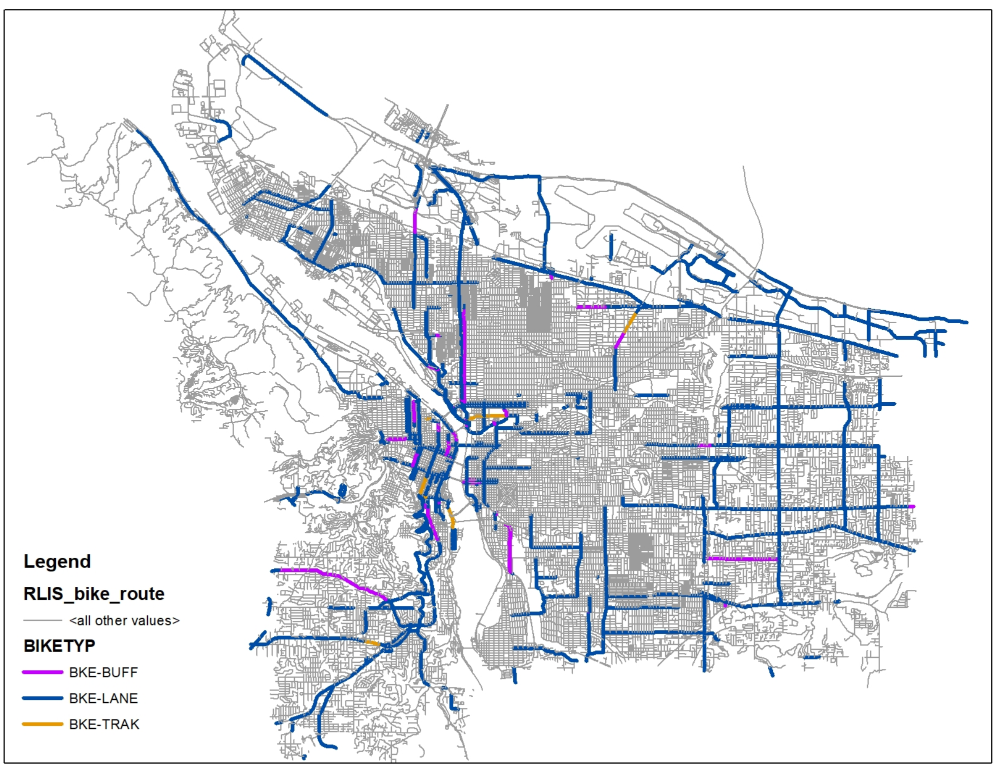
Bicycle infrastructure type is an essential attribute for bicycle stress level evaluation. Therefore, I conducted a detailed comparison of bicycle infrastructure types with two different data sources before proceeding to evaluate the network measures themselves. As discussed in the previous section, there are two major data sources of street network data:

local data archives (i.e. RLIS for the City of Portland) and crowdsourced OSM data, which were used for this comparison. .

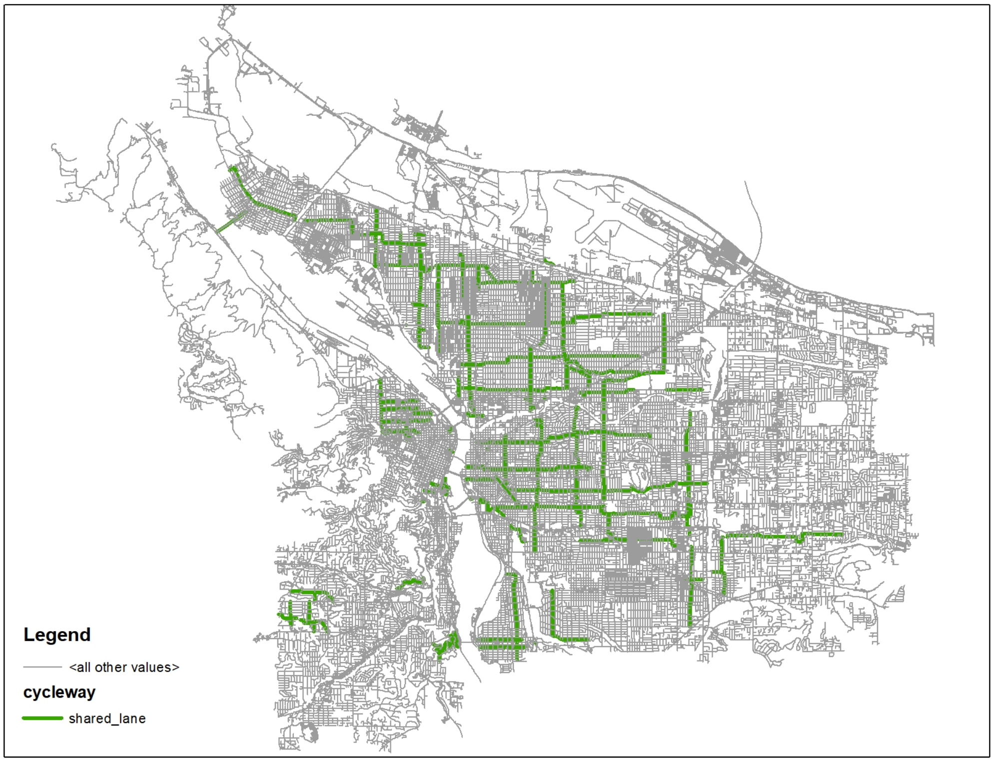
There are some terminology differences between RLIS and OSM bicycle infrastructures. In general, three major bicycle infrastructure types were compared: on-street bike lane (i.e. cycle track, buffered bike lane and bike lane), bike boulevards/shared lanes, and off-street paths.

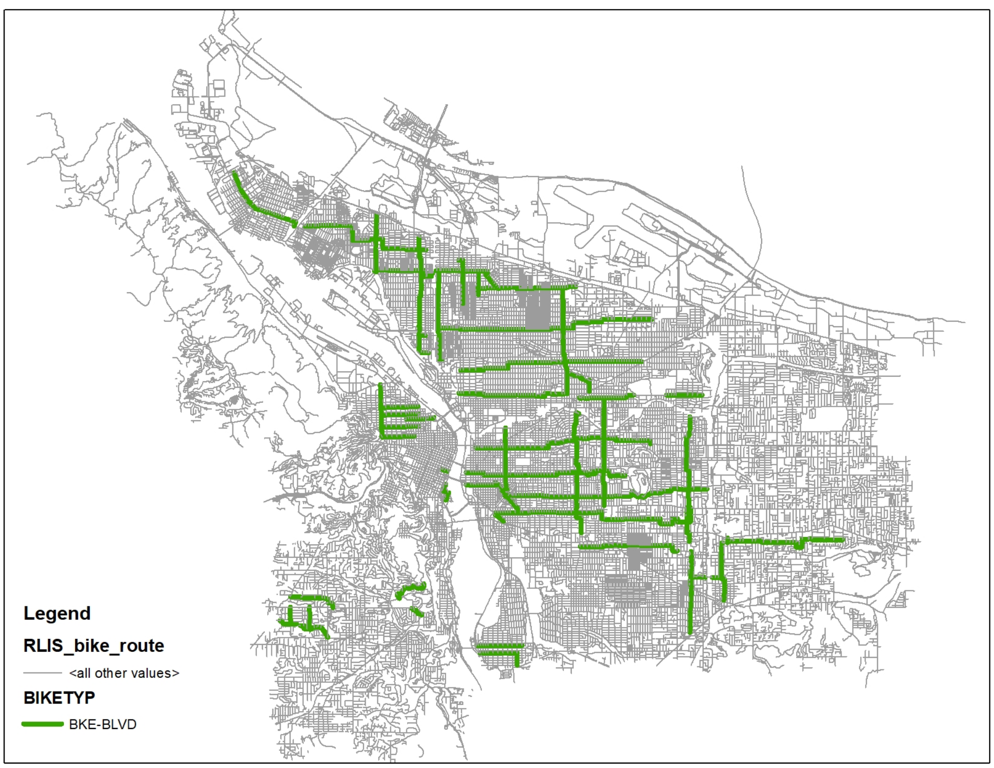
First, I compared the differences of bicycle facility distribution between the two data sources in 2017. In terms of on-street bike lanes (Figure 4a), both RLIS and OSM showed that there were very limited number of cycle tracks distributed around downtown Portland and NE Portland; OSM does not differentiate between bike lane and buffered bike lane. However, based on visual inspection, the distribution of those two types of lanes in RLIS dataset is similar to the distribution of all the bike lanes in OSM. In terms of bike boulevards (Figure 4b), OSM named it as shared lane. The distribution of this type of bike infrastructure is similar between OSM and RLIS as well. They concentrate in inner East Portland. In terms of off-street paths (Figure 4c), the two data sources also show similar distribution of the regional off-street paths. In sum, RLIS and OSM share similar distribution of different bicycle infrastructure types. Given the aforementioned advantages of OSM data, it is reasonable to use the OSM data to identify different bicycle infrastructure types for this project.



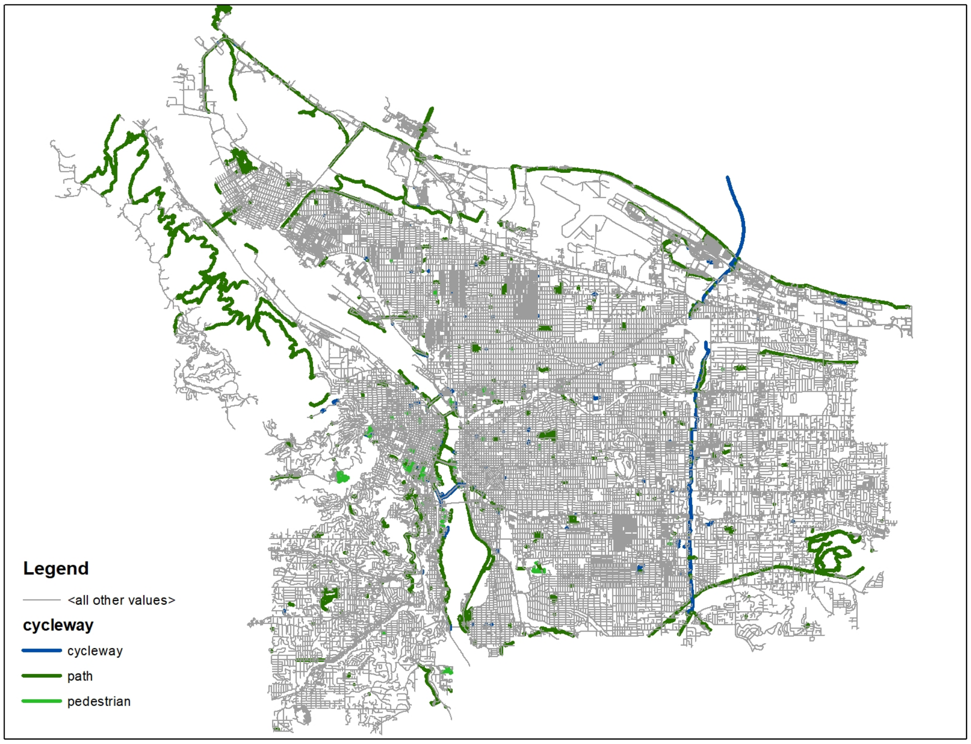


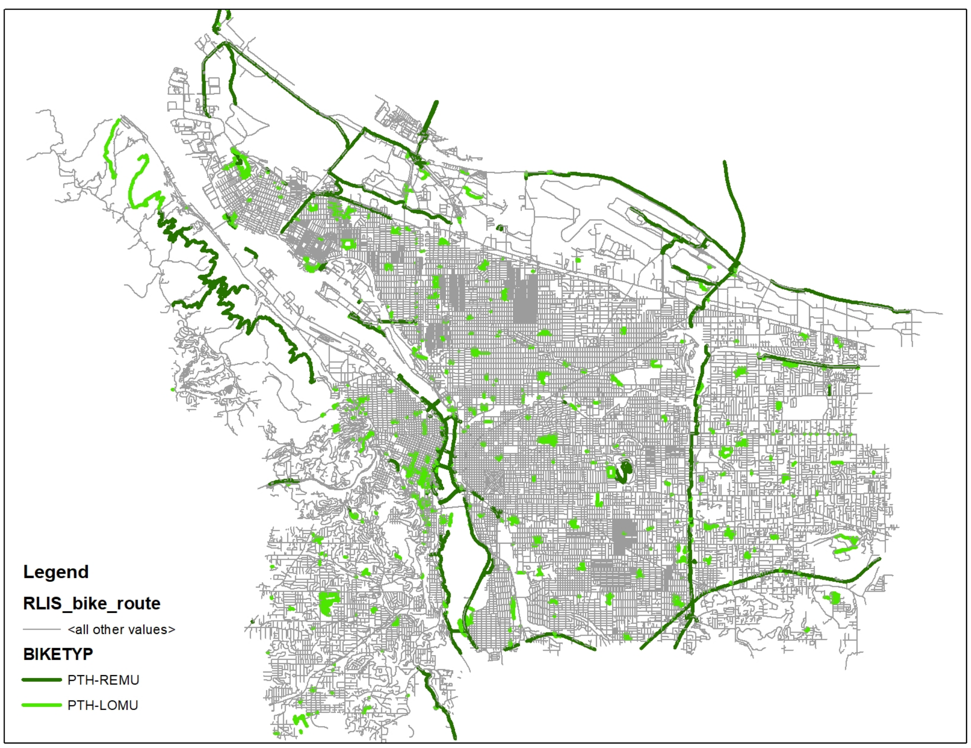
(a) On-street Bike Lane (Top: OSM; Bottom: RLIS)





(b) Shared Bike Lanes (Top: OSM; Bottom: RLIS)

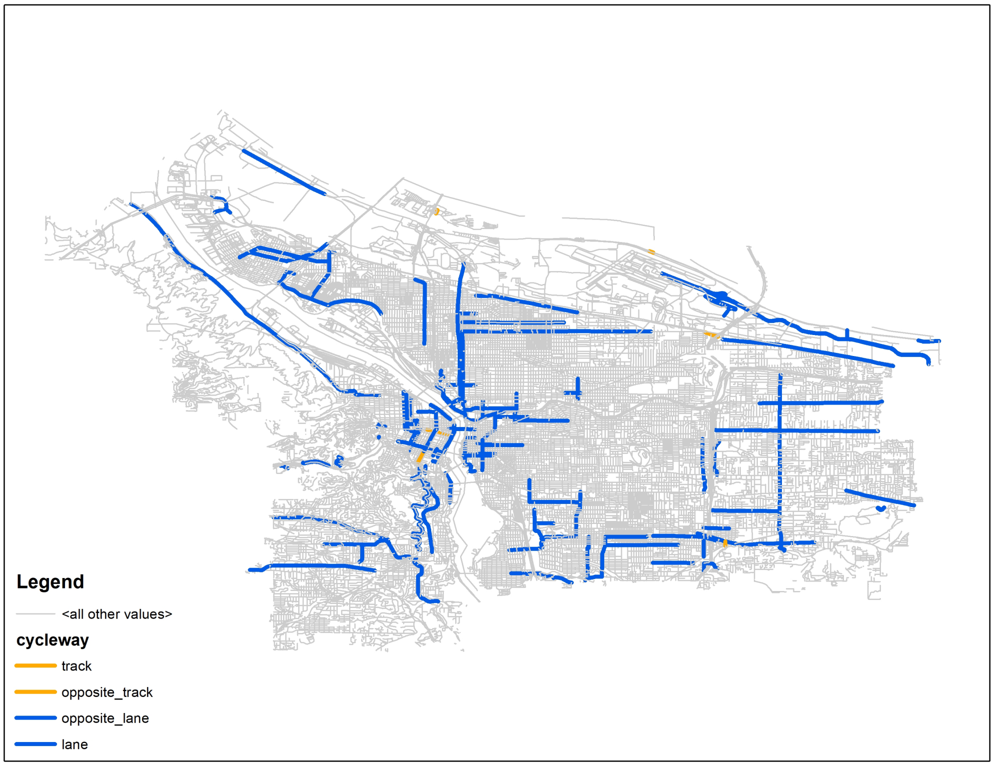




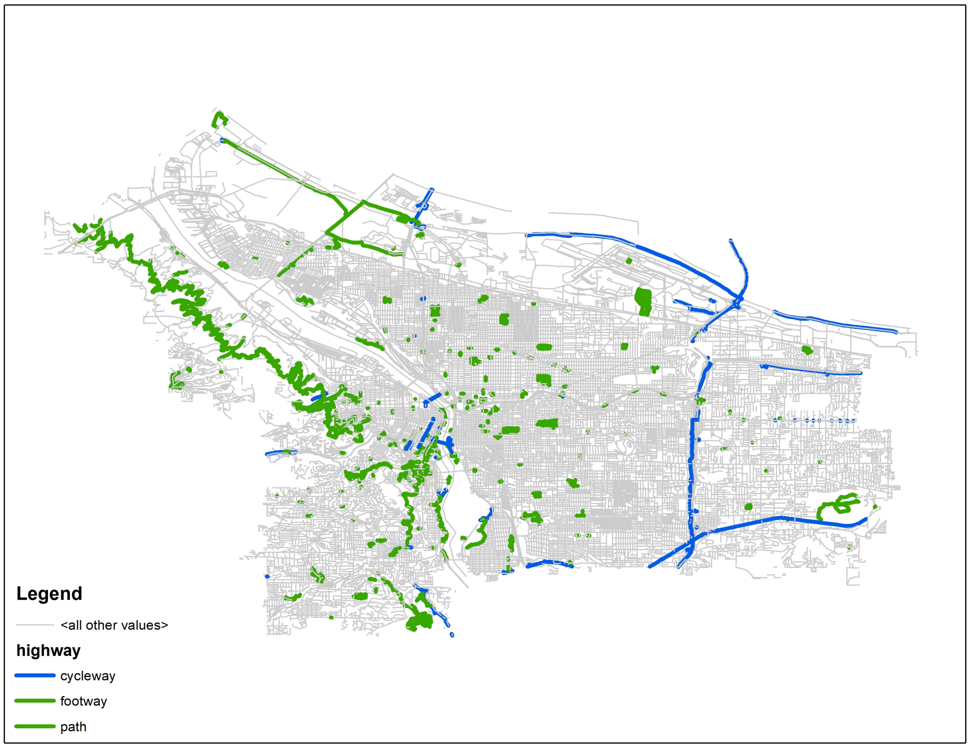
(c) Off-street Paths (Top: OSM; Bottom: RLIS)

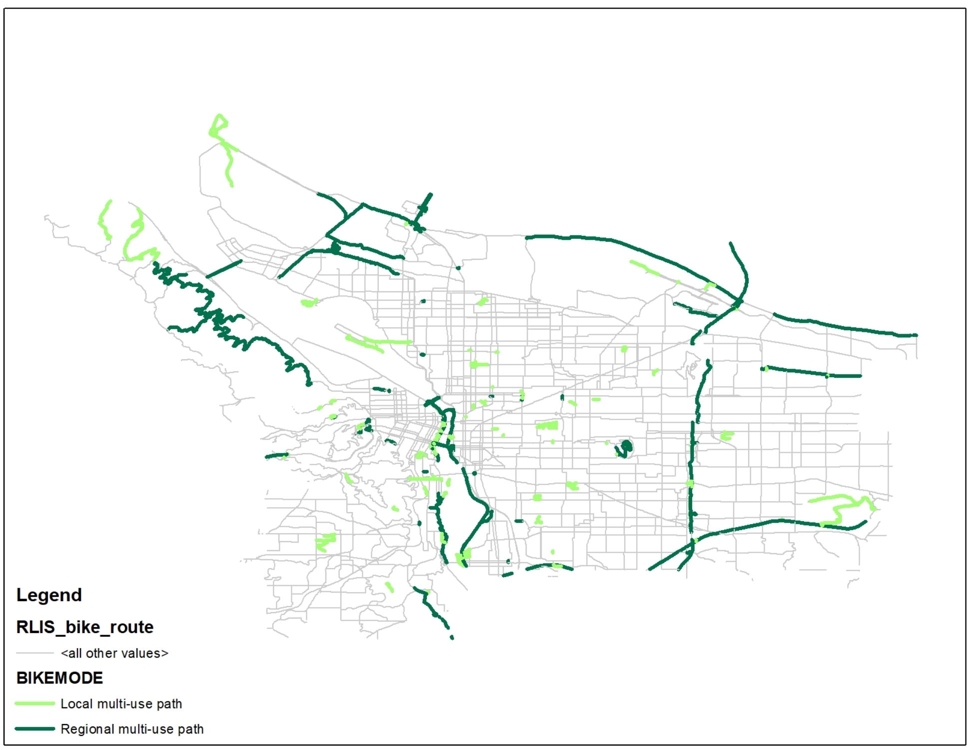
Figure 4. OSM and RLIS Bicycle Facility Comparison in 2017

The completeness of OSM data has been increasing over the years. Therefore, I also compared the bicycle infrastructure distribution in OSM and RLIS to examine their similarity in 2011. The most significant difference is that OSM neglected to label any bike boulevards in Portland, which is an important low stress bike facility in the city. In addition, there are less bike lanes labeled in the OSM dataset compared to RLIS dataset as well. In terms of regional and local multi-use paths, the two datasets shared similar distribution, except that OSM labeled more detailed pedestrian oriented streets than RLIS. Therefore, in order to build the Portland bicycle network in 2011, I incorporated the bicycle facility data from RLIS into the bicycle infrastructure distribution of OSM.



(a) On-street Bike Lanes (Top: OSM; Bottom: RLIS)





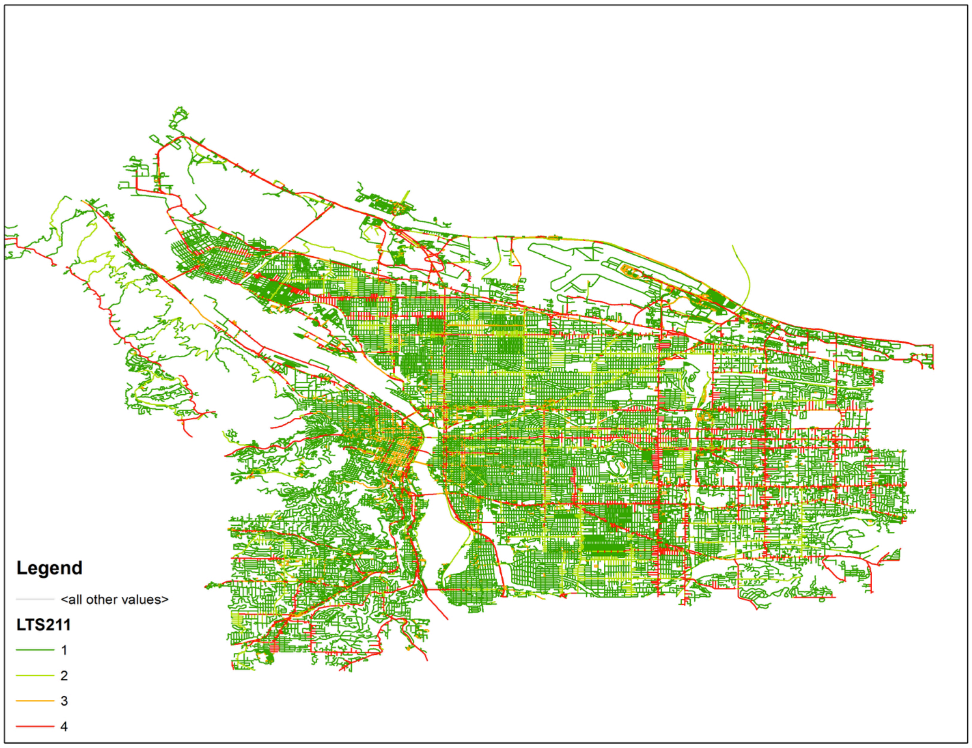
(b) Off-street Paths (Top: OSM; Bottom: RLIS)

Figure 5. OSM and RLIS Bicycle Facility Comparison in 2011

Examination of Different Types of LTS Calculation

As shown in the maps (Figure 6) below (evaluated with the original LTS), the major arterials generally had higher traffic stress, and the majority of the residential streets had lower traffic stress.

As shown in the maps (Figure 7) below (evaluated with the updated LTS), southwest Portland and the southeast region close to city boundary generally had higher traffic stress than the same regions in the maps above, which were evaluated with the original LTS.



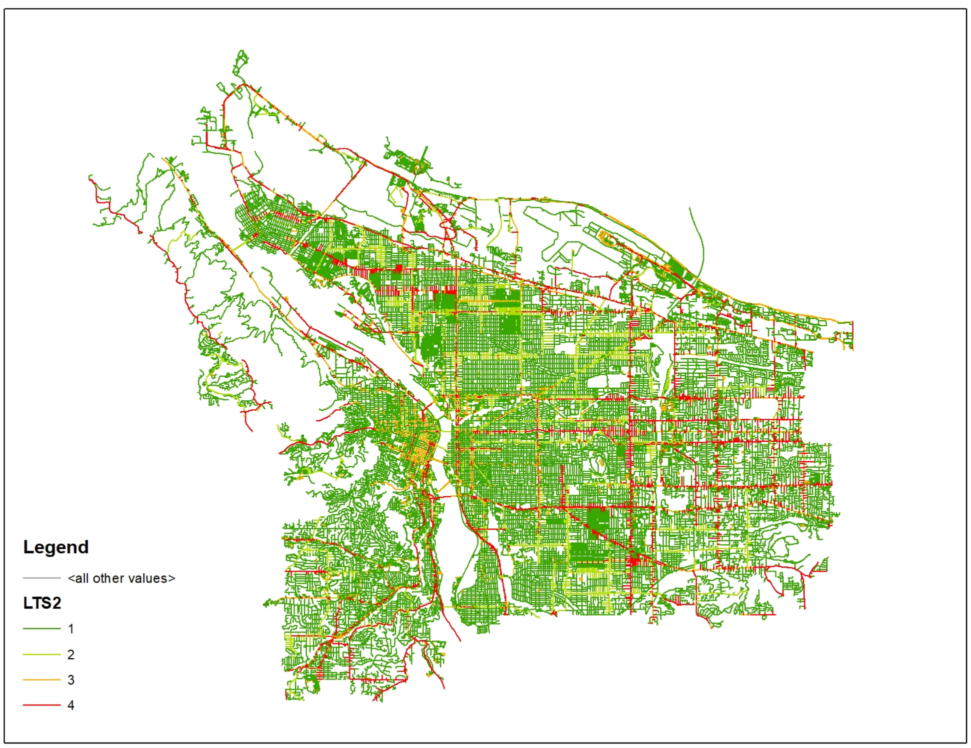
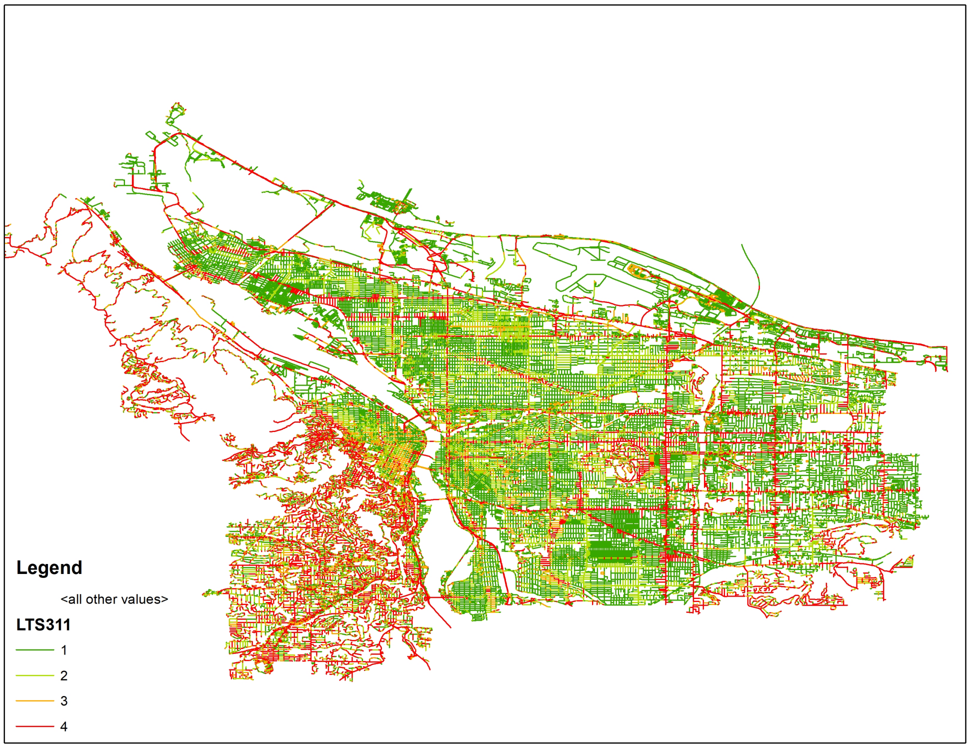


Figure 6. Portland Street Level of Traffic Stress (Original; Top: 2011; Bottom: 2017)



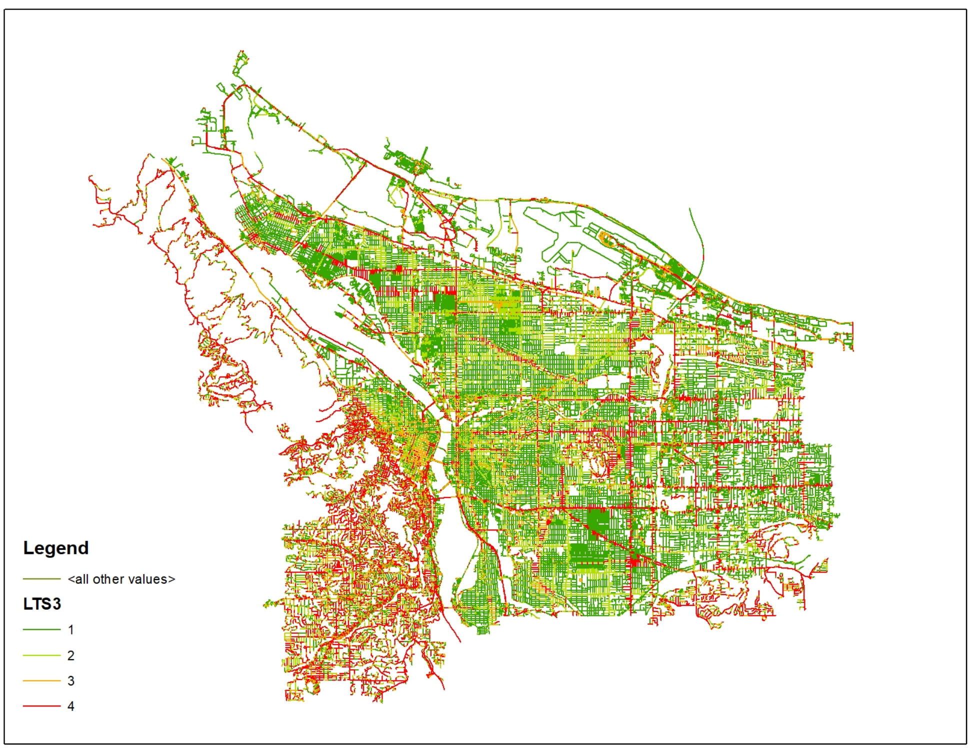


Figure 7. Portland Street Level of Traffic Stress (Updated; Top: 2017; Bottom 2011)

In terms of the difference between 2011 and 2017, the major changes occurred in far East Portland, NE Portland and southern downtown area. Theses changes were the area with significant infrastructure investments during the six years, such as Tilikum Crossing, and bike boulevard construction on Bush Street, SE 100th Ave, etc. As LTS level 1 and LTS level 2 were defined as low stress level, and LTS level 3 and LTS level 4 were defined as high stress level, the percentage of high stress street segments decreased from 21.0% to 18.8% (the original version), or from 45.0% to 43.1% (the updated version).

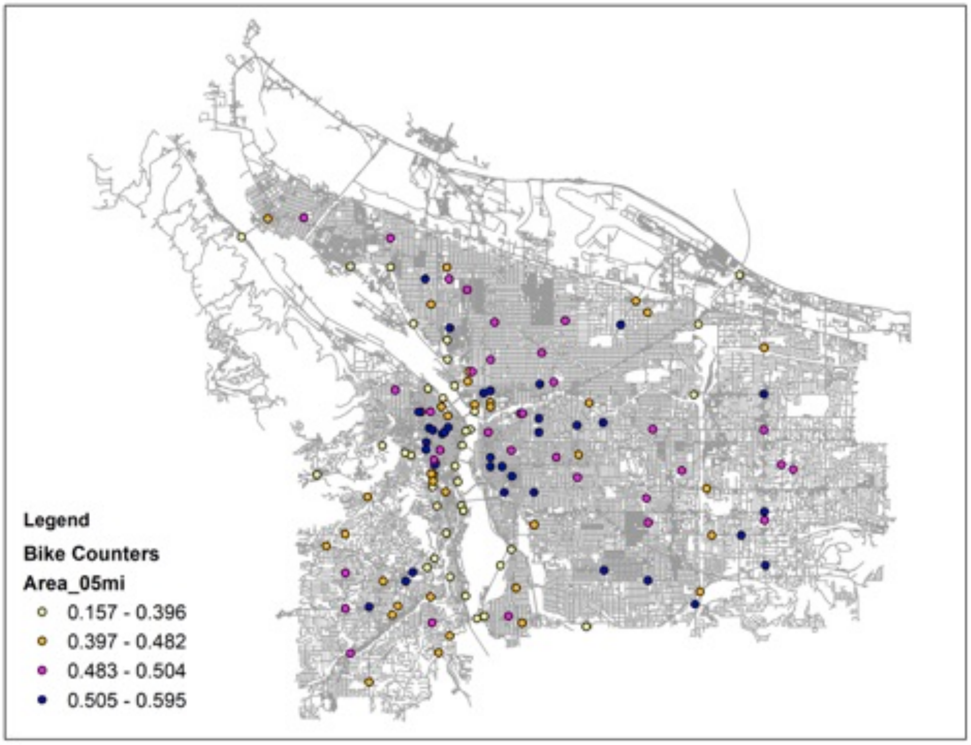
Bicycle Network Measures

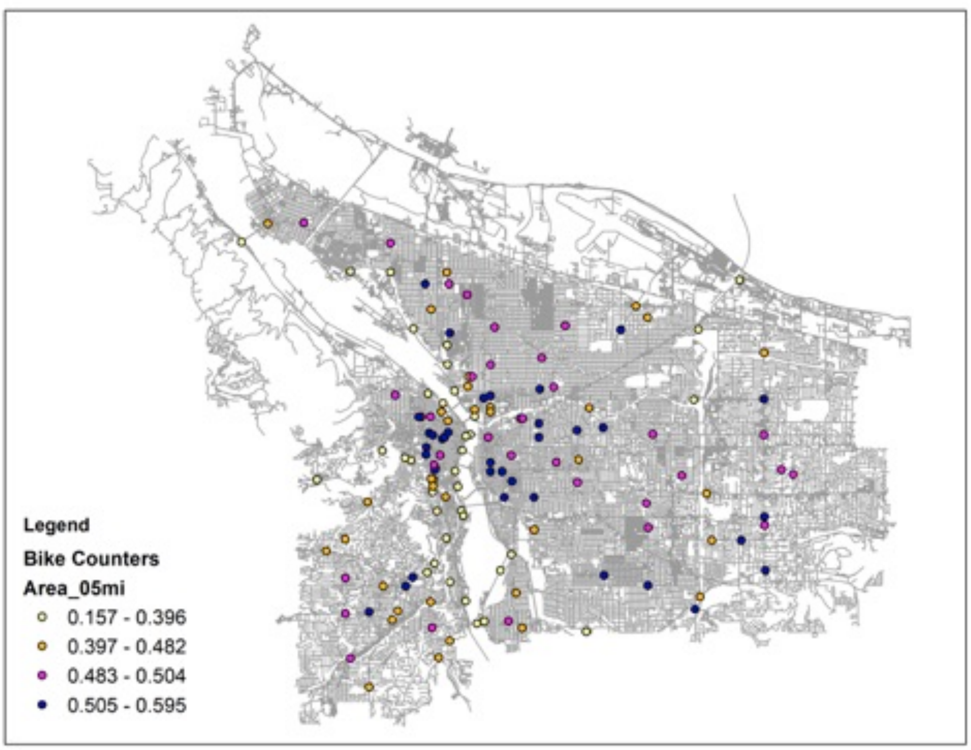
To better understand bike network measures of different bike counters, the following figures (Figure 8) show the distribution of the regional bike network measures.

- In terms of catchment area size, the bike counters along the rivers and the areas with less connected street networks had smaller catchment size. This measure only took into account of street layout; therefore, it is not surprising that no difference is observed between the original and the updated LTS.
- The second measure evaluated the amount of low stress network within the catchment area. There were significant differences between the original and the updated measure. As for the original measure, the percentages of low stress segments vary in the range of 53%-100%, and the bike counters in downtown area generally had less low stress streets. However, the updated measure, which took into account of specific bike facilities and terrain information, showed that bike counters in hilly southwest Portland had less lower stress street segments. The lower limit of the updated measure also dropped to 24%, which was much less

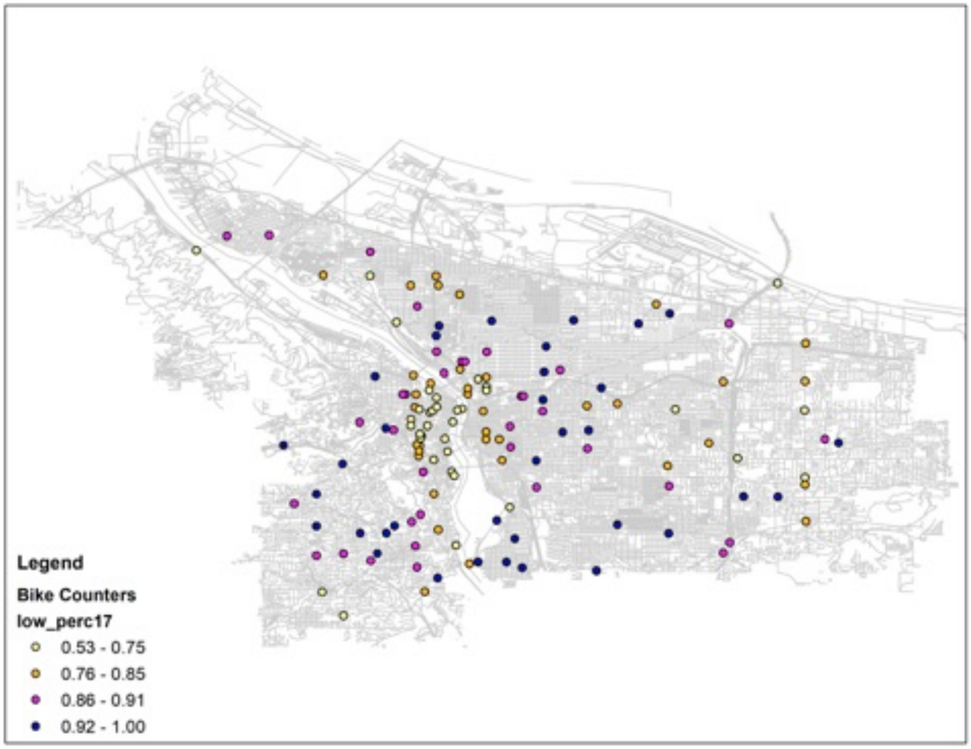
than the original measure. In general, bike counters in East Portland had more low stress streets.

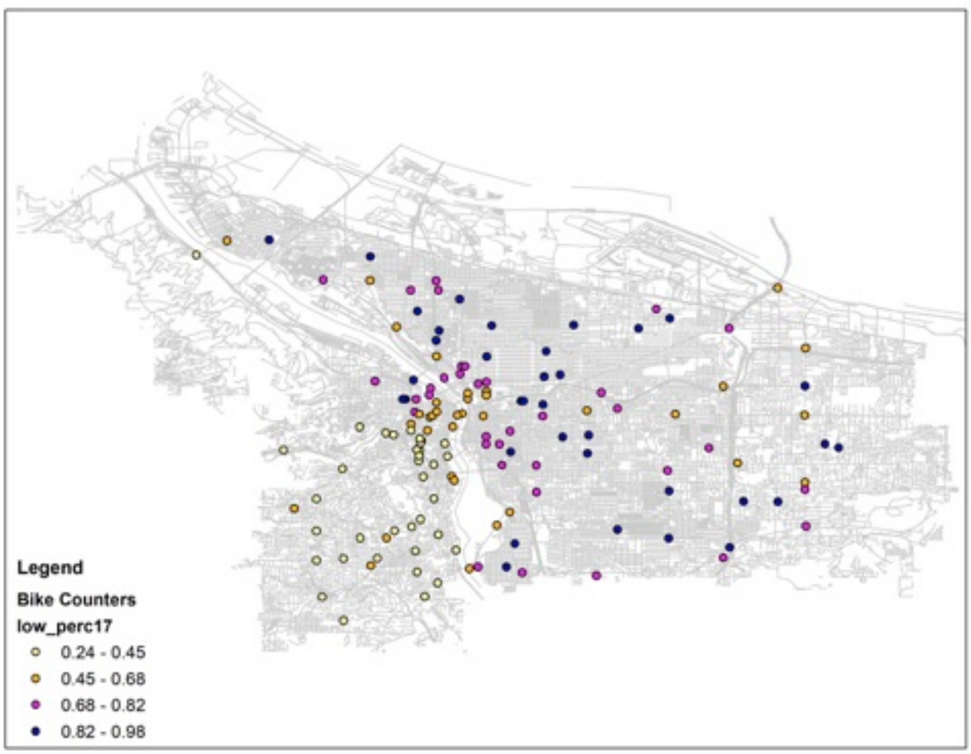
- The third measure evaluated the stress level of the street adjacent to the bike counters. The level of stress was based on the specific streets the bike counter located, which led to a sparse distributed outcome. In general, the bike counters in East Portland had lower values for this measurement.
- The last measure only utilized low stress segments (LTS1 and LTS2) to calculate the catchment area. The ranges using original measure and updated measure were very different. In general, bike counters in East Portland had larger low stress catchment area, while bike counters at southwest Portland and far East Portland had smaller low stress catchment area.



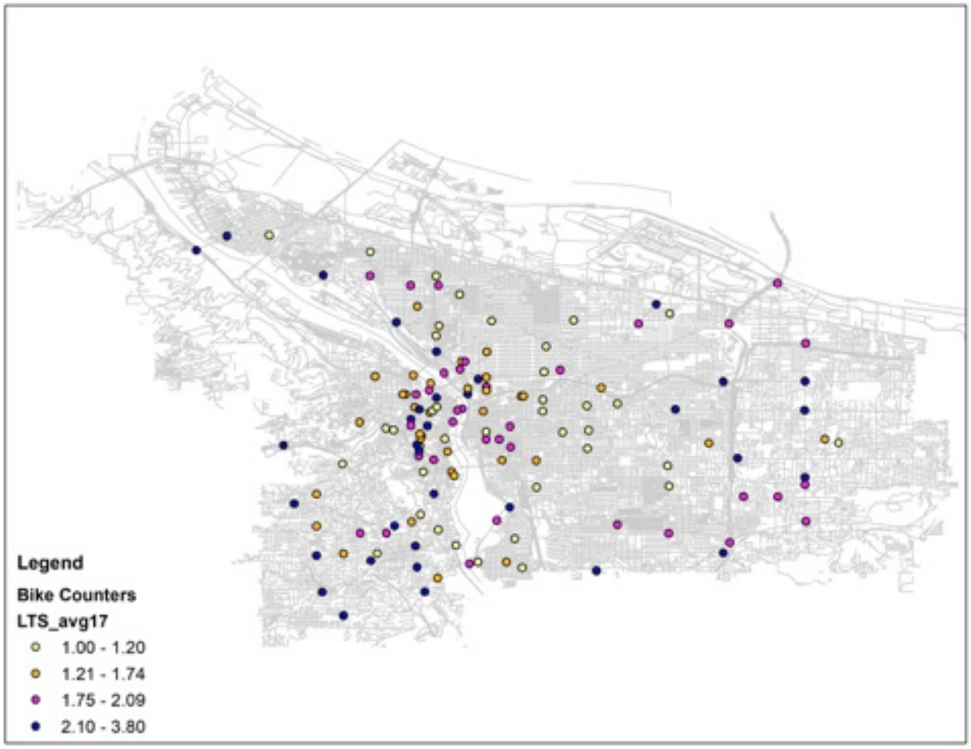


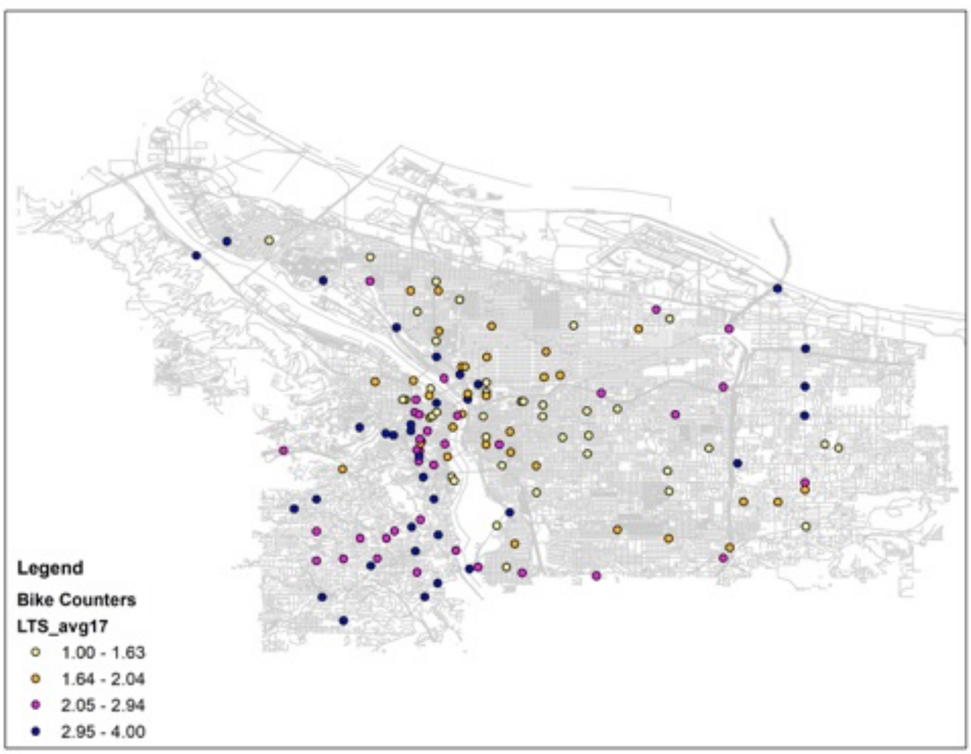
(a) Catchment area size (0.5 mile buffer zone) (Top: Original LTS; Bottom: Updated LTS)



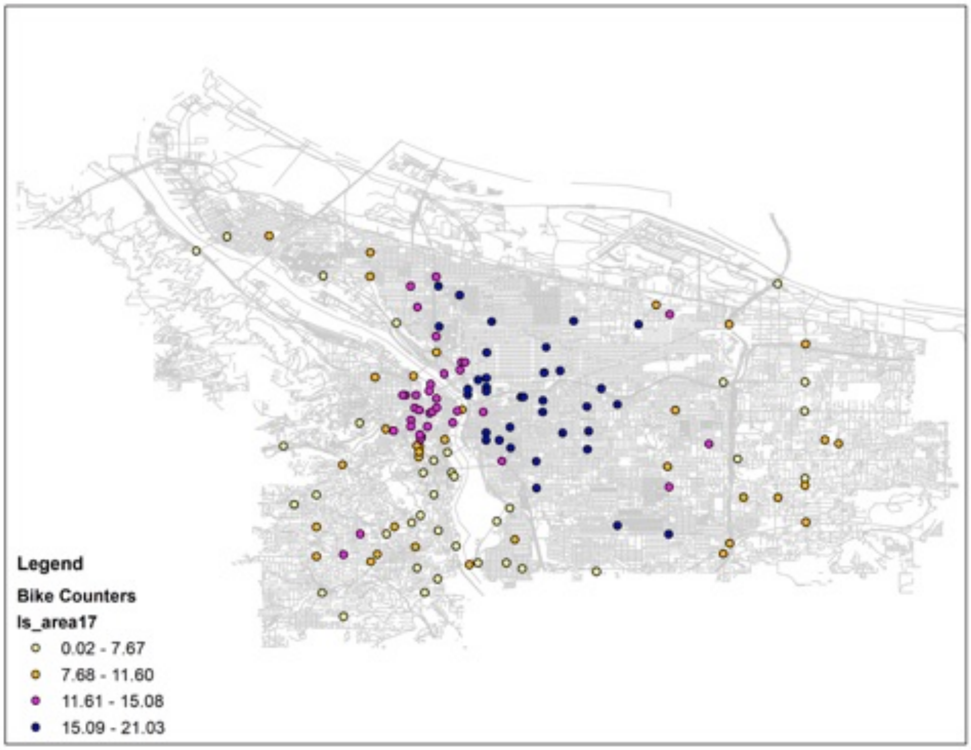


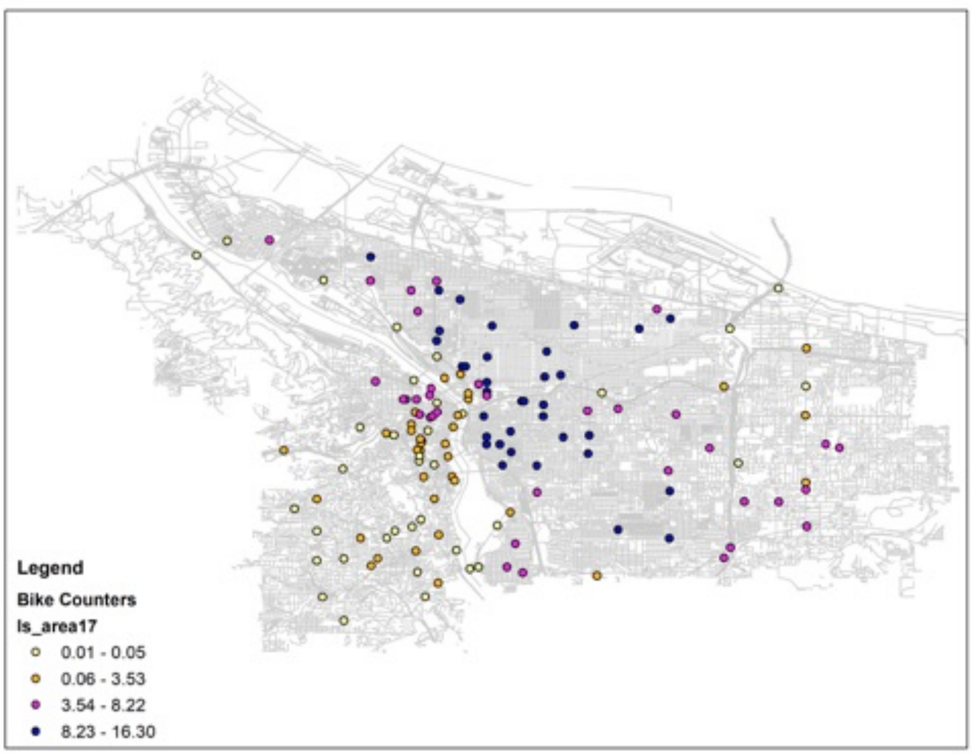
(b) Percentage of low stress segments (Top: Original LTS; Bottom: Updated LTS)





(c) Average LTS of closest segments (Top: Original LTS; Bottom: Updated LTS)





(d) Low stress segments catchment area (Top: Original LTS; Bottom: Updated LTS)

Figure 8. Bike Network Measures of Different Bike Counters in Portland

Case 2: Minneapolis, MN

Examination of Different Types of LTS Features

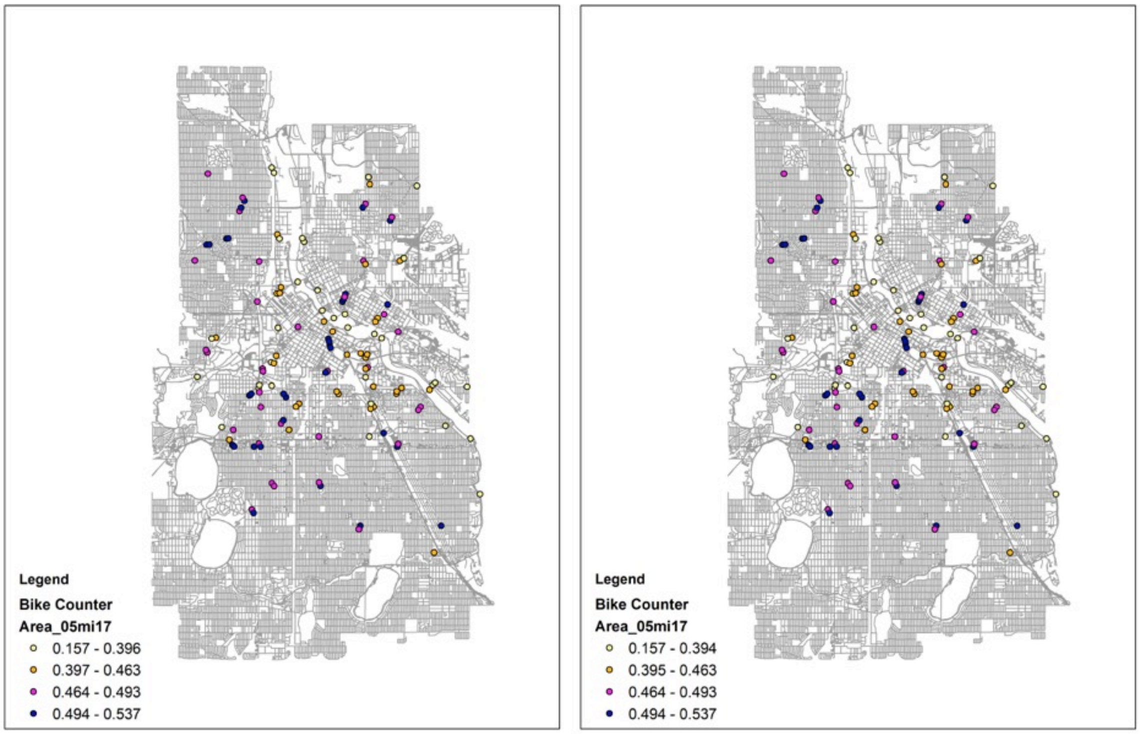
The City of Minneapolis has invested in many bicycle infrastructures. New protected bike lanes and new bikeway have been constructed across the city during the past decade. The major changes happened in the downtown area. For example, the protected bike lanes were constructed along two river-crossing roads - Central Avenue and 10th Avenue SE around University of Minnesota. In addition, bike lanes were also installed across the city on arterials and major streets, such as Central Avenue North and Lyndale Avenue North. In general, the regions in the map with apparent change in stress level are consistent with the knowledge of where bicycle infrastructure improvement had happened (Figure 9). The percentage of high stress street segments decreased from 13.5% to 10.3% (the original LTS version), or from 18.4% to 15.9% (the updated LTS version).

Figure 9. Minneapolis Street Level of Traffic Stress (Top: 2011; Bottom 2017; Left: original version; Right: updated version)

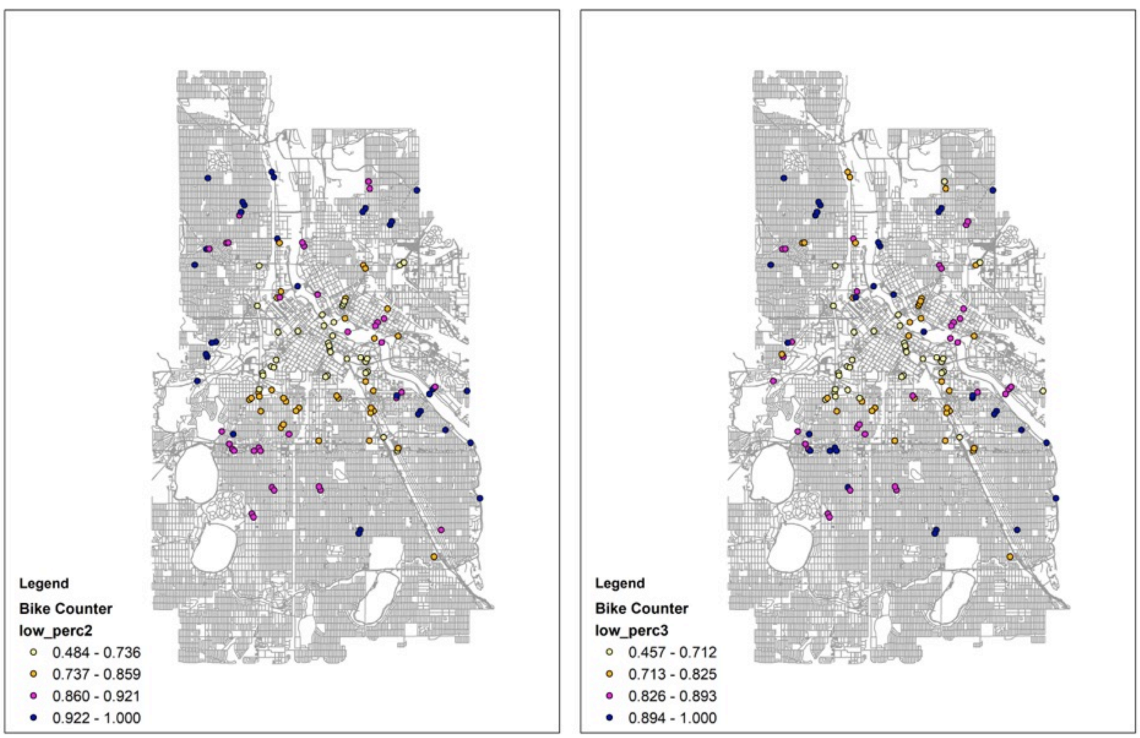
Bicycle Network Measures

To better understand bike network measures of different regional bike counters, the following figures (Figure 10) show the distribution of these bike network measures.

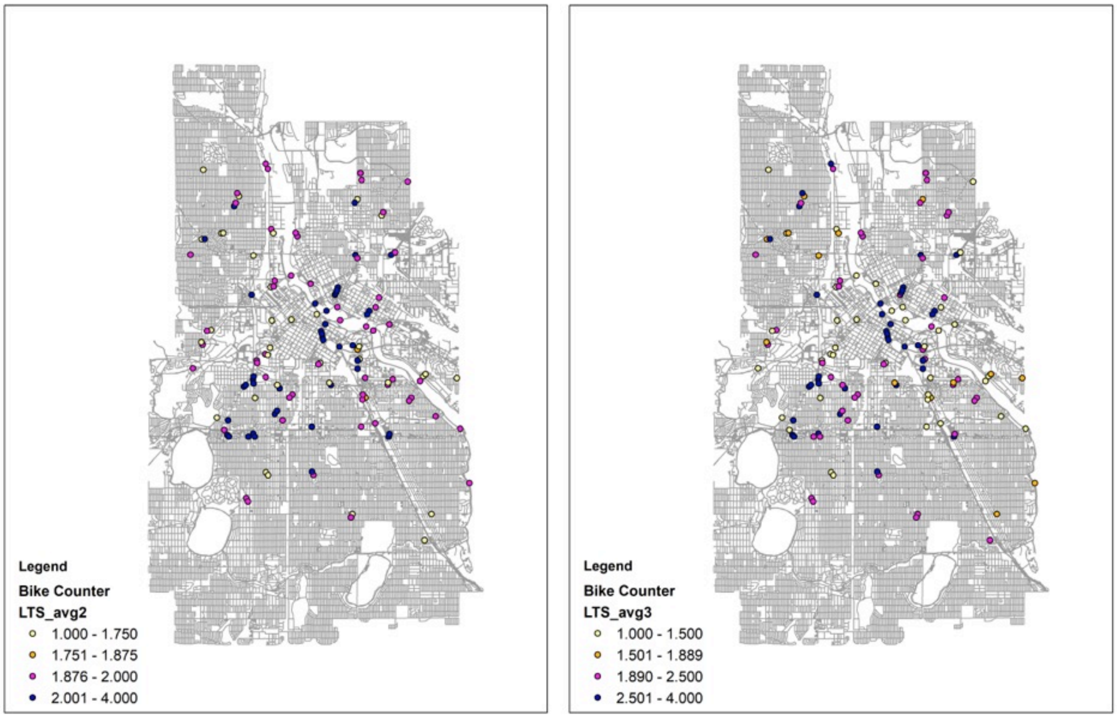
- In terms of catchment area size, which only takes into account of street layout, there is no difference between the original and the updated version. Like Portland, bike counters near river had smaller catchment area zone.
- The second measure evaluates the amount of low stress network within the catchment zone. Unlike Portland, there was not much difference between the original and the updated measure. This was probably due to the fact that Minneapolis has a less hilly terrain than Portland. As shown in the maps, the bike counters in residential area generally had more low stress segments.
- The third measure evaluates the stress level of the streets adjacent to the bike counters. Similar to Portland, the bike counters with high values of this metric distribute sparsely in the map.
- The last measure only utilized low stress segments (LTS1 and LTS2) to calculate the catchment area. The distribution of this measure is similar to the second measure.



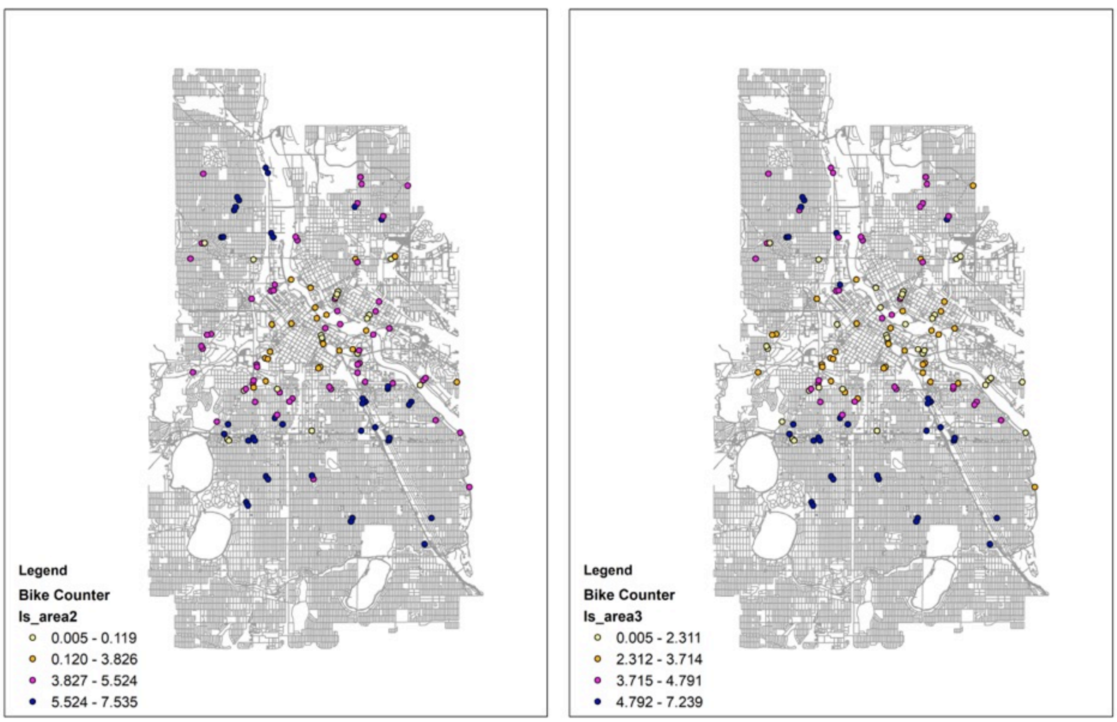
(a). Catchment area size



(b) Percentage of low stress segments



(c) Average LTS of closest segments



(d). Low stress segments catchment area

Figure 10. Bike Network Measures of Different Bike Counters in Minneapolis (Left: Original LTS; Right: Updated LTS)

Discussion of Bicycle Network Measures

Based on LTS calculation, two sets of bicycle network measures were developed: region level and route level. A relatively comprehensive assessment of the quality of a bike network can be achieved by evaluating it with a combination of these network measures. In particular, the regional level measures focused on the network connectivity and comfort; and the route level measures focused on route directness and quality for cyclists.

It is expected that many of these measures were correlated, since they often captured certain common aspects of the network. However, in the meantime, each of them had its unique focus, and evaluating or comparing these bicycle network measures simultaneously could be very informative. For example, for a given bike counter over a time period, if the first regional measure, the catchment area based on street layout only, stayed the same while the last regional measure, the catchment area reachable by low stress network, increased notably, it would suggest that the bicycle network improvement was specific to reduce comfort level but the street layout stayed the same. Similarly, if the second measure, the percentage of low stress segment length, stayed the same while the third measure, the stress level of the segments adjacent to the bike counter, decreased notably, it would suggest that the local improvement had no regional effects. Lastly, if the second measure, the percentage of low stress segment length, stayed the same while the last measure, the catchment area reachable through low stress network, increased significantly, it would suggest the change had improved the overall extensiveness of the network with a minimal amount of investment.

The two route level measures were correlated as well. The percentage of low stress segment length along a route is relatively easy to implement but it is a coarser measure of stress level than the ratio of weighted to actual route length. The latter had the disadvantage of having to specify a weight scale for stress levels. The weight chosen for each stress level could play an important role in this measure.

Bike infrastructure database serves as the foundation to evaluate the bike network measures. So I compared the bike infrastructure information from two sources. The crowdsourced OSM data is a good resource for bicycle level of stress calculation, especially in recent years. It offers bicycle infrastructure and street characteristics information in one dataset. Although some of the street characteristics information requires additional calibration with local data achieves, the OSM data generally provides high-quality data sources, and it has the advantage of consistency and replicability across different cities.

The updated LTS measures performed better in Portland to account for the hilly terrain, but the difference between the two versions of LTS measures was negligible in Minneapolis, which has relatively flatter terrain. This suggested that the updated measures performed better in incorporating bicycle network characteristics that impacted bicycle ridership and should be adopted in future studies, because it had an obvious advantage in hilly regions and it also gave an unbiased evaluation of stress levels in other regions.

What are the Impacts on Bicycling Activity: Bike Count Analysis

Case 1: Portland, OR

Descriptive Analysis

Bike counts was selected as the indicator of bicycling activity. Among 141 bike counters, a majority of them were distributed around city center and inner East of Portland (Figure 11). Bike counts were not normally distributed but right-skewed, as shown in the histogram density plot (Figure 12).

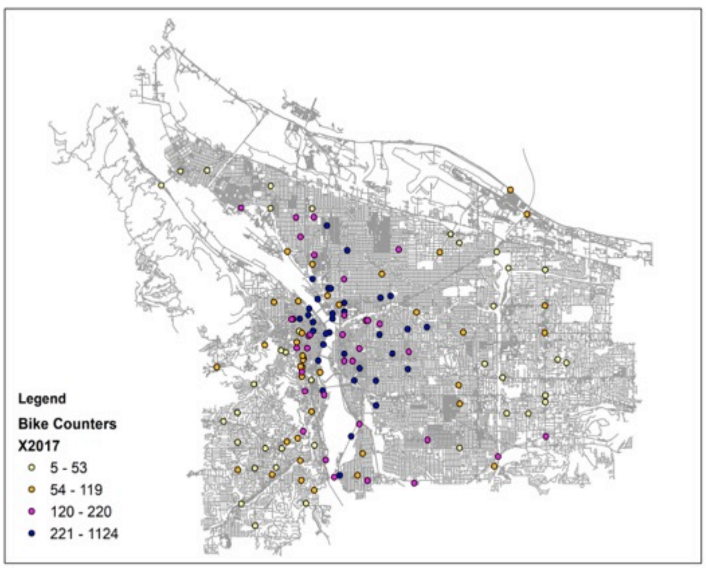


Figure 11. Distribution of the Bike Counters in Portland

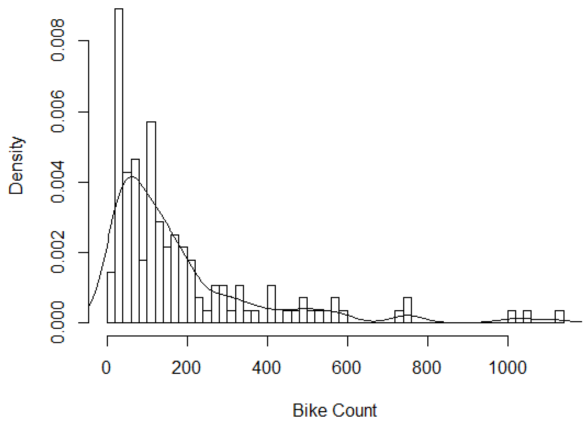


Figure 12. Histogram of the Bike Counts in Portland

The descriptive statistics of the variables were listed in Table 6. In terms of the bike network measures, the mean value of the original LTS measures and the mean value of the updated LTS measures were compared. In general, the stress level of the bike network in Portland is higher when measured by the updated LTS measures, which is consistently reflected by the higher mean level of stress for the street segments adjacent to the bike counter and the lower percentage of low stress segments. The updated LTS measures prioritized the effects of slope over other roadway characteristics in determining the stress score of the road segments. As for the case of Portland, where the terrain is hilly in some parts of the city, such as Southwest Portland, the updated LTS measures were better in measuring the comfort level, e.g. the amount of physical efforts required for cyclists. As a result, the updated LTS measures are better in describing the stress levels in hilly terrains, compared to the original measures.

Table 6. Variable Descriptive Summary

Variables	Unit	Mean	Range
Bike Count	Count	188	5 - 1124
Catchment area (0.25 mi)	Square Mile	0.12	0.06-0.15
Catchment area (0.5 mi)	Square Mile	0.44	0.16-0.59
Catchment area (1 mi)	Square Mile	1.70	0.58-2.18
Average LTS of adjacent segments (original)	Level 1-4	1.8	1-3.8
% of low stress segments (original)	Percent	82.8	53.1-99.7
Low stress segments catchment area (original)	Square Mile	4.34	0.01 – 8.11
Average LTS of adjacent segments (updated)	Level 1-4	2.2	1-4.0
% of low stress segments (updated)	Percent	65.2	24.4 – 98.1
Low stress segments catchment area (updated)	Square Mile	4.41	0.01 – 6.29
Population density	1000 People/Square Mile	7.569	0.126-17.836
% of households with 0 vehicles	Percent	19.9	0-66.7
% of white population	Percent	80.2	62.8-90.6
% of elder population	Percent	12.9	5.8-25.6
% of population with college degree or above	Percent	70.8	22.2-93.6
Median household income	1000 Dollars	66.0	19.6-168.3
Crime	Count	1220	0-3941
Transit accessibility	Level	22,277	0-92,883
Job housing balance	Ratio	12.1	0.1-595.4
# of intersections in half-mile buffer zone	Count	162	12-562
Auto network density	Miles/Square Mile	2.9	0-22.4
Multi-modal network density	Miles/Square Mile	3.3	0-15.4
Pedestrian network density	Miles/Square Mile	21.0	0.1-69.4
Betweenness	Count	131.6	0-2268
Closeness	Inverse of distance	0.928	0.486-1.262

Correlation Analysis

The following figure (Figure 13) shows the correlation among the selected independent variables. The darker blue dots with a larger size indicates a stronger positive correlation, while the darker red dots with a larger size indicates a stronger negative correlation.

It is apparent that the street design/network variables highly correlate with each other, and they also correlate with closeness and some of the bicycle network measures. As a result, I exclude those street design/network variables in the future modeling. In addition, some demographic variables, such as education level, income, crime, and race, also highly correlate with each other. This information gives hints on where multi-collinearity could occur among the variables in regression models.

In terms of the four bike network measures, catchment area size positively correlates with low stress catchment area size, while average LTS of closest segments negatively associates with the other three measures, since higher the average LTS value is, the worse the network is in terms of comfort level. The correlation among those measures indicates, although these measures were developed to represent different aspects of the network, they supplement with each other to give a complete view of the network characteristics of the region. In addition, the correlation of between updated measures and other covariates, such as income and education level, are more obvious compared to the correlation between original one and other covariates. It indicates the updated measures already incorporate more of those other characteristics in Portland.

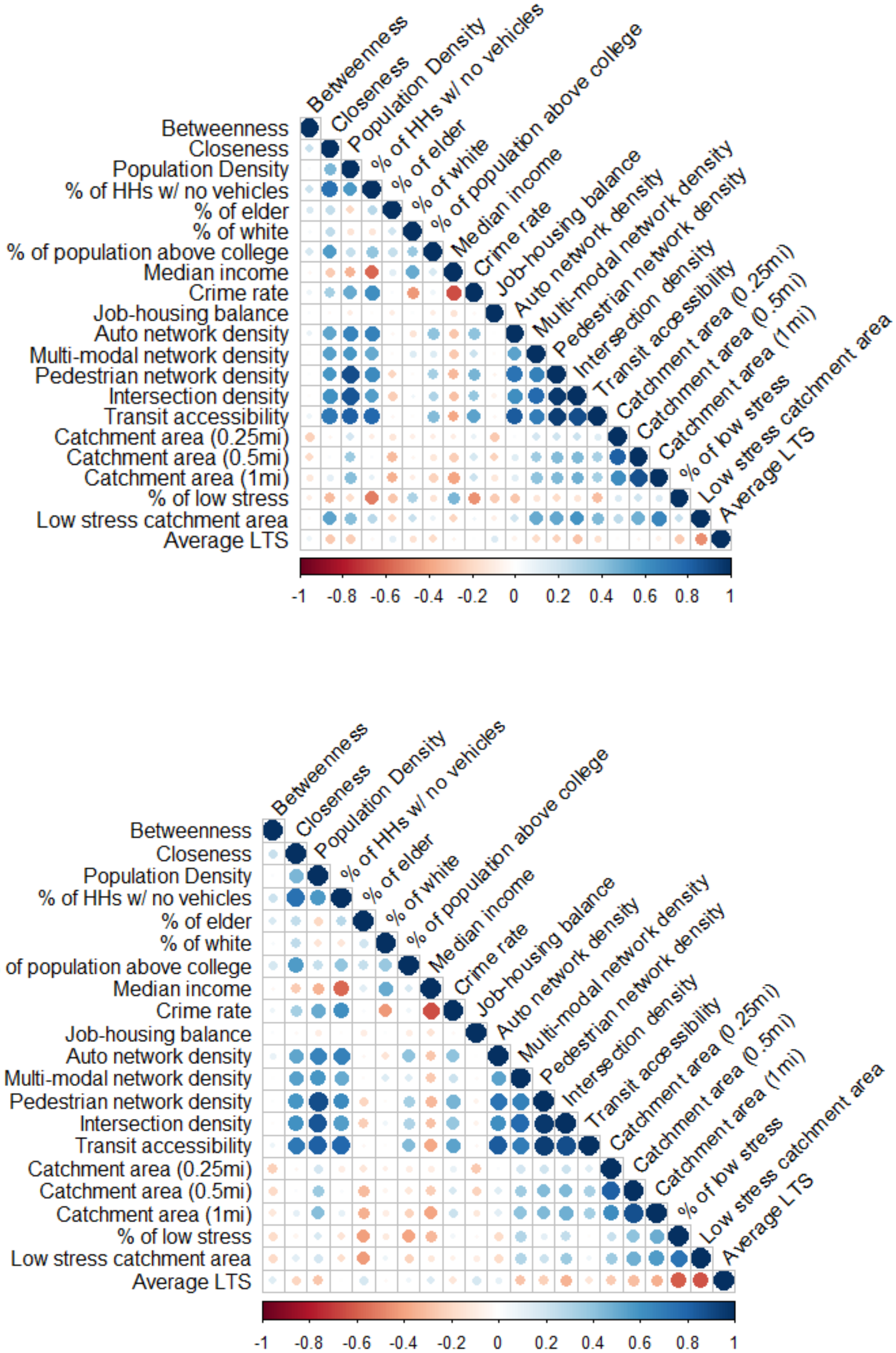


Figure 13. Correlation Plots among Independent Variables of Bike Counts Model in Portland (Top: Original LTS; Bottom: Updated LTS)

Regression Analysis

In order to compare the applicability of network measures, two sets of models, OLS and negative binomial models, were applied to analyze the impacts of bike network measures on bike counts in Portland in 2017, controlling for other factors. Particularly, bike network measures were calculated based on two different LTS versions for each model method: Figure 14 and Figure 15 are bike network measures based on the original LTS, while Figure 16 and Figure 17 are measures based on the updated LTS version. 15 variables were kept in the following models, while each bicycle network measure was tested seperately to compare the power of explaination. The covariate “percentage of households with 0 vehicle” was excluded because it stronglly correlates with other demograhic variables. Based on comparing the log likelihood and AIC statistics, I found that the negative binomial models performed better than the OLS models, and the models with the updated LTS measures performed better than the orginal LTS measure. The following interpretation is based on the negative binomial model with the updated LTS measures to explain the effects of different bike network measures.

The three catchment area sizes, including 0.25 mile, 0.5 mile, and 1 mile, all negatively associate with bike counts, which is counter-intuitive. There are three possible reasons to explain this result. First, referring to Figure 8(a) - the distribution of catchment area size of different bike counters, the bike counters along the river generally have smaller catchment sizes due to topology factor. In fact, most of those bike counters locate along the multi-use paths close to Willamette River, where the bike volumn is very high. Second, using bike counts as a bicycle activity indicator has the drawback of only reflecting the passing-by bicycle volume, thus the catchment size of the location may not neccesarily associate with the bike counts. Third, this measure only evaluates the street network layout rather than the actual comfort or the quality for bicycle trip. Therefore, the other three measures are expected to supplement this measure in the next step.

The other three measures based on the updated LTS show significant association with bike counts. To be more specific, each one percent increase of low-stress segment street is associated with 0.07 times increase in bike counts; each one unit increase of average LTS level is associated with 1.3 times decrease in bike counts; and each one square kilometer increase in low-stress network catchment area size is associated with 1.04 times increase in bike counts. When combining all four measures together into a pooled model, only catchment area size and the percentage of low-stress segment are statistically significant in determining bike counts.

These results indicate more low stress street segments is positively associated to more bike volume, and stress level in the surrounding areas with intermediate size (0.5 mile) is more important than the stress level in the street segments adjacent to bike counters and large areas (2 miles). The comparison of AIC statistics among different models indicates that percentage of low-stress segments is the most powerful indicator among the four regional measures to predict bike counts, which is followed by average LTS of adjacent segments.

In terms of other variables, population density negatively affects bicycle usage, indicating bicyclists prefer to bike in less populated areas. The areas with more white population, less elder population, and less higher level educated population associate with higher bike counts. In addition, the bike counts value at each location is also likely affected by the whole network of traffic flow. The covariate closeness, which measures the closeness of one bike counter to other bike counters, is positively associated with the bicycle counts of that intersection.

	Dependent variable:						
	Bike Count (2017)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Betweenness	-0.005	-0.009	-0.001	0.001	0.004	0.004	-0.009
	(0.049)	(0.049)	(0.048)	(0.048)	(0.048)	(0.048)	(0.050)
Closeness	630.486***	622.418***	639.202***	640.868***	625.192***	607.642***	547.821***
	(99.292)	(98.944)	(99.137)	(100.198)	(101.312)	(116.417)	(131.352)
Population density	-14.109***	-12.458**	-13.295**	-14.684***	-14.931***	-15.247***	-13.148**
	(5.197)	(5.353)	(5.465)	(5.148)	(5.184)	(5.327)	(5.493)
% of elder population	-211.481	-312.315	-275.012	-147.273	-169.572	-143.968	-184.518
	(379.725)	(386.215)	(393.561)	(404.940)	(384.882)	(399.345)	(412.503)
% of white population	378.994	461.761	423.703	330.474	360.100	329.977	384.365
	(287.927)	(294.278)	(298.441)	(302.602)	(287.732)	(298.204)	(308.573)
% of pouplation with college degree or above	-353.708***	-371.867***	-379.550***	-341.351***	-348.362***	-328.453**	-319.820**
	(124.971)	(125.228)	(131.828)	(126.681)	(124.902)	(133.028)	(134.160)
Median household income	-1.353	-1.618	-1.549	-1.354	-1.335	-1.207	-1.549
	(0.984)	(1.003)	(1.043)	(0.994)	(0.984)	(0.998)	(1.053)
Crime	-0.013	-0.013	-0.014	-0.012	-0.012	-0.011	-0.007
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.020)
Job-housing balance	-0.309	-0.373	-0.310	-0.222	-0.242	-0.235	-0.342
	(0.272)	(0.273)	(0.271)	(0.279)	(0.264)	(0.266)	(0.289)
Catchment Area (0.25mi)	-593.672						
	(894.949)						
Catchment Area (0.5mi)		-277.642					-401.039*
		(204.292)					(237.344)
Catchment Area (1mi)			-39.312				
			(55.249)				
% of low stress segments (original)				68.347			44.874
				(181.558)			(203.707)
LTS average (original)					-11.009		4.273
					(22.769)		(25.571)
Low stress segment catchment area (original)						4.882	13.446
						(10.750)	(13.916)
Constant	-140.173	-114.271	-153.773	-253.862	-177.899	-204.133	-92.438
	(223.705)	(207.937)	(212.291)	(226.830)	(208.285)	(197.168)	(261.562)
Observations	140	140	140	140	140	140	140
R2	0.361	0.368	0.361	0.359	0.360	0.360	0.375
Adjusted R2	0.311	0.319	0.312	0.310	0.310	0.310	0.310
Note:							*p<0.1; **p<0.05; ***p<0.01

Figure 14. Regression Results of Bike Counts in Portland (1)

	Dependent variable:						
	Bike Count (2017)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Betweenness	-0.005	-0.009	-0.001	0.012	0.012	0.008	0.002
	(0.049)	(0.049)	(0.048)	(0.048)	(0.048)	(0.049)	(0.049)
Closeness	630.486***	622.418***	639.202***	615.322***	601.389***	607.362***	598.378***
	(99.292)	(98.944)	(99.137)	(98.332)	(101.074)	(106.208)	(109.620)
Population density	-14.109***	-12.458**	-13.295**	-15.599***	-15.446***	-14.895***	-13.314**
	(5.197)	(5.353)	(5.465)	(5.101)	(5.137)	(5.152)	(5.354)
% of elder population	-211.481	-312.315	-275.012	57.188	-101.460	-63.895	-90.582
	(379.725)	(386.215)	(393.561)	(397.594)	(382.851)	(422.936)	(421.384)
% of white population	378.994	461.761	423.703	255.175	311.429	329.177	357.045
	(287.927)	(294.278)	(298.441)	(289.402)	(287.795)	(291.557)	(295.527)
% of pouplation with college degree or above	-353.708***	-371.867***	-379.550***	-249.955*	-304.562**	-310.547**	-270.581**
	(124.971)	(125.228)	(131.828)	(133.522)	(127.676)	(135.609)	(135.925)
Median household income	-1.353	-1.618	-1.549	-0.714	-1.235	-1.218	-1.074
	(0.984)	(1.003)	(1.043)	(1.013)	(0.974)	(0.984)	(1.052)
Crime	-0.013	-0.013	-0.014	-0.008	-0.013	-0.010	-0.010
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)
Job-housing balance	-0.309	-0.373	-0.310	-0.167	-0.173	-0.216	-0.281
	(0.272)	(0.273)	(0.271)	(0.262)	(0.266)	(0.268)	(0.275)
Catchment Area (0.25mi)	-593.672						
	(894.949)						
Catchment Area (0.5mi)		-277.642					-334.145
		(204.292)					(217.441)
Catchment Area (1mi)			-39.312				
			(55.249)				
% of low stress segments (updated)				179.193*			193.827
				(92.764)			(128.252)
LTS average (updated)					-30.766		-14.959
					(21.011)		(26.747)
Low stress segment catchment area (updated)						7.636	-4.584
						(10.494)	(15.069)
Constant	-140.173	-114.271	-153.773	-362.938*	-110.682	-221.138	-203.760
	(223.705)	(207.937)	(212.291)	(209.207)	(206.825)	(196.764)	(258.474)
Observations	140	140	140	140	140	140	140
R2	0.361	0.368	0.361	0.377	0.369	0.361	0.393
Adjusted R2	0.311	0.319	0.312	0.328	0.320	0.312	0.330
Note:							*p<0.1; **p<0.05; ***p<0.01

Figure 15. Regression Results of Bike Counts in Portland (2)

	Dependent variable:						
	Bike Count (2017)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Betweenness	-0.0001	-0.0001	-0.0001	-0.00002	0.00000	0.00002	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Closeness	3.682***	3.653***	3.763***	3.677***	3.563***	3.383***	2.821***
	(0.415)	(0.413)	(0.414)	(0.421)	(0.424)	(0.487)	(0.534)
Population density	-0.062***	-0.052**	-0.055**	-0.066***	-0.068***	-0.073***	-0.059***
	(0.022)	(0.022)	(0.023)	(0.022)	(0.022)	(0.022)	(0.022)
% of elder population	-3.063*	-3.671**	-3.619**	-2.909*	-2.587	-2.253	-2.583
	(1.583)	(1.607)	(1.638)	(1.695)	(1.606)	(1.664)	(1.673)
% of white population	1.849	2.172*	2.191*	1.976	2.058*	1.793	1.890
	(1.204)	(1.228)	(1.246)	(1.270)	(1.205)	(1.247)	(1.255)
% of pouplation with college degree or above	-1.353***	-1.497***	-1.610***	-1.306**	-1.379***	-1.133**	-1.163**
	(0.522)	(0.522)	(0.550)	(0.531)	(0.523)	(0.556)	(0.545)
Median household income	-0.004	-0.005	-0.005	-0.003	-0.004	-0.002	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Crime	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.00004	-0.00001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Job-housing balance	-0.001	-0.001	-0.001	-0.0001	0.0001	0.0001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Catchment Area (0.25mi)	-4.697						
	(3.734)						
Catchment Area (0.5mi)		-1.690**					-2.887***
		(0.850)					(0.964)
Catchment Area (1mi)			-0.328				
			(0.230)				
% of low stress segments (original)				0.065			-0.286
				(0.762)			(0.829)
LTS average (original)					-0.098		0.009
					(0.095)		(0.104)
Low stress segment catchment area (original)						0.048	0.132**
						(0.045)	(0.057)
Constant	2.822***	2.973***	2.772***	2.047**	2.328***	2.039**	3.607***
	(0.936)	(0.868)	(0.887)	(0.953)	(0.873)	(0.826)	(1.065)
Observations	140	140	140	140	140	140	140
Log Likelihood	-823.352	-822.152	-822.999	-824.086	-823.657	-823.488	-819.043
theta	1.981*** (0.225)	2.012*** (0.229)	1.990*** (0.226)	1.963*** (0.223)	1.974*** (0.224)	1.977*** (0.225)	2.094*** (0.239)
Akaike Inf. Crit.	1,668.703	1,666.303	1,667.998	1,670.171	1,669.315	1,668.977	1,666.085
Note:							*p<0.1; **p<0.05; ***p<0.01

Figure 16. Regression Results of Bike Counts in Portland (3)

	Dependent variable:						
	Bike Count (2017)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Betweenness	-0.0001	-0.0001	-0.0001	0.0001	0.0001	0.0001	0.00001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Closeness	3.682***	3.653***	3.763***	3.627***	3.323***	3.326***	3.471***
	(0.415)	(0.413)	(0.414)	(0.393)	(0.417)	(0.441)	(0.428)
Population density	-0.062***	-0.052**	-0.055**	-0.080***	-0.076***	-0.075***	-0.062***
	(0.022)	(0.022)	(0.023)	(0.020)	(0.021)	(0.021)	(0.021)
% of elder population	-3.063*	-3.671**	-3.619**	-0.214	-2.075	-1.034	-1.113
	(1.583)	(1.607)	(1.638)	(1.584)	(1.574)	(1.749)	(1.640)
% of white population	1.849	2.172*	2.191*	0.624	2.120*	1.852	1.104
	(1.204)	(1.228)	(1.246)	(1.160)	(1.187)	(1.210)	(1.156)
% of pouplation with college degree or above	-1.353***	-1.497***	-1.610***	-0.465	-1.093**	-0.909	-0.669
	(0.522)	(0.522)	(0.550)	(0.534)	(0.526)	(0.562)	(0.531)
Median household income	-0.004	-0.005	-0.005	0.003	-0.003	-0.003	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Crime	-0.0001	-0.0001	-0.0001	0.00000	-0.00003	-0.00002	-0.00000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Job-housing balance	-0.001	-0.001	-0.001	0.001	0.001	0.0005	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Catchment Area (0.25mi)	-4.697						
	(3.734)						
Catchment Area (0.5mi)		-1.690**					-2.107**
		(0.850)					(0.848)
Catchment Area (1mi)			-0.328				
			(0.230)				
% of low stress segments (updated)				1.939***			1.865***
				(0.372)			(0.501)
LTS average (updated)					-0.269***		-0.082
					(0.087)		(0.104)
Low stress segment catchment area (updated)						0.096**	-0.004
						(0.043)	(0.059)
Constant	2.822***	2.973***	2.772***	0.528	2.630***	1.774**	1.754*
	(0.936)	(0.868)	(0.887)	(0.838)	(0.854)	(0.818)	(1.009)
Observations	140	140	140	140	140	140	140
Log Likelihood	-823.352	-822.152	-822.999	-814.032	-820.047	-821.990	-810.118
theta	1.981*** (0.225)	2.012*** (0.229)	1.990*** (0.226)	2.229*** (0.256)	2.066*** (0.236)	2.015*** (0.229)	2.346*** (0.271)
Akaike Inf. Crit.	1,668.703	1,666.303	1,667.998	1,650.064	1,662.094	1,665.980	1,648.236
Note:							*p<0.1; **p<0.05; ***p<0.01

Figure 17. Regression Results of Bike Counts in Portland (4)

Case 2: Minneapolis, MN

Descriptive Analysis

Among 128 bike counters, a majority of them were distributed around city center and South of the city (Figure 18). Similar as Portland, bike counts were not normally distributed but right-skewed, as shown in the histogram density plot (Figure 19)

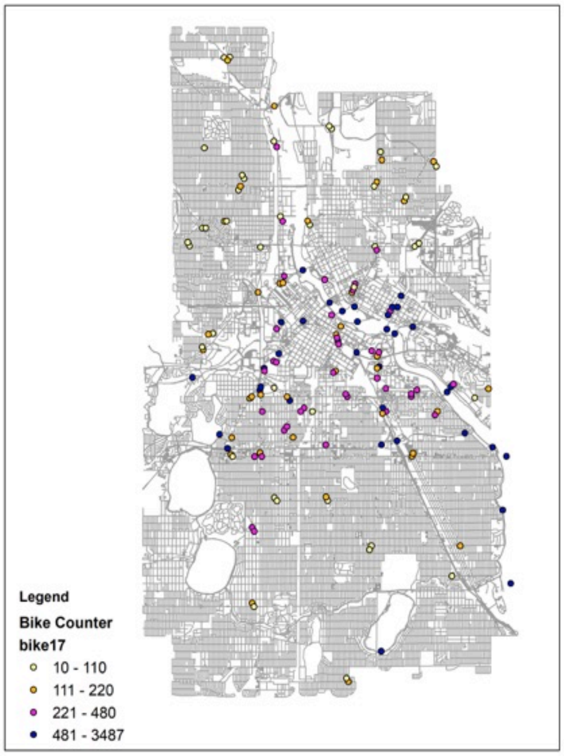


Figure 18. Distribution of the Bike Counters in Minneapolis

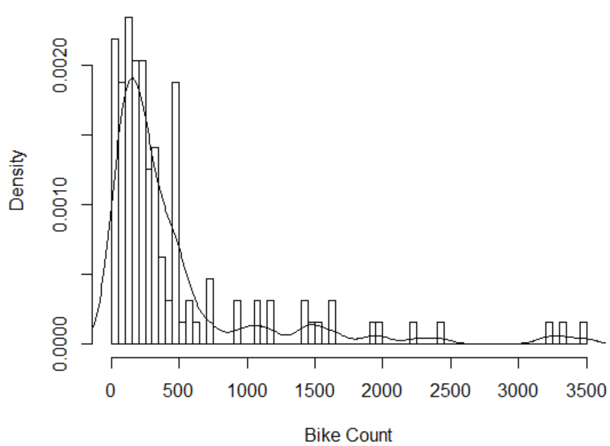


Figure 19. Histogram of the Bike Counts in Minneapolis

Following the bicycle network measures developed in this project, both the original and the updated versions were calculated for Minneapolis bicycle network. Similarly, other control variables were collected to examine the factors that might influence bicycle facility usage. These control variables included street design and land use characteristics, demographic, and geographical relationship characteristics.

The descriptive statistics of the independent variables for the year of 2017 were listed in Table 7. In terms of bike network measures, the average LTS of the closest segments around bike counters and the percentage of low stress segment in catchment area are very close in their mean values between the original and the updated LTS measures. But the original measures have a higher low stress catchment area than the updated measures.

Table 7. Variable Descriptive Summary

Variables	**Unit**	**Mean**	**Range**
Bike Count	Count	220	10-3487
Catchment area (0.5 mi)	Square Mile	0.44	0.16-0.54
Average LTS of adjacent segments (original)	Level 1-4	2.3	1 - 4.0
% of low stress segments (original)	Percent	83.0	48.4- 100
Low stress segments catchment area (original)	Square Mile	4.31	0.01 – 7.53
Average LTS of adjacent segments (updated)	Level 1-4	2.2	1 - 4.0
% of low stress segments (updated)	Percent	79.9	45.7 - 100
Low stress segments catchment area (updated)	Square Mile	3.46	0.01 – 7.23
Population density	1000 People/Square Mile	10.41	2.70 – 20.98
% of households with 0 vehicles	Percent	23.6	4.2 – 43.9
% of white population	Percent	60.1	17.0 – 92.2
% of elder population	Percent	8.8	1.3 – 20.3
% of population with college degree or above	Percent	69.1	26.6 – 93.2
Median household income	1000 Dollars	52.8	22.9 – 113.0
Crime	Count	219	19 - 951
Transit accessibility	Level	53,157	2,734 – 167,652
Job housing balance	Ratio	3.6	0.1 – 18.9
# of intersections in half-mile buffer zone	Count	196	12 - 706

Auto network density	Miles/Square Mile	4.4	0 - 27.5
Multi-modal network density	Miles/Square Mile	4.0	0.2 – 18.8
Pedestrian network density	Miles/Square Mile	27.7	2.4 – 71.0
Betweenness	Count	131.6	0-1.516
Closeness	Inverse of distance	1.29	0.78 – 1.67

Correlation Analysis

Correlation analysis among the selected independent variables is presented below (Figure 20). Similar as the City of Portland, street design/network variables highly correlate with each other, and they correlate with closeness, population density, and percentage of households with no vehicles. So I excluded those street design/network variables in the modeling analysis. In addition, some demographic variables, such as education level, income, crime rate, and race, also highly correlate with each other. In terms of bike network measures, percentage of low stress segments metric negatively correlate with closeness and job-housing balance, indicating the bike counters with more low stress segments are more likely to locate in residential area with sparse bike counters.

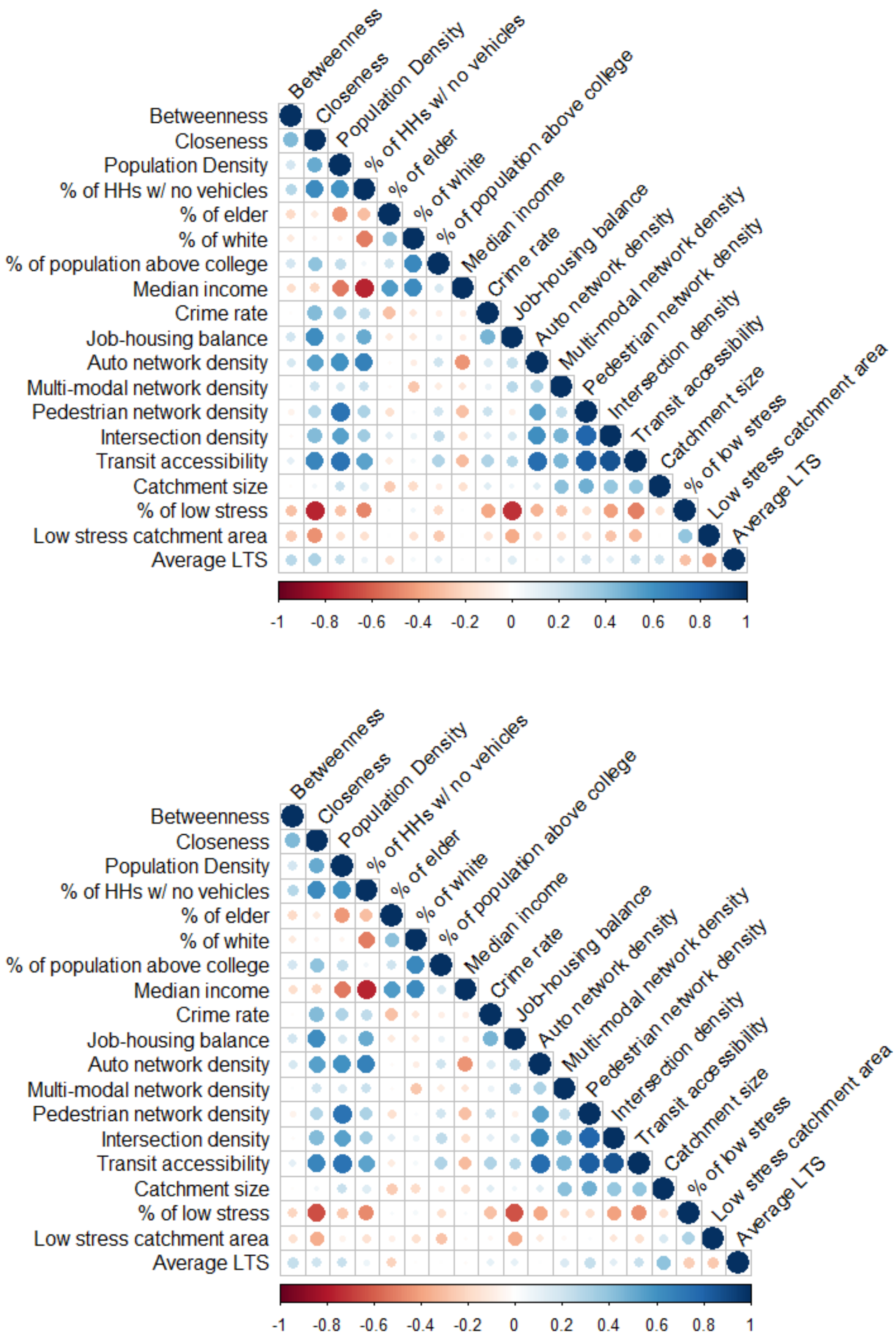


Figure 20. Correlation Plots among Independent Variables of Bike Counts Model in Portland (Top: Original LTS; Bottom: Updated LTS)

Regression Analysis

Based upon the takeaways from the City of Portland, negative binomial model was utilized to analyze the bike count data. In terms of the buffer distances of the catchment area measure, only the half-mile buffer was modeled for this case.

Generally speaking, the regression results indicate that the four bicycle network measures in Minniapolis have similar effects on bike counts as in Portland. Particularly, it is worth to note that the catchment area size measure is also negatively associated with bike counts. Similar reasonings that are used to explain the counter-intuitive relationship between catchment area size and bike counts in Portland also apply here. Minneapolis also has a major river which cutts across the city center. Therefore, the bike counters along the river, e.g. around the Minneapolis city center or University of Minnesota, have smaller catchment sizes, but higher bicycle traffic. Again, it suggests that using only topology oriented measures to evaluate the bicycle network is insufficient.

Unlike Portland, the percentage of low stress segments measure in this case does not show the strongest effects on bike counts when compared to the other three measures, based on AIC value. This is probably due to the relatively lower bicycle traffic volume in residential areas in Minneapolis than in Portland, where low stress segments are concentrated. We could also tell from the distribution of bike counts across the city (Figure 21), that bicycle traffic tends to be mostly focused in the city center of Minneapolis, but more dispersed across the whole city area in Portland. Thus, the low stress segments metric plays a less prominent role in determining bike counts in Minneapolis than in Portland.

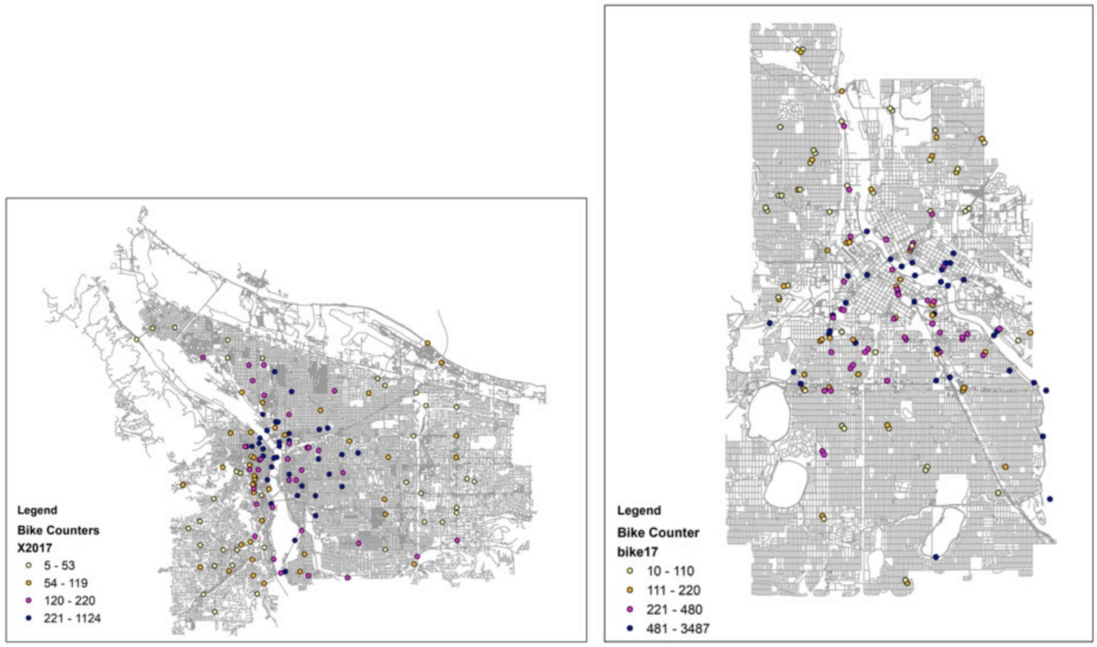


Figure 21. Bike Count Distribution Comparison in Portland and Minneapolis

The other two measures shows similar effects on bike counts as in Portland. To be more specific, each one unit increase of average LTS level is associated with 1.4 times decrease in bike count in terms of the original measure, and 1.8 times decrease in bike counts with the updated measure; and each one square mile increase in the low-stress network catchment area size is associated with 1.20 times increase in bike counts in the original measure, and 0.13 times increase of bike counts in the updated measure. When combining all four measures together into a pooled model, only catchment area size is statistically significant in the original measures. In the updated measures, all measures, except low stress segments percentage, are statistically significantly associated with bike counts. In terms of other variables, population density positively affects bicycle usage. The areas with more white population, less elder population, less higher level educated population, and less crime numbers are associated with higher bike counts.

	Dependent variable:				
	Bike Count (2017)				
	(1)	(2)	(3)	(4)	(5)
Betweenness	0.00004	0.00003	0.0003	0.001*	0.001***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Closeness	0.856	2.311***	2.006***	1.733**	-0.322
	(0.652)	(0.895)	(0.760)	(0.743)	(0.891)
Population density	0.051*	0.030	0.035	0.007	0.030
	(0.028)	(0.033)	(0.031)	(0.030)	(0.032)
% of elder population	-0.777	-0.117	0.083	4.664	6.941**
	(2.849)	(3.372)	(3.284)	(3.132)	(3.309)
% of white population	1.270	0.912	2.318**	3.285***	2.674***
	(0.831)	(0.985)	(0.935)	(0.930)	(0.971)
% of pouplation with college degree or above	-0.570	-1.639*	-1.642*	-1.542*	-0.239
	(0.785)	(0.938)	(0.899)	(0.871)	(0.905)
Median household income	0.0003	0.014	0.004	-0.010	-0.026***
	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)
Crime	-0.001*	-0.002***	-0.002***	-0.002**	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Job-housing balance	0.066***	0.023	0.049*	0.079***	0.158***
	(0.023)	(0.032)	(0.026)	(0.026)	(0.031)
Catchment Area (0.5mi)	-7.659***				-7.098***
	(1.011)				(1.202)
% of low stress segments (original)		0.172			2.058
		(1.408)			(1.386)
LTS average (original)			-0.351***		0.039
			(0.119)		(0.129)
Low stress segment catchment area (original)				0.203***	0.028
				(0.047)	(0.052)
Constant	7.275***	2.929	3.644***	1.926**	5.809***
	(0.776)	(1.981)	(0.706)	(0.817)	(2.181)
Observations	128	128	128	128	128
Log Likelihood	-883.000	-911.334	-903.689	-899.208	-903.819
theta	1.362*** (0.155)	0.936*** (0.103)	1.049*** (0.117)	1.109*** (0.124)	1.124*** (0.126)
Akaike Inf. Crit.	1,787.999	1,844.667	1,829.379	1,820.417	1,835.637
Note:					*p<0.1; **p<0.05; ***p<0.01

Figure 22. Regression Results of Bike Counts in Minneapolis (1)

	Dependent variable:				
	Bike Count (2017)				
	(1)	(2)	(3)	(4)	(5)
Betweenness	0.00004	0.00001	0.0005*	0.0002	0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Closeness	0.856	2.306***	1.863***	1.572**	1.640**
	(0.652)	(0.792)	(0.673)	(0.750)	(0.650)
Population density	0.051*	0.026	0.061**	0.002	0.057**
	(0.028)	(0.031)	(0.028)	(0.031)	(0.026)
% of elder population	-0.777	0.753	0.442	3.773	0.866
	(2.849)	(3.225)	(2.958)	(3.216)	(2.665)
% of white population	1.270	1.591*	2.718***	2.799***	2.234***
	(0.831)	(0.937)	(0.845)	(0.944)	(0.775)
% of pouplation with college degree or above	-0.570	-1.355	-1.968**	-1.111	-1.125
	(0.785)	(0.898)	(0.814)	(0.892)	(0.740)
Median household income	0.0003	0.006	0.002	-0.007	-0.003
	(0.008)	(0.009)	(0.008)	(0.009)	(0.007)
Crime	-0.001*	-0.002***	-0.001**	-0.002**	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Job-housing balance	0.066***	0.069**	0.045*	0.075***	0.089***
	(0.023)	(0.029)	(0.024)	(0.027)	(0.024)
Catchment Area (0.5mi)	-7.659***				-6.608***
	(1.011)				(1.067)
% of low stress segments (updated)		2.456**			0.867
		(1.086)			(0.895)
LTS average (updated)			-0.594***		-0.239**
			(0.091)		(0.097)
Low stress segment catchment area (updated)				0.136***	0.127***
				(0.049)	(0.044)
Constant	7.275***	0.627	3.788***	2.690***	4.789***
	(0.776)	(1.451)	(0.643)	(0.787)	(1.329)
Observations	128	128	128	128	128
Log Likelihood	-883.000	-904.085	-887.167	-903.575	-870.291
theta	1.362*** (0.155)	1.045*** (0.116)	1.291*** (0.146)	1.051*** (0.117)	1.607*** (0.185)
Akaike Inf. Crit.	1,787.999	1,830.170	1,796.334	1,829.151	1,768.582
Note:					*p<0.1; **p<0.05; ***p<0.01

Figure 23. Regression Results of Bike Counts in Minneapolis (2)

Discussion of the Bike Counts Analysis

This comparative bike counts analysis across two cities is a highlight of this project. First, it proves the consistency and replicability of the open source OSM data across different cities. Secondly, it suggests that the bicycle network measures constructed for this project are robust, since they can explain bicycle network characteristics in both cities. Thirdly, the fact that the effects of bicycle network on bicycling activity are similar across different cities contributes to more robust conclusions.

Below, I will briefly discuss the similarities and differences between the two cases in more detail:

- Similarities:
    - The four bicycle network measures showed similar impacts on bicycling activity, in terms of the direction of effects on bike counts.
    - The bicycle network measure using catchment area size without taking into account the stress level shows negative effects on bike counts for both cities. This is probably due to the street layout that there is a river running across the downtown of both cities, so that the bike counters with more traffic volume tend to have smaller reach area due to topology.
- Differences:
    - The two versions of bicycle network measures performed differently in the two cities. The updated version, taking into account of more bikeway infrastructure and terrain, explained more variation of bicycling activity than the original version in Portland. However, in Minneapolis, there was not much difference of those two versions bicycle network measures. This was mostly explained by the flatter terrain in Minneapolis compared to Portland, so the slope did not play a prominent role in determining stress levels in the former case. This also proved the robustness of the updated LTS method, such that it reflected the terrain of the cities, without influencing other characteristics in cities that were affected by terrain.

- Unlike Portland, the percentage of low stress segments measure did not show a stronger effect on bike counts than the other measures. This is probably due to the relatively lower bicycle traffic in residential areas in Minneapolis compared to Portland, where low stress segments are concentrated.

What are the Impacts on Bicycling Activity: Causal Inference Analysis

Case 1: Portland, OR

The results of the cross-sectional analysis in the previous section shows that the percentage of low-stress segment within half-mile buffer zone and low-stress network catchment area are positively associated with bike counts, while average LTS of the segments adjacent to the bike counters is negatively associated with bike counts. However, whether there is a causal relationship between bike network measures and bike ridership needs further investigation. This section presents the results of the difference-in-difference analysis, which compares the changes of the bike network between 2011 and 2017, and examined the causal effects on bike counts.

As identified in the LTS calculation section, roughly 2%-3% of all street segments (depending on the different versions of LTS calculation) were improved from high-stress segments to low-stress segments from 2011-2017. In terms of the bike network measures, the changes between the two years are described below (Table 8). None of the bike counters showed appreciable changes in the first measure, half-mile catchment area, between the two years, which is not surprising since this measure only depends on street layout. Both the percentage of low-stress segments and low-stress catchment area increased 4% or more in 2017, compared to 2011. A comparison of the improvement between half-mile catchment area and low-stress catchment area indicates that the bike network was improved, despite the topology of individual street segments had no change. Similarly, average LTS adjacent to bike counters decreased, suggesting the stress level around counters had also been improved during the years. The improvement of low-stress catchment area based on the original LTS measures is more prominent than the one based on the updated LTS measures. This might reflect that the updated LTS measure is more stringent, so that the bicycle infrastructure changes wouldn't trigger as substantial changes in the original measures.

Table 8. Bike Network Measures Changes Between 2011-2017 (Portland)

LTS version	Year	Half-mile catchment area	% of low stress segments	LTS average	Low-stress catchment area
Original LTS	2011	0.44	79.4%	1.94	4.33
	2017	0.44	82.8%	1.80	4.44
	Mean	+ 0%	+ 4.3%	- 7.2%	+ 21.9%
	Median	+ 0%	+ 2.8%	- 7.1%	+ 14.8%
Updated LTS	2011	0.44	62.5%	2.35	1.68
	2017	0.44	65.2%	2.25	1.35
	Mean	+ 0%	+ 4.3%	- 4.3%	+ 7.0%
	Median	+ 0%	+ 2.9%	- 6.8%	+ 1.0 %

The DID analysis explores the effect of a treatment, in our case bicycle network improvement, on a "treatment group" versus a "control group", through comparing the changes in outcome variables over time in each group (Table 9). Given that different bike network measures evaluate different aspects of the network improvement, the treatment group was defined as the bike counters where the changes of at least two of the bike network measures were each above the mean value of the change in that measure across all the bike counters. As a result, 44 bike counters out of 141 were defined as the treatment group in terms of the original LTS version, and 45 bike counters were defined as the treatment group in the updated LTS version. The rest were categorized into the control group. Since the definition of treatment and control groups was essential in this analysis, different versions of treatment and control group definitions were explored to ensure the robustness of the analysis.

The second version of the definition was identical to the first one, except it used the median value instead of the mean value as a threshold, which resulted in 76 treatment bike counters in terms of the original LTS measures, and 82 treatment bike counters in terms of the updated LTS measures. The third version was more stringent than the first two. It required that at least two out of the four bicycle network measures each changed over 10% between 2011-2017, which resulted in 44 treatment bike counters in the original LTS measures and 25 treatment bike counters in the updated LTS measures. As shown in the maps below (Figure 24), the treatment counters are mostly distributed in the downtown area, North Portland, SW Portland and far East Portland, this distribution mostly overlapped with the regions where most street segment LTS changes occurred, which suggests that these treatment definitions are useful in separating the treatment from the control group.

Table 9. Definition of Treatment Bike Counters

Method	Standard	Bicycle network measure	# of bike counters in treatment group
1	The change in at least 2 measures of the counter is above the mean change	Original LTS	44
		Updated LTS	45
2	The change in at least 2 measures of the counter is above the median change	Original LTS	76
		Updated LTS	82
3	The change in at least 2 measures is over 10%	Original LTS	44
		Updated LTS	25

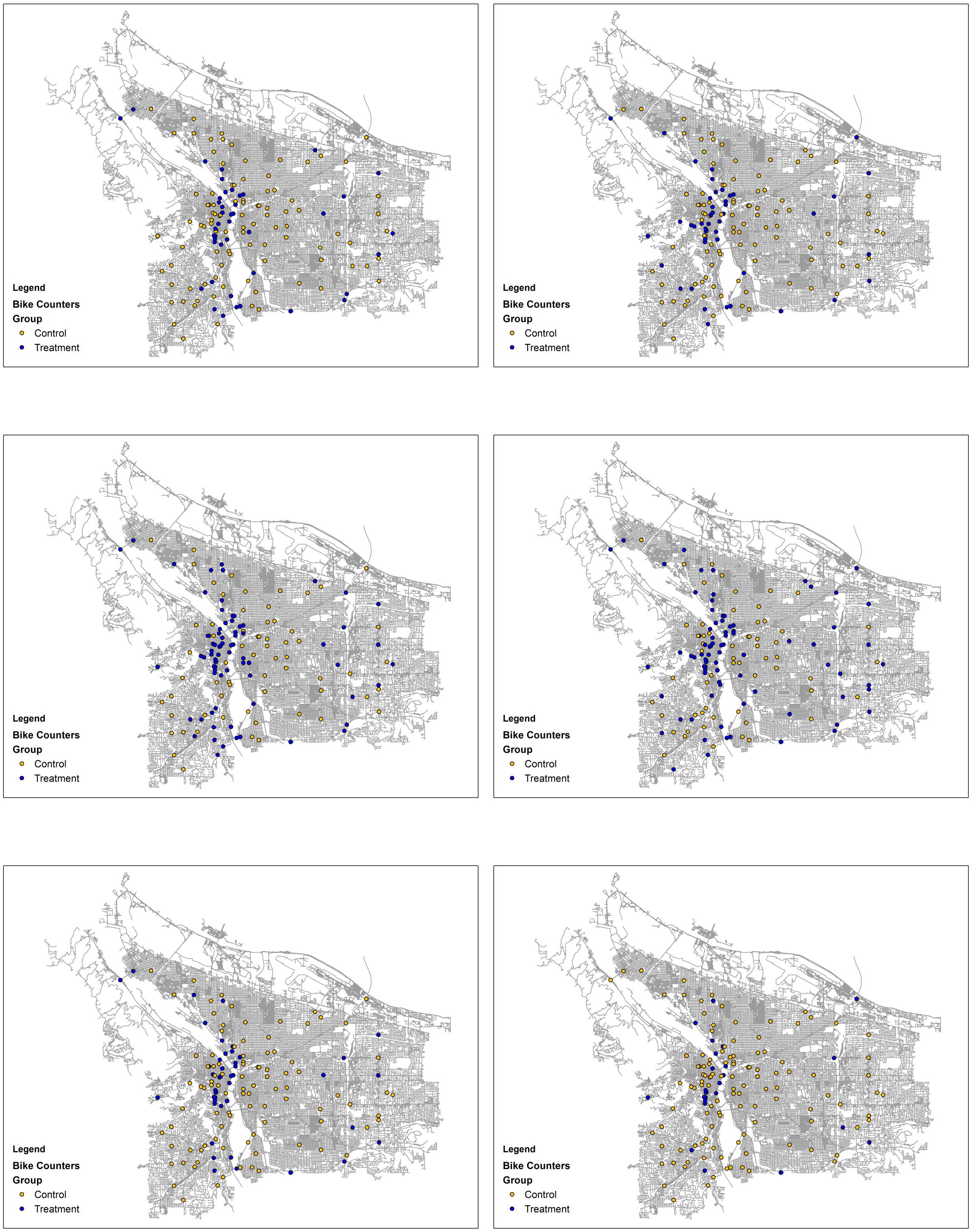


Figure 24. Treatment and Control Bike Counters (3 versions from top to bottom; Left: Original LTS; Right: Updated LTS)

As discussed in the methodology section, the DID approach looks at the change in the variable of interest in the treatment group before and after it is treated. In this case, I examined 2011 and 2017 where some areas in Portland experienced significant bicycle network improvements, and comparing the changes in bike counts to the control group, which had not received the bicycle network improvement. Control covariates, which were found to be significantly associated with bike counts in the cross-sectional analysis, were included in the DID models. Negative binomial methods, which had better performance than other models in the cross-sectional analysis, were tested. Based on the log-likelihood values and the AIC statistics in model output, the models using the updated LTS measures had better performance than the original LTS.

The treatment effect parameter is the coefficients of the DID estimators in the model outputs. However, all six models (Figure 25) returned non-statistically significant results, indicating that no causal relationship could be inferred between bicycle network characteristics and bike counts.

In terms of bicycle network measure covariates, the result is very similar to what were found in the cross-sectional analysis. The percentage of low stress segments in half-mile catchment area based on the updated LTS measures positively affects bike counts. It indicates more low stress street segments increases bike activities. The average LTS measure negatively affects bike counts, indiating low stress around the bike counters is also importment to bike activities. The size of the catchment area still negatively associates with bike counts. The potential reasons had been described in the above section. Low-stress catchment area metric is not statistically significant in all the models, probably due to its correlation with other bicycle network measures. The measure closeness, which measures the closeness of each counter to other counters positively associates with the bike counts of that intersection, emphasizing the importance of traffic flow in a bicycle network in this context.

Similarly, population density negatively affects bicycle usage, indicating bicyclists prefer less dense areas to bike. The areas with more white population, less elder population and less higher level educated population are associated with higher bike counts.

	Dependent variable:					
	Bike Count					
	Orignial LTS			Updated LTS		
	(1)	(2)	(3)	(4)	(5)	(6)
Betweenness	-0.0001	-0.0001	-0.0001	0.00003	0.00001	-0.00001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Closeness	3.009***	3.069***	3.007***	3.210***	3.221***	2.950***
	(0.350)	(0.352)	(0.356)	(0.303)	(0.300)	(0.305)
Population density	-0.049***	-0.050***	-0.048***	-0.057***	-0.054***	-0.060***
	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)
% of elder population	-3.065***	-3.053***	-2.851**	-2.245**	-2.057*	-1.522
	(1.137)	(1.140)	(1.149)	(1.124)	(1.124)	(1.124)
% of white population	1.914**	1.665*	1.678*	1.548*	1.745**	1.917**
	(0.869)	(0.869)	(0.873)	(0.811)	(0.828)	(0.809)
% of pouplation with college degree or above	-1.082***	-1.100***	-1.118***	-0.839**	-0.759**	-0.535
	(0.368)	(0.370)	(0.371)	(0.365)	(0.366)	(0.365)
Median household income	-0.004	-0.003	-0.003	0.001	0.002	-0.0002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Crime rate	0.00001	0.00001	0.00001	0.00004	0.00004	0.00005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Job housing balance	-0.001	-0.001	-0.001	-0.001	-0.0004	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Catchment Area	-2.044***	-2.084***	-2.177***	-1.756***	-1.725***	-1.678***
	(0.664)	(0.671)	(0.663)	(0.589)	(0.592)	(0.580)
% of low stress segments	0.369	0.263	0.283	1.287***	1.373***	1.399***
	(0.509)	(0.508)	(0.507)	(0.335)	(0.337)	(0.332)
LTS average	-0.017	0.017	0.010	-0.095	-0.061	-0.096
	(0.065)	(0.063)	(0.064)	(0.066)	(0.065)	(0.065)
Low stress catchment area	0.049	0.053	0.058*	-0.0003	0.001	-0.0001
	(0.035)	(0.035)	(0.035)	(0.040)	(0.040)	(0.040)
Treatment1	0.097					0.331**
	(0.134)					(0.154)
Treatment2		0.0004		0.197		
		(0.133)		(0.128)		
Treatment3			0.038		0.271**	
			(0.124)		(0.122)	
Time:Before	0.052	0.058	0.044	0.074	0.130	0.086
	(0.099)	(0.100)	(0.121)	(0.094)	(0.120)	(0.085)
DID estimator1	0.164					0.171
	(0.178)					(0.203)
DID estimator2		0.134		0.131		
		(0.178)		(0.167)		
DID estimator3			0.116		-0.010	
			(0.166)		(0.158)	
Constant	2.821***	2.979***	3.011***	1.990***	1.438*	1.643**
	(0.703)	(0.706)	(0.705)	(0.704)	(0.749)	(0.703)
Observations	280	280	280	280	280	280
Log Likelihood	-1,640.943	-1,642.295	-1,642.101	-1,626.686	-1,626.824	-1,623.464
theta	2.222*** (0.180)	2.203*** (0.179)	2.206*** (0.179)	2.436*** (0.199)	2.434*** (0.199)	2.489*** (0.204)
Akaike Inf. Crit.	3,315.886	3,318.590	3,318.202	3,287.371	3,287.648	3,280.928
Note:						*p<0.1; **p<0.05; ***p<0.01

Figure 25. Portland Bike Count DID Model Result

Case 2: Minneapolis, MN

Similar to the Case 1, a difference-in-difference analysis was conducted to examine the causal effects of bicycle network changes in Minneapolis on bike counts. As identified in the LTS calculation section, roughly 2%-3% of all street segments (depending on the different versions of LTS calculation) improved from high-stress segments to low-stress segments between 2011 and 2017. In terms of the bike network measures, the changes between the two years are described below. As the first measure, half-mile catchment area, only depends on street layouts instead of traffic stress, the mean half-mile catchment area of all bike counters did not change between the two years. The percentage of low-stress segments and low-stress catchment area both increased over 4% in 2017, compared to 2011. Similarly, average LTS around bike counters decreased, suggesting the stress level around counters improved during these years. The differences between the original measures and the updated measures are not as prominent as the Portland case.

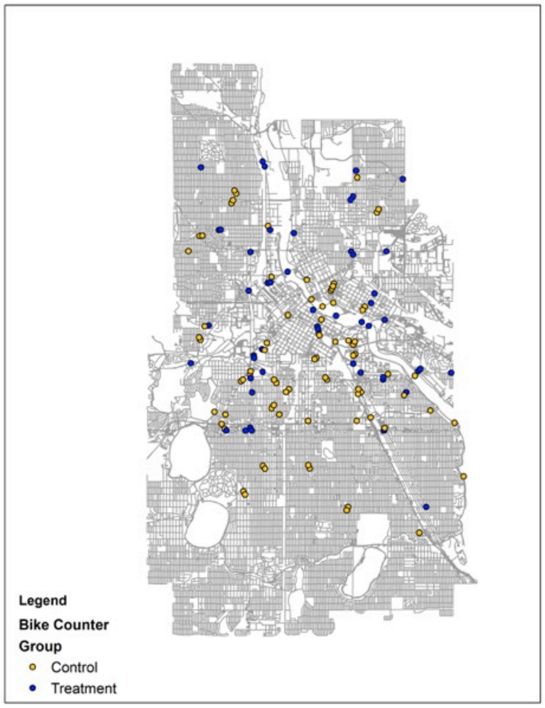
Table 10. Bike Network Measures Changes Between 2011-2017 (Minneapolis)

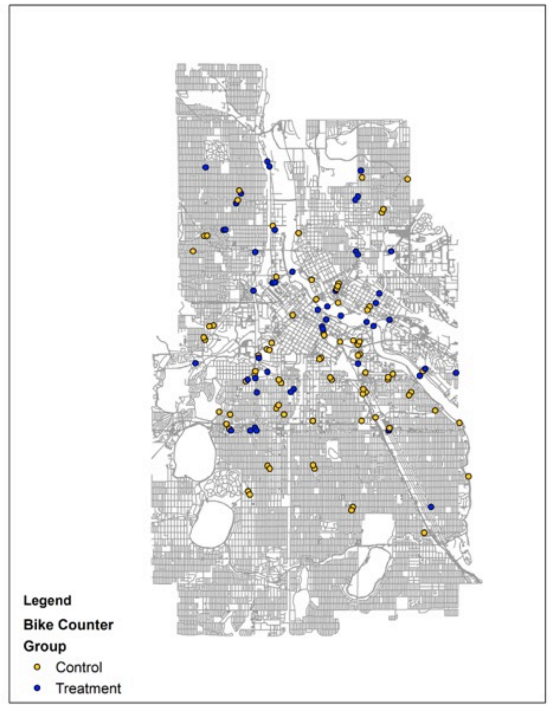
LTS version	Year	Half-mile catchment area	% of low stress segments	LTS average	Low-stress catchment area
Original LTS	2011	0.43	78.6%	2.51	4.10
	2017	0.43	82.8%	2.31	4.29
	Mean	+ 0%	+ 4.2%	- 8.0%	+ 4.6%
Updated LTS	2011	0.44	74.9%	2.46	3.28
	2017	0.44	78.9%	2.19	3.44
	Mean	+ 0%	+ 5.3%	- 11.0%	+ 4.9%

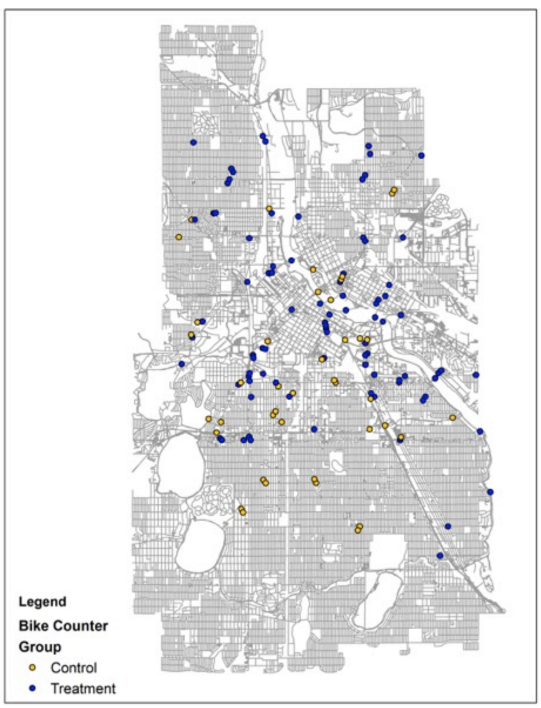
I used the same treatment and control group definitions as in Portland. Based on the first definition, 29 bike counters out of 150 were defined as treatment in terms of the original LTS version, and 42 bike counters were defined as the treatment group in the updated LTS version. Based on the second definition, 61 bike counters were selected in the treatment group for the original LTS measures, and 41 bike counters were selected in the treatment group for the updated LTS measures. The third definition generated 39 treatment bike counters in the original LTS measures and 46 treatment bike counters in the updated LTS measures. As shown in the maps below (Figure 26), the treatment bike counters were mostly concentrated in the city center near the river, and other areas with bikeway improvements, such as the Central Avenue and the Lyndale Avenue.

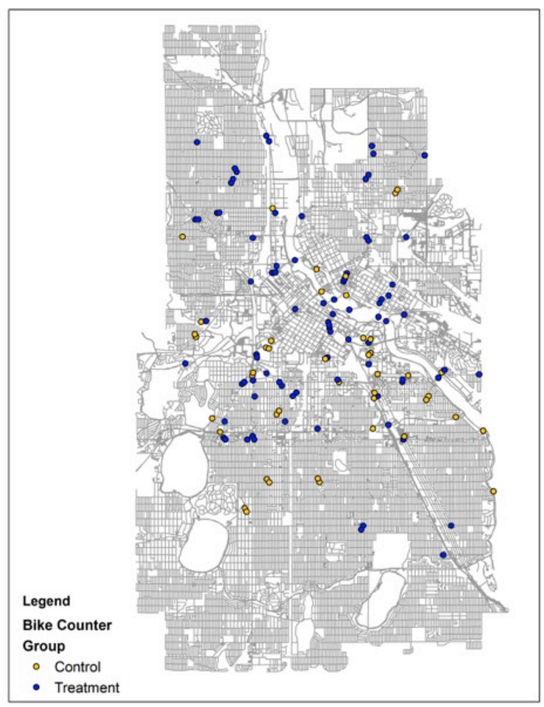
Table 11. Definition of Treatment Bike Counters

Method	Standard	Bicycle network measure	# bike counters in of treatment group
1	The change in at least 2 measures of the counter is above the mean change	Original LTS	50
		Updated LTS	49
2	The change in at least 2 measures of the counter is above the median change	Original LTS	87
		Updated LTS	84
3	The change in at least 2 measures is over 10%	Original LTS	39
		Updated LTS	46


Legend
Bike Counter
Group
Control
Treatment


Legend
Bike Counter
Group
Control
Treatment


Legend
Bike Counter
Group
Control
Treatment


Legend
Bike Counter
Group
Control
Treatment

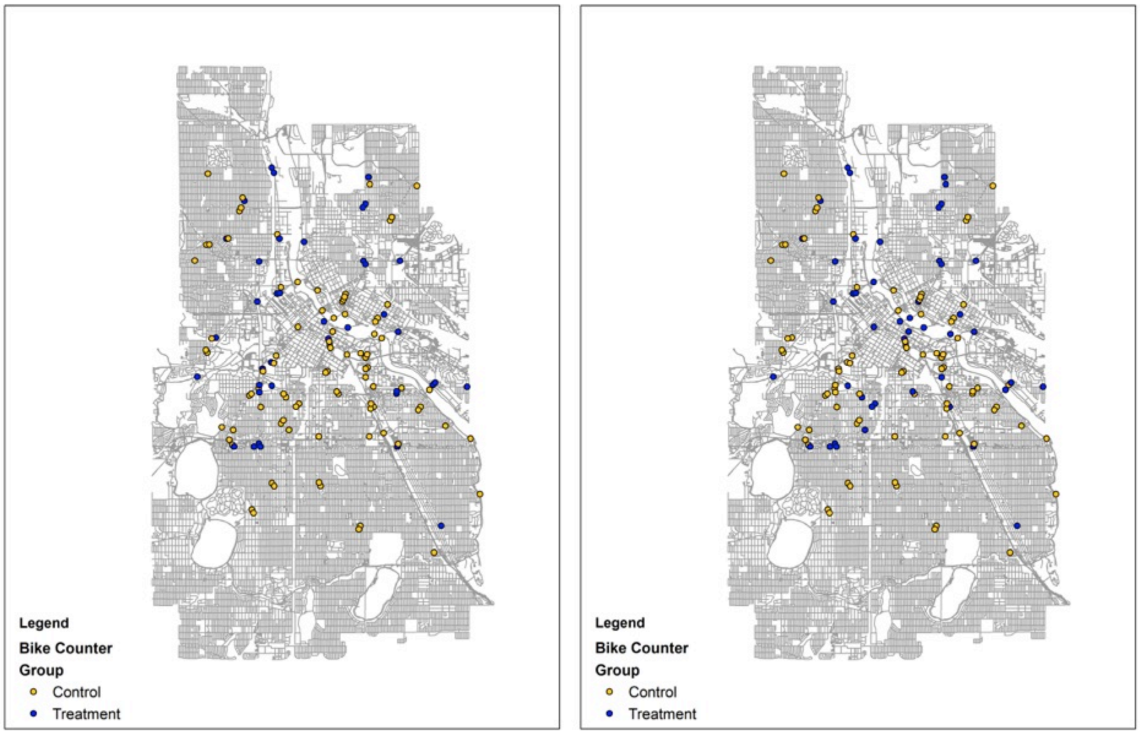


Figure 26. Treatment and Control Bike Counters (3 versions from top to bottom; Left: Original LTS; Right: Updated LTS)

Similar to the Case 1, the treatment effect parameter is the coefficients of the DID estimators in the model outputs. However, all six models (Figure 27) returned non-statistically significant results, indicating no causal relationship could be inferred between bicycle network measures and bike counts in Minneapolis either.

In terms of the bicycle network measure covariates, low-stress catchment area size positively and significantly affects bike counts, indicating more low stress street segments leads to higher bike volume. The size of catchment zone area is still negatively associated with bike counts. The average LTS measure negatively affects bike counts in the updated measures. However, the percentage of low-stress segment is not statistically significant in all the models, which is different from Portland. The measures of closeness and betweenness are positively associated with the bicycle counts of that intersection. These results underscore the importance of bicycle network in this context. In terms of other covariates, the areas with higher population density, more white population, less crime numbers are associated with higher bike counts.

	Dependent variable:					
	Bike Count					
	Orignial LTS			Updated LTS		
	(1)	(2)	(3)	(4)	(5)	(6)
Betweenness	0.0003*	0.0004**	0.0004*	0.0004**	0.0004**	0.0004**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Closeness	1.271**	1.237**	1.232**	1.698***	1.819***	1.769***
	(0.537)	(0.540)	(0.535)	(0.478)	(0.475)	(0.478)
Population density	0.058***	0.065***	0.061***	0.058***	0.060***	0.059***
	(0.020)	(0.020)	(0.020)	(0.019)	(0.019)	(0.020)
% of elder population	0.796	1.618	1.095	-0.399	-0.361	-0.072
	(2.064)	(2.036)	(2.074)	(2.028)	(2.049)	(2.027)
% of white population	1.999***	1.980***	2.004***	2.087***	2.026***	2.021***
	(0.598)	(0.605)	(0.600)	(0.569)	(0.566)	(0.570)
% of pouplation with college degree or above	-0.397	-0.583	-0.500	-0.644	-0.722	-0.627
	(0.553)	(0.550)	(0.550)	(0.527)	(0.525)	(0.528)
Median household income	-0.004	-0.003	-0.003	-0.001	-0.001	-0.001
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Crime rate	-0.001**	-0.001**	-0.001**	-0.001*	-0.001**	-0.001*
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Job housing balance	0.060***	0.059***	0.061***	0.065***	0.065***	0.067***
	(0.018)	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)
Catchment Area	-5.976***	-5.894***	-5.953***	-4.956***	-4.479***	-5.015***
	(0.763)	(0.750)	(0.763)	(0.775)	(0.762)	(0.784)
% of low stress segments	-0.718	-0.798	-0.790	0.569	0.634	0.674
	(0.748)	(0.756)	(0.750)	(0.622)	(0.619)	(0.617)
LTS average	-0.110	-0.102	-0.099	-0.267***	-0.248***	-0.264***
	(0.069)	(0.069)	(0.070)	(0.062)	(0.062)	(0.062)
Low stress catchment area	0.154***	0.156***	0.159***	0.130***	0.118***	0.135***
	(0.033)	(0.035)	(0.033)	(0.033)	(0.033)	(0.033)
Treatment1	-0.283*			-0.294*		
	(0.160)			(0.156)		
Treatment2		0.075			-0.369**	
		(0.171)			(0.161)	
Treatment3			-0.208			-0.264*
			(0.168)			(0.160)
Time:Before	0.066	0.235	0.076	0.126	0.090	0.133
	(0.137)	(0.188)	(0.129)	(0.130)	(0.172)	(0.128)
DID estimator1	0.016			0.055		
	(0.225)			(0.215)		
DID estimator2		-0.258			0.068	
		(0.233)			(0.219)	
DID estimator3			-0.031			0.051
			(0.238)			(0.219)
Constant	5.647***	5.463***	5.628***	4.092***	3.884***	3.871***
	(1.266)	(1.283)	(1.261)	(0.979)	(0.955)	(0.964)
Observations	256	256	256	256	256	256
Log Likelihood	-1,762.597	-1,764.309	-1,763.475	-1,748.909	-1,747.631	-1,749.394
theta	1.413*** (0.114)	1.397*** (0.113)	1.405*** (0.113)	1.545*** (0.126)	1.558*** (0.127)	1.540*** (0.125)
Akaike Inf. Crit.	3,559.194	3,562.619	3,560.949	3,531.818	3,529.261	3,532.789
Note:						*p<0.1; **p<0.05; ***p<0.01

Figure 27. Minneapolis Bike Count DID Model Result

Discussion of the DID analysis

Correlation does not equate to causation. Despite the fact that the network measures were all significantly associated with bike activities, they were not necessarily the ones that cause the change in bike activities. In order to evaluate whether there is a causal relationship, it is critical to analyze if a change in the variable of interest itself directly led to the change in bicycling outcome, controlling for other factors. Difference-in-difference analysis serves this purpose. Here, I briefly discuss some interesting findings and the possible explanations. A more detailed discussion of the limitations of applying DID approach to this dataset is included in the Limitation section at the end of this dissertation.

First, it is very encouraging to see that both cities had witnessed a notable overall improvement in the stress levels of bike infrastructure, which was indicated by the changes of mean values in the four network measurements. A comparison between the change in half-mile catchment area size and the change in low-stress catchment area size was the most informative in this regard, since they both measured catchment area size, but only the latter took comfort feature into account. No change was observed for half-mile catchment area size, while the low-stress catchment area size had a notable positive increase in both cities. This suggested that the overall layout of street network did not change much over this period, but the comfort level was improved in both cities. This is not surprising, given the remarkable investment directed to bike facilities over the most recent decade.

Second, the choice of treatment versus control group is very important in DID analysis. Therefore, I cautiously explored three different methods to divide the bike counters into treatment group and control groups, and evaluated whether the different definitions could impact the DID result. Although the different definitions resulted in different sets of treatment counter and control counters, all of these criteria performed reasonably well in separating the regions where most changes happened from the regions where not much improvement was seen. This point was reflected by the fact that the regions where the bike counters in the treatment group was distributed largely overlapped with the regions where the most street segment LTS changes occurred. In the model results, no significant difference on the coefficients of estimators was observed among the three different definitions. In the Limitation section, I discussed the issue related to defining treatment versus control groups without taking into account spatial auto-correlation and how this issue might severely constrain my ability to infer causal relationship. Therefore, at this point, I cannot conclude whether the different versions of definitions performed differently in DID analysis.

However, based on the DID model of bike counts, no causal relationship between the bicycle network and bicycle ridership was found. This might be because six years (from 2011 to 2017) was not long enough for significant behavior change to be observed. In addition, the outcome variable bike count only represented the static bicycle activities at certain predetermined bike counter locations, instead of travel flow in the whole network, which might reduce the representative power bike counts on bicycle activity in general. In the meantime, there may also be additional reasons that have influenced behavior change rather than bicycle network improvement itself. As a result, although no causal relationship could be inferred using DID analysis at this point, it is premature to conclude that the change in bike activity is not caused by the improvement of the bike network. Future work should explore other appropriate approaches to infer the causal relationship.

What are the Impacts on Bicycling Activity: Mode Choice Analysis

Bike mode choice is another indicator that can reflect the impact of bicycle network on bicycle activity. With more improved bicycle network, the connectivity between different places and the ease of cycling will increase the willingness of cycling for individuals, thus increase the possibility of choosing bicycling over other travel modes.

Among all the selected trips, 71.1% of them were auto trips, 6.1% of them were bike trips, and 22.8% of them were walk trips. The average travel route distance for auto was the longest with an average length of 2.89 miles, which is followed by bike trips with an average route distance of 2.28 miles. Walk trips, with an average of 1.22 mile, were significantly shorter than the other two modes. 18.4% of the trips were work-related, 4% of them were shopping or errand trips, and 17.6% of them were social or recreational trips. In terms of the bicycle network characteristics of those bike trips, the mean value of the ratio of weighted to actual travel route was around 1. This indicates most of the bike routes were likely composed of a combination of low stress and high stress street segments. The percentage of low-stress street segments calculated with the original LTS (72.2%) had a similar value with the ones calculated with the updated LTS (62.2%). In terms of the socio-demographic characteristics, the bicyclists were slightly female-biased (54.1%), predominantly white (93.1%), and a majority of them (60%) had a bachelor's degree or higher.

Table 12. Bike Mode Choice Variable Description

Category	**Variables**	**Variables/Indicators**	**Descriptive statistics**
Dependent variable	Mode choice	Mode choice (Auto, bike and walk)	Auto: 8990 Bike: 771

			Walk: 2876
Independent variable	Trip attributes	Travel distance (based on mode-specific network distance)	Auto: 2.89 miles Bike: 2.28 miles Walk: 1.22miles
		Trip purpose (percentage of work related trips)	Work: 18.4% Shopping: 18.0% Social: 17.6% Other: 46.0%
	Bicycle network characteristics	Weighted travel distance to actual travel distance	Bike: 0.99 (original LTS) 1.02 (updated LTS)
		Percentage of routes contain low stress streets	Bike: 72.2% (original LTS) 62.2% (updated LTS)
	Built environment	Population within 2 miles of home address	68408
	Socio-demographic characteristics	Age	44.9
		Gender	Male: 45.9%
		Race	White: 93.1% Nonwhite: 6.9%
		Education	< High school: 15.9% High school: 24.5% Bachelor: 29.4% Graduate: 30.2%
		Household size	2.81
		Household income (median)	$75,000 - $ 99,999
		# of vehicles household owns	1.98
		# of bikes household owns	1.87

Note: categories with underlines are reference level in future models

The result of the multinomial logit model was presented below. I found that the routes with a higher weighted to actual route length ratio, which means more high stress segments along the routes, were less likely to be chosen for bike travel mode. Consistently, the routes with higher percentages of low-stress streets were more likely to be used for biking. These results suggests that the decrease of a route’s stress level is positively associated with an increase in bike mode choice. Two different versions of LTS measurement show similar results. The routes with higher percentages of major street is significantly less likely to be used for walk.

Route length, as a proxy of travel cost in this context, is negatively associated with the utility of each travel mode. In terms of trip purpose, the probability of choosing bike for work trips is significantly higher than for other purposes, such as shopping and social. The variable, population around 2 miles of the home address, represents the density of built environment. It is positively associated with the probability of choosing biking over other travel modes, which indicates that dense built environment promotes bicycling mode choice.

In addition, socio-demographic characteristics also have a significant influence on travel mode choice. Travelers who are young, male, non-white, or had higher education are more likely to bike. In terms of household income, low-income travelers are more likely to choose bicycling over walking. In addition, individuals with a bigger household size, more vehicles, and less bikes are less likely to bike.

	Dependent variable:			
	Mode Choice			
	Original LTS		Updated LTS	
	(1)	(2)	(3)	(4)
auto:(intercept)	0.611 (0.653)	2.160*** (0.296)	0.220 (0.713)	2.120*** (0.289)
walk:(intercept)	2.065*** (0.657)	3.612*** (0.314)	1.675** (0.716)	3.573*** (0.307)
Weighted/actual route (original)	-1.336** (0.570)			
% of low stress streets(original)		0.306** (0.152)		
Weighted/actual route (updated)			-1.623*** (0.600)	
% of low stress streets(updated)				0.367** (0.151)
% of major arterials	-1.276*** (0.072)	-1.272*** (0.072)	-1.278*** (0.072)	-1.274*** (0.072)
Route length	-0.001*** (0.0001)	-0.001*** (0.0001)	-0.001*** (0.0001)	-0.001*** (0.0001)
auto:trip purpose-shopping	0.888*** (0.137)	0.886*** (0.137)	0.899*** (0.137)	0.896*** (0.137)
walk:trip purpose-shopping	0.270* (0.143)	0.267* (0.143)	0.281* (0.143)	0.278* (0.143)
auto:trip purpose-social	0.620*** (0.130)	0.616*** (0.130)	0.626*** (0.130)	0.621*** (0.130)
walk:trip purpose-social	0.446*** (0.134)	0.441*** (0.134)	0.451*** (0.134)	0.447*** (0.134)
auto:trip purpose-other	0.765*** (0.101)	0.763*** (0.101)	0.767*** (0.101)	0.765*** (0.101)
walk:trip purpose-other	-0.075 (0.107)	-0.077 (0.107)	-0.073 (0.107)	-0.075 (0.107)
auto:population density	-0.00002*** (0.00000)	-0.00002*** (0.00000)	-0.00001*** (0.00000)	-0.00001*** (0.00000)
walk:population density	-0.00002*** (0.00000)	-0.00002*** (0.00000)	-0.00002*** (0.00000)	-0.00002*** (0.00000)
auto:age	0.033*** (0.004)	0.033*** (0.004)	0.033*** (0.004)	0.033*** (0.004)
walk:age	0.016*** (0.004)	0.017*** (0.004)	0.016*** (0.004)	0.016*** (0.004)
auto:male	-0.843*** (0.083)	-0.841*** (0.083)	-0.841*** (0.083)	-0.839*** (0.082)
walk:male	-0.784*** (0.087)	-0.782*** (0.087)	-0.782*** (0.087)	-0.780*** (0.087)
auto:race-white	0.437*** (0.125)	0.434*** (0.125)	0.434*** (0.125)	0.431*** (0.125)
walk:race-white	0.511*** (0.135)	0.507*** (0.135)	0.508*** (0.135)	0.504*** (0.135)
auto:education-high school	-0.976*** (0.211)	-0.973*** (0.211)	-0.957*** (0.210)	-0.958*** (0.210)
walk:education-high school	-0.822*** (0.221)	-0.819*** (0.221)	-0.802*** (0.220)	-0.804*** (0.220)
auto:education-bachelor	-2.063*** (0.185)	-2.062*** (0.185)	-2.049*** (0.185)	-2.050*** (0.185)
walk:education-bachelor	-1.607*** (0.194)	-1.607*** (0.194)	-1.593*** (0.193)	-1.594*** (0.194)
auto:education-graduate	-2.082*** (0.197)	-2.086*** (0.197)	-2.074*** (0.196)	-2.079*** (0.197)
walk:education-graduate	-1.593*** (0.206)	-1.597*** (0.206)	-1.584*** (0.206)	-1.590*** (0.206)
auto:income	0.024 (0.026)	0.024 (0.026)	0.021 (0.026)	0.022 (0.026)
walk:income	0.074*** (0.028)	0.074*** (0.028)	0.071** (0.028)	0.072*** (0.028)
auto:household size	0.226*** (0.044)	0.226*** (0.044)	0.225*** (0.044)	0.225*** (0.044)
walk:household size	0.159*** (0.047)	0.159*** (0.047)	0.158*** (0.047)	0.158*** (0.047)
auto:# of vehicles	0.817*** (0.061)	0.819*** (0.061)	0.815*** (0.061)	0.817*** (0.061)
walk:# of vehicles	0.196*** (0.064)	0.199*** (0.064)	0.195*** (0.064)	0.197*** (0.064)
auto:# of bikes	-0.359*** (0.021)	-0.359*** (0.021)	-0.357*** (0.021)	-0.358*** (0.021)
walk:# of bikes	-0.385*** (0.023)	-0.385*** (0.023)	-0.383*** (0.023)	-0.384*** (0.023)
Observations	12,637	12,637	12,637	12,637
R2	0.129	0.129	0.129	0.129
Log Likelihood	-8,251.628	-8,252.365	-8,250.740	-8,251.445
LR Test (df = 33)	2,446.004***	2,444.531***	2,447.781***	2,446.371***
Note:				*p<0.1; **p<0.05; ***p<0.01

Figure 28. Portland Bike Mode Choice Model Results

How about Different Population Groups?

The results from the previous section suggest that the impacts of bike networks differ among different social-economic groups, Here, I applied market segmentation techniques to further investigate the differences in impacts based on two equity-related social-economic factors: gender and income. Also, the previous results suggest that the difference between the two versions of LTS measurements is negligible, and the two route level bicycle network measures are highly correlated. Therefore, for this analysis, I only used the updated LTS measures and the weighted to actual route length to evaluate the stresses.

The first set of models examined the different impacts on male versus female travelers. I found that the effects of bicycle networks on male and female travelers were different. Higher levels of route stress significantly decrease the possibility of choosing bike for female travelers, but this effect was not significant for males. In other words, women were more sensitive to route quality when choosing bicycling. Given the fact that previous research identified a significant gender gap in bicycle activities in the US (there were far fewer women bicyclists than men), investment in reducing the stress levels of bike routes will significantly increase the probability for women to choose bike as a travel mode, and narrow the gender gap.

	Dependent variable:	
	Mode Choice	
	Male	Female
	(1)	(2)
auto:(intercept)	1.118 (0.935)	-2.022* (1.115)
walk:(intercept)	2.329** (0.943)	-0.262 (1.117)
Weighted/actual route	-0.314 (0.791)	-3.264*** (0.939)
% of major arterials	-1.292*** (0.109)	-1.282*** (0.096)
Route length	-0.001*** (0.0002)	-0.001*** (0.0002)
auto:trip purpose-shopping	0.901*** (0.179)	0.911*** (0.217)
walk:trip purpose-shopping	0.236 (0.191)	0.336 (0.223)
auto:trip purpose-social	0.727*** (0.172)	0.445** (0.202)
walk:trip purpose-social	0.610*** (0.178)	0.233 (0.206)
auto:trip purpose-other	0.791*** (0.131)	0.725*** (0.163)
walk:trip purpose-other	-0.069 (0.140)	-0.092 (0.169)
auto:population density	-0.00002*** (0.00000)	-0.00001*** (0.00000)
walk:population density	-0.00002*** (0.00000)	-0.00001*** (0.00000)
auto:age	0.029*** (0.005)	0.037*** (0.006)
walk:age	0.017*** (0.005)	0.016*** (0.006)
auto:race-white	0.466*** (0.158)	0.378* (0.211)
walk:race-white	0.691*** (0.179)	0.361 (0.220)
auto:education-high school	-1.137*** (0.261)	-0.410 (0.379)
walk:education-high school	-1.062*** (0.281)	-0.199 (0.388)
auto:education-bachelor	-2.079*** (0.238)	-1.993*** (0.301)
walk:education-bachelor	-1.548*** (0.255)	-1.604*** (0.309)
auto:education-graduate	-1.918*** (0.258)	-2.274*** (0.312)
walk:education-graduate	-1.296*** (0.276)	-1.907*** (0.322)
auto:income	0.069** (0.034)	-0.061 (0.042)
walk:income	0.113*** (0.037)	-0.013 (0.044)
auto:household size	0.139** (0.057)	0.335*** (0.073)
walk:household size	0.125** (0.063)	0.213*** (0.076)
auto:# of vehicles	0.771*** (0.075)	1.016*** (0.109)
walk:# of vehicles	0.076 (0.081)	0.465*** (0.112)
auto:# of bikes	-0.350*** (0.028)	-0.363*** (0.032)
walk:# of bikes	-0.379*** (0.032)	-0.383*** (0.034)
Observations	5,787	6,850
R2	0.138	0.122
Log Likelihood	-3,942.360	-4,267.426
LR Test (df = 31)	1,267.568***	1,183.505***
Note:		*p<0.1; **p<0.05; ***p<0.01

Figure 29. Portland Bike Mode Choice Model Results (Gender Segmentation)

The second set of models examined the effects on different income levels. All individuals were divided to three income groups based on their annual household income, which included low-income group (less than $35,000), mid-income group ($35,000-$100,000), and high-income group (greater than $100,000). The model results showed that a higher-stress bicycle network was significantly associated with a lower possibility of bicycling for low-income and mid-income groups, but the effect on high-income group was insignificant. In terms of trip purposes, there was no significant difference in travel mode choices based on trip purposes in low-income population. This result could be explained as the following: low-income population is less likely to have enough flexibility to choose among different travel modes. For shopping and social purposes, high-income group prefers driving to other travel modes and displayed no preferences between bicycling and walking. In addition, the pseudo R^2 for the low-income model is much better than the rest two models. This might because there are more other reasons, such as social status and culture, that more likely to affect the mode choice for higher income population that have not been captured in this analysis.

	Dependent variable:		
		Mode Choice	
	Low-income	Mid-income	High-income
	(1)	(2)	(3)
auto:(intercept)	-3.762** (1.908)	0.779 (1.008)	2.642** (1.346)
walk:(intercept)	-2.565 (1.904)	2.542** (1.015)	3.370** (1.359)
Weighted/actual route	-4.331*** (1.624)	-2.150** (0.846)	1.530 (1.091)
% of major arterials	-0.918*** (0.201)	-1.543*** (0.100)	-1.125*** (0.127)
Route length	-0.001* (0.0003)	-0.001*** (0.0001)	-0.002*** (0.0003)
auto:trip purpose-shopping	0.429 (0.369)	0.833*** (0.184)	1.238*** (0.278)
walk:trip purpose-shopping	0.109 (0.373)	0.265 (0.194)	0.390 (0.292)
auto:trip purpose-social	0.448 (0.412)	0.719*** (0.181)	0.442** (0.215)
walk:trip purpose-social	0.581 (0.410)	0.535*** (0.188)	0.223 (0.223)
auto:trip purpose-other	0.900*** (0.319)	0.784*** (0.139)	0.663*** (0.174)
walk:trip purpose-other	0.433 (0.321)	-0.037 (0.147)	-0.347* (0.184)
auto:population density	0.00000 (0.00001)	-0.00002*** (0.00000)	-0.00002*** (0.00000)
walk:population density	0.00001** (0.00001)	-0.00002*** (0.00000)	-0.00002*** (0.00000)
auto:age	0.066*** (0.011)	0.039*** (0.005)	0.003 (0.007)
walk:age	0.049*** (0.011)	0.015*** (0.005)	0.007 (0.008)
auto:male	-1.646*** (0.257)	-0.776*** (0.113)	-0.571*** (0.144)
walk:male	-1.445*** (0.257)	-0.650*** (0.120)	-0.610*** (0.154)
auto:race-white	0.534 (0.339)	0.238 (0.184)	1.205*** (0.217)
walk:race-white	0.455 (0.339)	0.348* (0.197)	1.294*** (0.249)
auto:education-high school	-3.019*** (0.589)	-0.846*** (0.308)	-0.036 (0.391)
walk:education-high school	-2.768*** (0.599)	-0.431 (0.323)	-0.493 (0.416)
auto:education-bachelor	-3.811*** (0.589)	-2.403*** (0.257)	-0.592* (0.350)
walk:education-bachelor	-3.211*** (0.594)	-1.661*** (0.270)	-0.763** (0.371)
auto:education-graduate	-3.915*** (0.646)	-2.345*** (0.279)	-0.657* (0.353)
walk:education-graduate	-2.617*** (0.655)	-1.539*** (0.294)	-0.943** (0.376)
auto:household size	0.503*** (0.136)	0.118* (0.061)	0.324*** (0.088)
walk:household size	0.407*** (0.142)	0.097 (0.065)	0.309*** (0.093)
auto:# of vehicles	2.053*** (0.211)	0.663*** (0.077)	0.919*** (0.114)
walk:# of vehicles	0.231 (0.208)	0.126 (0.082)	0.558*** (0.120)
auto:# of bikes	-0.838*** (0.097)	-0.359*** (0.028)	-0.308*** (0.035)
walk:# of bikes	-0.765*** (0.102)	-0.457*** (0.033)	-0.252*** (0.037)
Observations	1,762	6,662	4,213
R2	0.282	0.140	0.117
Log Likelihood	-986.897	-4,311.477	-2,718.391
LR Test (df = 31)	776.758***	1,403.259***	721.442***
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure 30. Portland Bike Mode Choice Model Results (Income segmentation)

Discussion of the Mode Choice Analysis

Travel mode choice analysis is another way to assess the impacts of bike network on bike activities. Interestingly, both of the two bike network measures I designed to evaluate the quality of each route significantly impacted the likelihood of choosing bicycling. This result independently corroborated the previous findings based on bike counts data and suggests that the bike network was indeed a factor strongly influencing bike activities, measured by different output variables.

The two bike network measures, the ratio of weighted to actual route length and the percentage of low-stress segment length, turned out to be rather similar in their effects on mode choice. It is not surprising, because essentially both measures compared some forms of segment length to the actual route length. And the two measures were highly correlated. The only difference was that in the ratio of weighted to actual route length, the segment length was weighted, while in the other, the percentage of low-stress segment length, the length of the low-stress segment was not weighted. Therefore the reason why they perform similarly might be that the linear weight scale with a step of 0.1 is not strong enough to differentiate the effects of low-stress segment from the high-stress segment. In the future, it is worth to explore other weight scales, ideally estimated from route choice data.

Many social-economic variables also had significant impacts on travel mode choice. It is important for researchers and urban planners to understand this impact and incorporate the equity awareness in policy implementation to potentially mitigate environmental justice issues. In this regard, the findings from the market segmentation analysis provided useful information to guide future policies. First, I found that females were more sensitive to stress levels of bike route, compared to males. Previous research identified a significant gender gap in bicycle activities in the US: there were fewer women bicyclists than men (Aldred et al., 2016; Pucher & Buehler, 2008). Future investment in reducing the stress levels of bike routes will disproportionately increase the probability for women to choose bike as a travel mode option. This effort will likely contribute to narrow the existing gender gap in bicycle activities. Second, I found that the high-income population was insensitive to the stress levels of bike route, while low-income and middle-income populations were more likely to be impacted by this factor in deciding their travel mode. It is important for people to have equal opportunities to enjoy the benefits of bicycling. My result suggested that reducing the stress levels in bike route could be an effective way to achieve this goal. To sum up, the efforts invested in improving bicycle network, especially to reduce the stress levels, could not only increase bike mode choice, but they may also have disproportionately positive effects on female and low-income populations.

Conclusion

This dissertation addresses the research question of how does the bicycle network impact bicycle activity. To be specific, how to properly measure the bicycle network at different geographical scales, and how the bicycle network impacts bicycle ridership and bike mode choice in different cities. In particular, a longitudinal research design was employed to explore the causal relationship between the bicycle network and bicycle ridership.

The bicycle network is often characterized through three aspects: network topology, the quality of network, and route quality. However, no empirical studies have comprehensively examined these bicycle network measures with regards to their robustness, sensitivity and applicability. In addition, few empirical studies had investigated the effects of the bicycle network, instead of individual infrastructure components, on bicycling activity (Buehler & Dill, 2016). Moreover, none of the existing studies utilized a longitudinal design, which could provide causal inference. This study filled the research gaps by modeling the impacts of bicycle network on bike counts and bike mode choice longitudinally.

I first compared and chose the appropriate data sources to measure the bicycle network. I followed the approach of the Level of Traffic Stress to assess the quality of bicycle networks. Bicycle infrastructure and roadway characteristics, such as the number of lanes, speed limit, and mixed traffic, were the essential information to collect in the LTS approach. Comparing the crowdsourced OSM data and local city archive data, I found that the OSM data generally provided more accurate bicycle infrastructure information in recent years. In terms of roadway characteristics, there was no single data source that could provide all the required information. The OSM offered a decent database to gather all the needed information to measure the bicycle network. As a result, the crowdsourced OpenStreetMaps (OSM) was chosen as the major data source in this project due to its consistency, replicability, and scalability.

How to Measure Bicycle Network?

The development of the bicycle network measures was guided by previous literatures (Louch et al., 2016; Twaddell et al., 2018) and the conceptual framework (Figure 1) of this project. A relatively comprehensive assessment of a bike network could be achieved by evaluating it with a combination of these network measures. The bicycle network measures were conducted at both regional level and route level. In particular, the regional level measures focused on the network connectivity and comfort; and the route level measures focused on route directness and route quality for cyclists.

After data was assembled, the level of traffic stress of all the street segments in both case cities, Portland, OR and Minneapolis, MN, was calculated according to the LTS definition (Mekuria et al., 2012). Then, an updated LTS measure was constructed using additional stress features, such as high-quality bicycle infrastructure and steep-grade, to reflect the differences from the original LTS definition.

Next, different bicycle network measures were constructed for the regional level, i.e. bike counters and the route level, i.e. travel routes. The development of the network measures incorporated the principles of a complete network, including cohesion, directness, comfort and safety. Regional level measures consisted of four measures: (1) the catchment area size within certain buffer distances from the bike counter, without taking into account of traffic stress; (2) the percentage of low stress street segments within the catchment area; (3) the average traffic stress of the street segments adjacent to the bike counter; (4) the catchment area size in the low stress network. The four measures evaluated different aspects of the bicycle network: the first one only evaluated the cohesion of the network, while the latter three focused on the comfort and safety feature of the network. In particular, the percentage of low stress segments metric evaluated the general quality of the bicycle network in the surrounding area, the average stress of the street segments adjacent to the bike counter assessed the closest street segments that the cyclists travel on; and the low-stress catchment area metric assessed the extensiveness of the reachable areas through the low-stress network.

In terms of the route level measures, the bicycle network is evaluated as the ratio of weighted travel route length to the actual travel length. It represented the perceived travel costs based on the stress of the route. The other route level measures, the percentage of low stress segment length, highly correlated with the former measure and also performed similarly in all the models.

What are the Impacts of Bicycle Networks on Bicycling Activity?

The impacts of bicycle networks on bicycling activities were examined with regression models on bike counts and bike mode choice. In general, I found that the low stress bicycle network was associated with high bicycle ridership and high probability of choosing bikes among other travel modes, after controlling other covariates. In particular, the low-stress catchment area metric significantly affected bike counts in both case cities.

It indicated the importance of the extensiveness of bicycle network on promoting bicycling activity. In addition, the results also suggested that the improvement of bicycle network would disproportionately benefit disadvantaged populations, such as female and low-income groups, by increasing their probability of riding bikes.

Finally, the causal relationship between the bicycle network and bike ridership was investigated. By applying difference-in-difference (DID) approach, treatment and control bike counters were defined based on the amount of improvement in each counter between 2011 and 2017, measured by the bicycling network metrics. Three different versions of the treatment and control groups were tested. Although significant association between the bicycle network metrics and bike counts was found in the cross-sectional analysis, no causal relationship between bicycle network improvement and bike counts could be inferred from the longitudinal DID analysis.

Future Research Directions

Bicycle Network Measurement

I constructed four regional level measurement and two route level measurement. It is worth noting that these measures cannot capture all the principles for a complete bicycle network assessment (Louch et al., 2016). For example, accessibility to destinations and alternatives were not incorporated due to data limitation and computation simplicity. Future work could incorporate the important destinations component to measure how exactly the network contribute to connect the places people want to go.

Due to the scope of this project, the bicycle network measures explored in this study are mainly based on the level of traffic stress (LTS), which is one of the most common bicycle network metrics currently applied by practitioners and researchers. However, other bicycle network measures, such as BLOS and route quality, are worthwhile to be analyzed in the future. In addition, intersection features were not included in this analysis due to data limitation. Future work could incorporate intersection characteristics into the network measures to construct more comprehensive representation of the network property.

Few empirical studies have systematically evaluated the bike network. This fact opens many exciting territories for empirical research, but it also brings some difficulties to appropriately parameterize measures. Due to the lack of precedence, several parameters in this project were chosen subjectively based largely on data availability. For example, the classification of stress levels based on the slope of the terrain was a test of sensitivity on the impact of terrain on network measurement. Similarly, the catchment area was only evaluated at three chosen levels: 0.25 mile, 0.5 mile, and 1 mile. Sampling the parameter space more widely can potentially improve the accuracy.

The weights used in the route measurement were chosen preliminarily on a linear scale, i.e. from 0.9 to 1.2, for computational simplicity. While previous literature utilized similar weights (Cervero et al., 2018), it is possible that the relationship between the increase in stress level and the increase in route difficulty is non-linear. Future work should more thoroughly explore the parameter space or base the parameter choice on empirical data. For example, in the case of weight scale, other scales of weight, such as exponential, could be explored. It is also possible to use route choice data to construct more realistic weights inferred from bicyclists' experiences.

Another limitation is the route level measurement utilized the shortest path to approximate bike trips. The shortest path criterion is a reasonable guiding principle to approximate real bike trips and it is relatively easy to compute. However, in reality, not all travellers would choose the shortest path for their trips. For example, a bicyclist might take a detour for better scenery rather than the shortest path. Future work should explore the impacts of street stresses on realistic trip routes, which could be collected from sources like Google Map Timeline.

Data

The open source OSM data provides a relatively comprehensive database for bicycle network analysis, so I used it as the main data source for the street network. However, there are some major issues related to this dataset. For example, many key roadway characteristics are missing in the OSM data. In addition, the data quality of the OSM dataset in the earlier years is generally worse than the more recent years. The issues related with inaccuracy and missing values in the early years posed some difficulties for the longitudinal study in this project. Since the OSM dataset has been continuously improved over the years and the data in the most recent year has very good quality, I expect that future work, which utilizes the OSM dataset for longitudinal studies, will not face the same challenges I encountered.

This project utilized bike counts and bike mode choice as indicators for bicycling activity. They are the most available data source to measuring bicycling activity at this stage. However, bike count only represents the static bicycle activities at certain location, instead of travel flow within the whole network. In addition, bike counters are often spatially auto-correlated, which means the bike counter in one intersection is likely to be impacted by the surrounding intersections.

The travel survey data utilized for mode choice analysis only contains survey results from one year, 2011, and one city, Portland. Compared to bike counts data, travel survey data, especially confidential spatial data, is much harder to obtain and they are often not easy to compare if the surveys are conducted independently by different organizations. In the future, if travel survey data across different cities and different years is available, it will be very interesting to investigate if the influences of bike network on travel mode choice vary temporally or spatially.

Also, I should point out that the ACS data set is on a five-year rolling basis, which means the dataset I obtained from the year of 2011 reflects the trend from 2009 to 2013, and correspondingly, the dataset I obtained from the year of 2017 reflects the trend from 2015 to 2019. Therefore, although one would expect that the difference between 2011 and 2017 is the accumulative effects over 6 years, due to the five-year rolling basis, the differences in the effects captured by the ACS dataset could be actually smaller. This fact might contribute to the insignificant result of DID analysis to some extent, because it essentially averaged out some potential effects. In the future, this problem could be overcome by sampling time points further apart, like 10 years, in the design of longitudinal studies.

Modeling Approach

One major issue of the modeling approach in this project is the lack of a benchmark model for each model constructed. Despite that both the four regional network measures and the two route level measures had significant impacts on bike activities, it is uncertain how much improvement of model fit can be attributed to including the network measures in general. To evaluate this aspect, it will be very helpful to construct a benchmark model for each model in this project, which includes all the selected independent variables, except the network measures.

In this project, I used Akaike Information Criterion (AIC) as the criterion for model choice. AIC is a classical model choice criterion, which strikes a balance between overall model fit and the problem of over-fitting. It is easy to tell whether one model is a better fit than the other with AIC, however, it is difficult to interpret the amount of improvement in a practical sense. For example, the model using the percentage of low stress segments as the only network metric is superior to the model using the catchment area size through low stress network as the only network metric in bike counts analysis for the City of Portland. But it is difficult to infer whether the advantage is large enough to justify using one measure over the other. Additionally, the four measures I constructed for bicycle network at regional level evaluated different aspects of bicycle network. But some of them could not be compared directly with each other because they were not on the same scale, which caused some difficulties in model interpretation. For example, the percentage of low-stress segments in catchment area was a percentage while the size of the catchment area in low-stress network was an absolute area value. One unit increased in the former was not directly comparable to one unit increased in the latter. One way to solve this issue is to use the concept of elasticity to compare the effects of measurement constructed on different scales.

One of the puzzling issues of this study is that despite I found all the network measurements significantly impact bicycling activity in the cross-sectional study in both cities, no causal relationship could be inferred using DID analysis. It is well established that other factors, such as psychological determinants and social norm (Akar & Clifton, 2009; Dill & Voros, 2007), also impact bike activities, other than the selected variables in this project, which could contribute to the causal relationship. However, this result was also likely caused by the limitations of applying DID approach to my dataset. Although DID analysis is a powerful approach to infer causal relationship in urban studies, its performance relies on a few key assumptions. For example, in the classical DID analysis, the interruption is often defined as a single event which happened at a given time stamp, instead of multiple events occurring over a long time course. In this project, the improvement of bicycle network was not defined by a single event, e.g. bike infrastructures construction. Instead, it was the accumulation of many efforts in different regions over a long time period. It is unclear how the violation of this assumption would impact the result. In addition, the spatial heterogeneity of bicycle network improvement could also complicate the analysis. For example, the improvement in various regions may not impact bicycling activity in the same direction or in the same amount, due to the variation in existing bicycle infrastructure, economic background, or people's biking habits. This heterogeneity could cancel out some strong local effects. In my analysis, I explored three different definitions of treatment and control group. But all of them used a certain cut-off value, based either on the mean value, the median, or an subjective cut-off number, and therefore, they did not take into account of spatial heterogeneity. Finally, it is also worth noting that the treatment group and control group in DID analysis should be strictly independent. However, the different bike counters in my analysis were likely spatially auto-correlated, which means the bike counters in the treatment group located in the proximity of a control counter could have an effect on the latter. As a result, the signal of the treatment would be dampened even if there were a significant effect. To address these issues, future efforts should be directed to explore other ways to define treatment versus control group. For example, using the unit of treatment versus control on biking routes, instead of bike counters, could mitigate the spatial auto-correlation problem. It is also worth to explore additional methods, such as synthetic control method, to test the causal relationship.

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