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STREET NETWORK CONNECTIVITY, TRAFFIC CONGESTION, AND TRAFFIC SAFETY

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RESEARCH

UDOT
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16. Abstract

Over the last two decades, street connectivity has gained substantial attention in urban planning circles as a critical environmental aspect to achieve many community goals. Despite advocacy for interconnected areas, the literature on the effects of street connectivity on transportation outcomes is still intuitive. In this study, we examine the effect of street connectivity on congestion levels and crash rates in neighborhoods across Utah's Wasatch Front. We employ propensity score matching to select pairwise neighborhood samples with similar characteristics that differ greatly in street connectivity. We use principal component analysis to develop a connectivity index incorporating multiple aspects of street connectivity. Congestion levels are computed as the Travel Time Index on arterials and collectors. Crash rates are calculated at three different severity levels— total, injury, and fatal. Finally, we use t-tests to determine whether significant differences exist between high- and low-connectivity neighborhoods. Our results show that more connected neighborhoods have significantly lower congestion levels, but they do not have measurably lower (or higher) crash rates, presumably due to the prevalence of four-way intersections. This study can help guide data-driven decision-making on street connectivity standards for many of the growing urban areas across the country and globe.

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UNIT CONVERSION FACTORS

Units used in this report and not conforming to the UDOT standard unit of measurement (U.S. Customary system) are given below with their U.S. Customary equivalents:

- 1 meter (m) = 3.28 feet (ft)
- 1 kilometer (km) = 0.62 mile (mi.)

SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. (Adapted from FHWA report template, Revised March 2003)

LIST OF ACRONYMS

AGRC	Automated Geographic Reference Center
APA	American Planning Association
FHWA	Federal Highway Administration
GIS	Geographical Information System
GPS	Global Positioning System
HH	Household
LBS	Location-Based Service
MAG	Mountainland Association of Governments
PCA	Principal Component Analysis
PSM	Propensity Score Matching
SCI	Street Connectivity Index
TTI	Travel-Time Index
UDOT	Utah Department of Transportation
UTA	Utah Transportation Authority
VMT	Vehicle Miles Traveled
WFRC	Wasatch Front Regional Council

EXECUTIVE SUMMARY

The Wasatch Front Regional Council, Utah Department of Transportation, Utah Transit Authority, and Mountainland Association of Governments released the Utah Street Connectivity Guide in March 2017. The Guide is an excellent overview piece but would be even more compelling if backed by local empirical research quantifying the benefits of interconnected streets. Planners in this region often point to the Avenues and Daybreak as examples of what can be achieved with more connected street networks. But where is the proof?

This study aims to relate congestion levels and crash rates to measures of street connectivity in Wasatch Front neighborhoods and suggests appropriate land development code provisions to foster street connectivity. Our research shows that short blocks and four-way intersections reduce VMT and increase walking, bicycling, and transit use. But do they do so at the expense of traffic safety, and do they also measurably reduce congestion? These are questions that have not been answered empirically.

This study involved the following steps:

Step1. Neighborhood Selection for Street Connectivity Measurement: This section shows how neighborhoods were defined and selected for street connectivity measures.

Step2. Street Connectivity Index: A principal component analysis was conducted to create one consolidated index combining multiple connectivity measures for each neighborhood.

Step3. Neighborhood Matching: Propensity Score Matching (PSM) was used to match neighborhoods with good and poor connectivity so as to obtain unbiased results of connectivity effect, where each paired sample is different in terms of connectivity but controlled for socio-demographic or environmental variables that plausibly affect congestion and safety.

Step4. Outcome Variables and Statistical Analysis: This section describes how congestion and safety variables were operationalized in this study. Descriptive statistics and t-tests were used to analyze the relationships of street networks with congestion and safety variables.

The propensity score match found 31 neighborhood pairs (in total 62) out of 40 initially sampled. After matching, we evaluated whether the selected neighborhoods are systematically different in terms of street connectivity and also whether they are balanced on other attributes. T-tests results for the matched samples show that the two types of neighborhoods are statistically different in street connectivity index, having a connectivity index of 97.54 and 146.41, respectively, in the control and treatment groups. However, they do not differ in terms of all other variables, including the three covariates used in the PSM (activity density, major road mileage, and median household income).

Our analysis of 31 neighborhood pairs shows that there are statistically significant lower congestion levels in neighborhoods with better connectivity, as measured by the travel-time index or TTI (peak hour travel time divided by off-peak travel time). This finding is aligned with earlier studies revealing more balanced traffic distributions and greater traffic volume capacity associated with networks with more connectivity.

Highly connected neighborhoods did not have significantly higher or lower crash rates at three different levels of severity—all, injury, and fatal—compared to less-connected neighborhoods. One possible reason for this is the small sample size, where many of the local neighborhoods were not included in the comparison. These results might also be attributable to more four-way intersections in connected networks. Intersection areas are traditionally understood as where crashes are mostly concentrated. Nevertheless, it is noteworthy that higher connectivity does not evidently compromise road safety, even though it might allow more vehicles to pass through the neighborhood.

Taken together, improving street connectivity at a neighborhood level could be considered as a viable community development strategy to mitigate congestion on major arteries without compromising road safety. Another important finding is that some better-connected neighborhoods display a TTI value less than 1, implying that some drivers might take advantage of less congested roads by driving faster in peak hours. Even though our data show no higher crash rates in better-connected areas, this speeding behavior could lead to other road safety concerns. Thus, street connectivity guidelines might need to include other traffic-calming approaches to maintain road safety, such as speed humps, raised crosswalks, and traffic circles.

1.0 INTRODUCTION

1.1 Problem Statement

WFRC, UDOT, UTA, and MAG released the Utah Street Connectivity Guide in March 2017. The Guide is an excellent overview piece but would be even more compelling if backed by local empirical research quantifying the benefits of interconnected streets. Compared to urban grids, suburban curvilinear street networks tend to increase trip distances, generate high speeds between intersections, concentrate traffic at the intersections of major roads rather than disperse traffic across the networks, and discourage walk, bike, and transit trips. Since 1990, planners and engineers have been touting the advantages of more connected and grid-like street networks. Planners in this region often point to the Avenues in Salt Lake City and Daybreak in South Jordan as examples of what can be achieved with more connected street networks. At least two jurisdictions in this region (Lehi and Saratoga Springs) have already adopted street connectivity standards for new developments. Yet the literature on street connectivity is mainly theoretical and intuitive rather than empirical. The benefits of street connectivity would be greatly enhanced by hard numbers on mobility and safety advantages of highly connected networks vs. curvilinear networks.

1.2 Objectives

This research project aims to relate congestion levels and crash rates to measures of street connectivity in selected Wasatch Front neighborhoods and suggest appropriate land development code provisions to foster street connectivity.

1.3 Scope

The above objectives were accomplished through the following major tasks:

1. Conduct a literature review on street connectivity measures and its relation to congestion and road safety.

2. Distribute surveys through Utah APA to examine local street connectivity ordinances.
3. Compile the best available congestion data by reviewing multiple sources (e.g., HERE, INRIX, StreetLight), extract crash data from UDOT's database, and, using GIS, develop various measures of street connectivity for select neighborhoods in the Wasatch Front.
4. As part of a quasi-experimental design, using propensity score matching techniques and sample pairwise-neighborhoods has similar built-environmental and socio-demographic characteristics but differs in street design.
5. Use descriptive statistics, difference-of-means tests, visualization (e.g., neighborhood-to-neighborhood comparison) to examine the relationships of street connectivity to traffic congestion and safety.
6. Write a report and manuscripts for publications and conferences.

Deliverables of the research include an interim report summarizing tasks 1 thru 3 and this final report.

1.4 Outline of Report

The report includes five chapters:

- Introduction
- Literature Review and Survey Result
- Data Collection and Research Method
- Data Evaluation and Results
- Discussion and Conclusion

The first part of the report starts with introducing the problem statement and objectives of the research; then, it explains previous research conducted on street connectivity and its relations to congestion and road safety. In addition, chapter three contains the results from the survey on Utah's street connectivity ordinances.

The second part of the report includes chapters on data collection, methodology, and results. Chapter 3 describes the process of finding and compiling the congestion and crash data from multiple sources. It also describes the steps that have been taken in GIS to select neighborhoods in the Wasatch Front. Chapters 4 and 5 are dedicated to data evaluations and report the findings on street connectivity relationships to traffic congestion and safety.

2.0 LITERATURE REVIEW AND SURVEY RESULTS

Over the last two decades, street network connectivity has gained substantial attention in urban studies and planning practice as a critical neighborhood feature to create walkable and livable cities. In neighborhoods with a better street network, separated places are spatially connected, and people can efficiently move from one place to another with more transportation choices. Many studies analyze street connectivity in relation to travel behaviors, neighborhood walkability, destination accessibility, health outcomes, traffic safety, and other outcomes for urban livability. Moreover, many U.S. cities have adopted ordinances to establish connected street networks in new residential subdivisions (Handy et al., 2003).

Street network characteristics have been incorporated into various guidelines for creating better communities. In a guide to the best development practices, the street network should be designed with multiple connections and relatively direct routes (Ewing et al., 1996). The Congress for New Urbanism (2000) prompted a design of interconnected street networks to reduce the number and length of automobile trips and conserve energy. The Smart Growth Network (2002, p.63) encouraged communities to "plan and permit road networks of neighborhood-scaled streets … with high levels of connectivity and short blocks." The U.S. Green Building Council (USGBC, 2019) articulated a Neighborhood Development Guide (LEED-ND), where street connectivity is incorporated as one of the key rating system metrics.

While the street connectivity concept refers to how well streets are connected, there is considerable variation in street connectivity measurements. Moreover, even though well-connected networks could provide many transportation benefits, some studies showed that denser, well-connected streets might exacerbate traffic congestion (Kuqmyak, 2012) or safety issues (Moeinaddini et al., 2014).

In the next section, we dive into the literature to understand different street connectivity metrics and their usage. This is followed by a review of the literature on the effect of network connectivity on congestion and traffic safety.

2.1 Street Connectivity Measures in Literature

While the street connectivity concept generally refers to how well streets are connected, the approaches to measuring vary considerably, and each metric focuses on a different aspect of connectivity (see Table 2.1). One of the common methods is to focus on the number of intersections (Ewing and Cervero, 2010; Gladhill and Monsere, 2012; Hajrasouliha and Yin, 2015; Hamidi et al., 2015; Kaczynski et al., 2014; Knight and Marshall, 2015; Koohsari et al., 2014; Marshall and Garrick, 2011; Wang et al., 2013; Wang et al., 2018; Yu, 2014; Yu, 2015). There are two common ways of quantifying intersections: 1) intersection density is defined as the number of intersections per unit area (e.g., square mile); and 2) the percentage of 4-way intersections refers to the number of 4-way intersections (or 4-or-more-way intersections) divided by the number of all types of intersections. These two metrics are often found in travel behavior modeling (e.g., trip length, mode choice) as key variables estimating the built environment, particularly street design characteristics (Ewing and Cervero, 2010). One study finds that, as 4-way intersections give more routing options than 3-way intersections, the percentage of 4-way intersections is the purest measure of street connectivity (Hamidi et al., 2015). Intersection density is more related to block size, a measure of walkability promoted by Allan Jacobs in Great Streets (Jacobs, 1993).

Another approach to measure road connectivity is directly based on blocks (Hess et al., 1999; Marshall and Garrick, 2009; Oakes et al., 2007; Ozbil et al., 2011; Zhang et al., 2012). Two metrics are typical: 1) block length means the average spacing between intersections; and 2) block size is measured by the width and length, the area, or perimeter (Zhang et al., 2012). Because of its straightforward concept, maximum block length standards have often been implemented in planning practice (Handy et al., 2003), but not often in the reviewed literature. Only one study calculated the block length as a measure of street design, where the researchers sampled 20 block faces for each neighborhood and performed field surveys to get the average block lengths (Cervero and Kockelman, 1997).

Table 2.1 Street Connectivity Measures in Literature.

Street Connectivity Measure	Metric	References
Intersection density	The number of intersections per unit area (e.g., square mile, square kilometer)	Ewing and Cervero (2010); Gladhill and Monsere (2012); Hajrasouliha and Yin (2015); Hamidi et al. (2015); Kaczynski et al. (2014); Knight and Marshall (2015); Koohsari et al. (2014); Marshall and Garrick (2011); Wang et al. (2013); Wang et al. (2018); Yu (2014); Yu (2015)
Percentage of 4-way intersections	The number of 4-way intersections (or 4-or-more-way intersections) divided by the number of all intersections	Ewing and Cervero (2010); Gladhill and Monsere (2012); Hamidi et al. (2015)
Block length	The mean block length	Cervero and Kockelman (1997)
Block size	The mean block area	Hess et al. (1999); Marshall and Garrick (2009); Oakes et al. (2007); Ozbil et al. (2011); Zhang et al. (2012)
Link-node ratio (connectivity index)	The number of links divided by the number of nodes	Ewing (1996); Knight and Marshall (2015); Marshall and Garrick (2011); Tal and Handy (2012)
Street density	Street length per unit area (e.g., square mile)	Knight and Marshall (2015); Wang et al. (2018)
Dead-end density per unit area	The number of cul-de-sacs per unit area (e.g., square mile)	Marshall and Garrick (2011)
Walk-shed	1/3mile walk-shed	Tal and Handy (2012)
Geometric / typological categories	Categorical (4 = grid, 3 = warped parallel, 2 = mixed, 1 = loops and lollipops, 0 = could not determine)	Gladhill and Monsere (2012)
	Binary (Curvilinear vs. not)	Marshall and Garrick (2011)

Some studies measure connectivity as how many links are connected to each node—link-node ratio (Knight and Marshall, 2015; Marshall and Garrick, 2011; Tal and Handy, 2012). The link-node ratio indicates the number of links divided by the number of nodes in a given area. The link count represents the number of street segments between two nodes, and node count is the sum of the number of intersections and the number of dead ends (cul-de-sacs). While adding a new dead end will decrease the link-node ratio by having two nodes and one link added eventually, adding a new link connecting two existing dead ends will lead to a higher link-node ratio.

There were many other approaches to measure connectivity, including street density (Knight and Marshall, 2015; Wang et al., 2018), the number of blocks or nodes in a given area (Moeinaddini et al., 2014), destination-based travel-shed (Chin et al., 2008; Tal and Handy, 2012; Tresidder, 2005), dead-end density (Marshall and Garrick, 2011), categorical topology characteristics (Gladhill and Monsere, 2012; Marshall and Garrick, 2011), and Space Syntax methods (Hajrasouliha and Yin, 2015). Although these measures capture important network characteristics, the usage is limited to a few studies. Particularly, Knight and Marshall (2015) noted that the space syntax methods have never been held in the public sector because they are difficult to calculate, interpret, visualize, or explain to the general public.

2.2 Effect of Street Connectivity on Congestion

Among many different congestion measures, including road traffic volumes, person miles of travel, average travel speeds, person travel time, volume-to-capacity ratios (Rao and Rao, 2012), road network designs are related mainly to VMT per household or person in the literature (Bhat, et al., 2009; Boarnet et al., 2003; Chapman and Frank, 2004; Ewing et al., 2009; Ewing and Cervero, 2010; Frank et al., 2009; Frank and Engelke, 2005; Greenwald, 2009; Pushkar et al., 2000; Vance and Hedel, 2007). Increased intersection density has been proven to be significantly associated with VMT reduction after controlling for other socio-economic and environmental factors (Boarnet et al., 2003; Chapman and Frank, 2004; Ewing et al., 2009; Frank and Engelke, 2005; Greenwald, 2009; Pushkar et al., 2000). Also, increased percentages of 4-way intersections (Boarnet et al., 2003), greater street block density (Bhat et al., 2009), and more paved roads per unit area (Vance and Hedel, 2007) showed a significant relationship with decreased VMT.

Although fewer per capita VMT should contribute to reducing total regional congestion (Litman, 2020), it might not necessarily lead to less traffic congestion on major roads in a neighborhood. A few studies investigated segment- or network-level congestion measures in relation to road network characteristics. Some studies carried out traffic simulation and found that more connections in selected street networks resulted in better road performance, such as a significant reduction of network travel times and delays (Zlatkovic et al., 2019), decreased average traffic volumes (Ayo-Odifiri et al., 2017), or higher traffic accommodation (Tasic et al., 2015). Alba and Beimborn (2005) explored how local street connectivity affects traffic volumes on nearby arterials. The results showed a measurable reduction in traffic congestion levels on the arterials with increased street connectivity.

Despite some evidence of the effect of increased road connectivity on reduced VMT or road traffic volumes, only limited evidence has been assembled on segment-level travel delays. In addition, most congestion-and-connectivity literature focuses on one or two measures of street connectivity (e.g., intersection density), potentially failing to encompass other critical aspects of network connectivity characteristics (e.g., block size, link-node ratio).

2.3 Effect of Street Connectivity on Safety

While street network connectivity is understood to impact road safety significantly, whether the impact is positive is controversial across the literature. Some studies argue that neighborhoods with greater street connectivity are less safe in crash rates (Guo et al., 2017; Lovegrove and Sayed; 2006; Marks, 1957; Rifaat and Tay, 2009). Foundational work by Marks (1957) examined the linkages between street design patterns and crash rates, and found that gridiron streets with more four-way intersections involved eight times more crashes than hierarchical, limited-access networks. More recent studies refined measures of crash rates based on crash characteristics (two-vehicle crashes: Rifaat and Tay, 2009; pedestrian-vehicle crashes: Guo et al., 2017) and also similarly revealed lower crash risks in irregular or loop street designs compared to grid patterns (Dumbaugh and Rae, 2009).

However, other studies identified that areas with better street connectivity might be safer than those with poorly connected networks (Marshall and Garrick, 2011; Rifaat et al., 2012; Zhang et al., 2012). Marshall and Garrick (2011) measured crash rates at various severity levels—total, injury, and fatal crashes—and found fewer crashes across all severity levels associated with higher intersection density, attributable to lower vehicle speeds in areas with more intersections. Zhang et al. (2012) tested multiple street connectivity variables—block density, intersection density, street density, average block length—and concluded that greater connectivity is safer with regard to pedestrian-bicyclist accidents. Rifaat et al. (2012) showed that loops and lollipop street patterns are associated with higher pedestrian crash severity, compared to gridiron network patterns.

The key problems with these inconsistent results can be attributed to the following reasons. First, the estimation of connectivity widely varies by research study, and many studies relied on one or a few particular measurements (Guo et al., 2017; Marks, 1957; Rifaat et al., 2012). As connectivity can be defined by many different aspects, a neighborhood's connectivity measured by a single metric would not adequately represent how well the road network is connected. Second, although areas with more VMT tend to have more crashes (Dumbaugh and Rae, 2009), some studies failed to appropriately account for the impact of travel volumes and crash severity levels (Guo et al., 2017; Rifaat et al., 2012). Lastly, even if higher intersection densities are likely to result in reduced vehicle speeds and, accordingly, less severe crashes (Ewing and Dumbaugh, 2009), the severity of crashes was not included in their modeling approaches (Zhang et al., 2012).

2.4 Street Connectivity Regulations in Utah

Street connectivity standards may take many forms other than link-node ratios, as discussed in the literature review: block length limits, cul-de-sac length limits, block size (area), intersection density minimums, and minimum percentages of 4-leg intersections (Utah Street Connectivity Guide, 2017). There may be others as well. In an effort to identify connectivity standards in local land development ordinances within the state of Utah, we designed and distributed a mini-survey targeted at planners across the state via email through the APA Utah chapter. Our main question was if the jurisdiction has any type of street connectivity requirements or guidelines. Before reaching out to Utah APA members, we were aware of at least two localities in the Wasatch Front, which have connectivity requirements for new subdivisions, those being Lehi and Saratoga Springs. In these jurisdictions, the ratio of street links to nodes (street segments over intersections) must exceed some minimum. The methodology for analyzing the email survey results was reviewing the combination of primary (responses from cities) and secondary data, including zoning, other land development codes that contain any such requirement, and WFRC ordinances. After receiving planners' responses and following up for more information and supportive documents, we sent them the results for accuracy and clarification.

Based on the total 13 responses from localities and reviewing Wasatch Front cities' ordinances, almost all of them had block length limitation (different limits but not greater than 1200 ft) in their street connectivity requirements except Orem and Lindon city. The next most popular street connectivity requirements that cities participating in the survey required for the new subdivisions in their jurisdiction were the link-node ratio and the cul-de-sac limit—those being Morgan County, Lehi, Ephraim, Hurricane, and Kaysville. Also, Provo and Lehi added the block size (area) to their requirements. The table below shows cities that were interviewed with more details of how the standards have been applied. Table 2.2 includes those jurisdictions that have additional or specific requirements and the ones inclined to establish such requirements.

Table 2.2 Street Connectivity Ordinances in Utah.

Locality Name	County/ City	Street Connectivity Regulations			
		Block Length	Cul-de-Sac Length	Link-Node Ratio	Others*
Morgan County	County	Max. 600-1,000ft.	Max. 250-400 ft.	Min. 1.5-1.75	V
Ephraim	City	Max. 1,300 ft.	Max. 650 ft.	-	V
Hurricane	City	-	Max. 600 ft.	-	V
Kaysville	City	-	Max. 600 ft.	-	V
Lehi	City	Max. 600-1,000ft.	Max. 250-400 ft.	Min. 1.5-1.75	V
Lindon		-	-	-	V
Orem	City	-	-	-	V
Provo	City	Max. 500 ft.	-	-	V
Saratoga Springs	City	Max. 1,000 ft.	-	-	V
Syracuse	City	Max. 1,320 ft.	-	-	V
Tooele	City	Min. 300 ft. Max. 1,000 ft.	-	-	V
West Bountiful	City	Min. 500 ft. Max. 1,200 ft.	-	-	V

*It includes interventions for large blocks or general recommendations for higher street connectivity.

As an example, Lehi City has a detailed and organized section for street connectivity under Chapter Seven, Design Standard Section 30, Connectivity Standards. (Connectivity Standards, 2018): "These standards are intended to create a connected transportation system between neighborhoods and commercial areas within the City, including definitions and concepts like block length, chicane, connectivity index, cul-de-sac length, curb extension, isolated development, links, nodes, pedestrian walkway, street stub, and superblocks." Then it required that "the circulation plan shall address street connectivity and pedestrian circulations. Pedestrian circulation also shows the connectivity index, block length dimensions, cul-de-sac length dimensions, pedestrian facilities, and any proposed traffic-calming features."

"Additionally, the circulation plan shall take into account access and connectivity on adjacent parcels. On a case-by-case basis, the Planning Director and City Engineer may require changes to stub road locations if it will increase the connectivity within an adjacent property." Moreover, there is a section about Residential Connectivity Standards that shows all new residential subdivisions with ten or more units or more than one acre shall meet at least the minimum required connectivity index, not exceed the maximum block length and cul-de-sac lengths, for private and public roads which can be found in the tables below.

Table 2.3 Private and Public Roads Connectivity Standards, Lehi City.

Density	Index Score
0-2.5 DU/AC	1.5
2.6-4 DU/AC	1.6
4.1+ DU/AC	1.75

Table 2.4 Private and Public Roads Connectivity Standards, Lehi City.

Density	Block Length
0-2.5 DU/AC	1,000 ft.
2.6-4 DU/AC	800 ft.
4.1+ DU/AC	600 ft.

Table 2.5 Private and Public Roads Connectivity Standards, Lehi City.

Density	Cul-de-Sac Length
0-2.5 DU/AC	400 ft.
2.6+ DU/AC	250 ft.

3.0 DATA COLLECTION AND RESEARCH METHODS

3.1 Study Area

The study area is the Wasatch Front, a metropolitan region of north-central Utah. The Wasatch Front includes Salt Lake City, Utah's capital city, and is home to about 80 percent of the state's population. Recognized as one of the fastest-growing regions in the U.S., Utah faces important planning decisions that affect communities in the present and the next few decades (WFRC, 2019). Increasing street connectivity is one of the major policies that the Wasatch Front Regional Council, the region's metropolitan planning organization, recommends to local communities, acknowledging its contribution to reducing VMT, increasing transit usage, and promoting walking and biking. Although a few recent studies proved increased traffic capacity in more connected street networks through traffic simulation (Tasic et al., 2015; Zlatkovic et al., 2019), little empirical study supported such benefits. The present study on comparative neighborhoods in the Wasatch Front will help guide many local developments and inform the decision-making of other growing municipalities that incorporate street network design into their development codes.

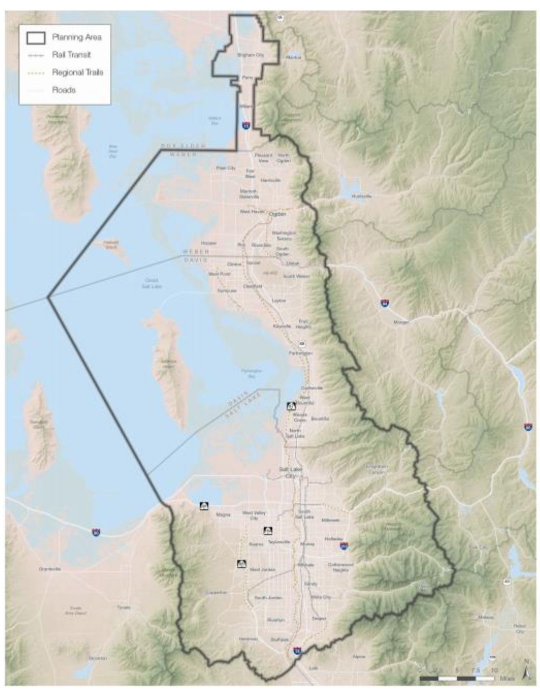


Figure 3.1 Study Area: Wasatch Front Region (image source: WFRC, 2019)

3.1.1 Unit of Analysis

One square-mile grid cells (one mile-by-one mile) were used as the unit of analysis. Some of the early literature used census geographies as neighborhood units (Marshall and Garrick, 2011; Wang et al., 2013). However, as census unit boundaries commonly follow street centerlines, it could be problematic to determine which features should be credited in calculating the number of intersections or crashes (Gladhill and Monsere, 2012). Because the newly drawn grid rarely shares the boundary with street centerlines, it allowed for the more accurate aggregation of key variables in this study—street connectivity, crash rates, and congestion.

3.1.2 Neighborhood Selection for Analysis

Based on a uniform grid of 1mi x 1mi cells that cover the Wasatch Front planning area, we applied several criteria to identify residential and mixed-use areas suitable for street connectivity measurement. We first selected cells with more than 1,500 activity density per square mile to rule out low-density or undeveloped areas. Urban sprawl studies generally identify low-density suburban neighborhoods as those with less than 1,500 people (Ewing et al., 2014; Hamidi and Ewing, 2014). Thus, the same cut-off value was employed, but because our sample contains mixed-use areas, we added population and employment together and divided by area. Then, we dropped cells where the length of major roads, including primary/minor arterials and major/minor collectors, is less than 2 miles because neighborhoods only with local roads are unlikely to experience traffic congestion. Lastly, cells where most of the area is devoted to campus, airport, or industrial use were excluded. The resulting number of neighborhoods in the sample is 297 grid cells (see Figure 3.2).

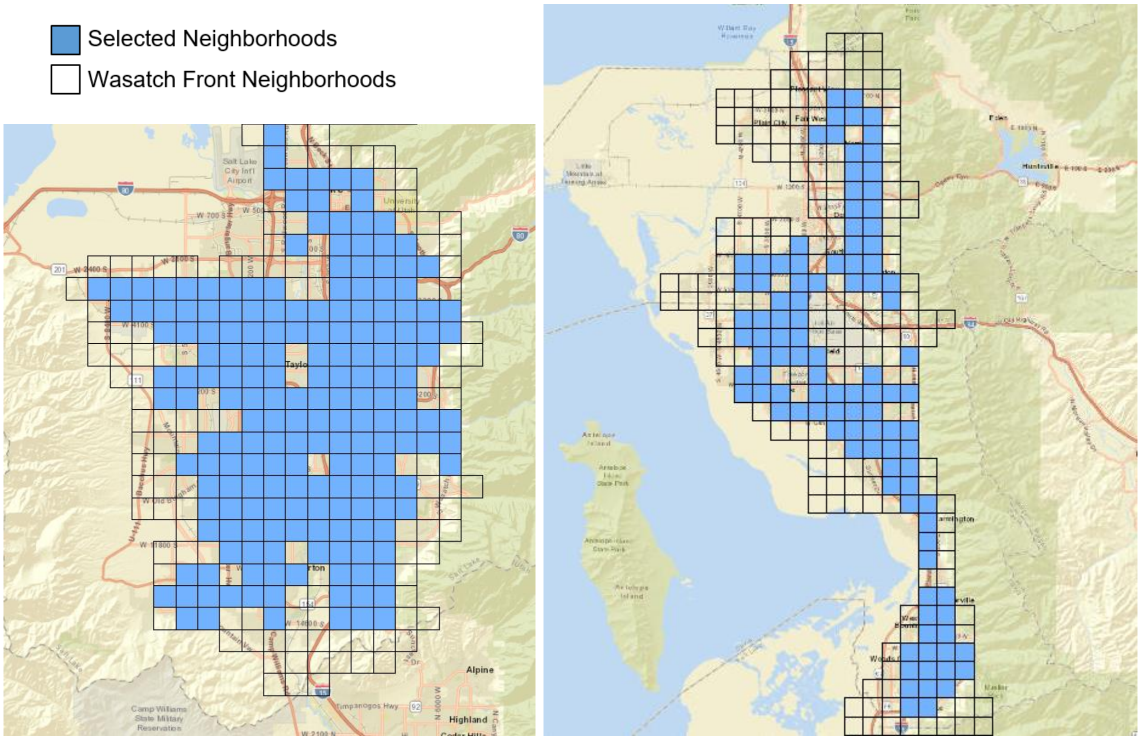


Figure 3.2 Neighborhoods selected for analysis
(left: Salt Lake County; right: Davis and Weber Counties)

3.2 Data

3.2.1 Independent Variable: Street Connectivity

Based on the grid cells, we estimated street network connectivity with four metrics that are widely adopted in the reviewed literature and local ordinances—*intersection density, percentage of 4-way intersections, link-node ratio,* and *block area* (See Table 2.1 and Table 2.2). Block length was not included due to a lack of valid data. The primary source of street connectivity measures is the statewide road network data obtained from the Utah Automated Geographic Reference Center (AGRC). Since this street data source only contains street centerlines segmented at all junction points that may or may not be intersections, ArcGIS was used to process the obtained street data and extract correct link, dead-end, and intersection features (see Figure 3.3). The modified street dataset allowed more valid estimations of link-node ratio, intersection density, and percentage of 4-way intersections. In the link-node ratio calculation, we counted nodes and links that are within or touch the cell boundaries. Intersection density was calculated as the number of intersections divided by the cell size (one square mile). The percentage of 4-way intersections is the number of 4-or-more-way intersections divided by the number of all intersections. The block size was computed based on the 2010 U.S. census block shapefile. We chose to use the median block size, instead of the mean block size, to avoid the possibility that one large block dominates the final estimate.

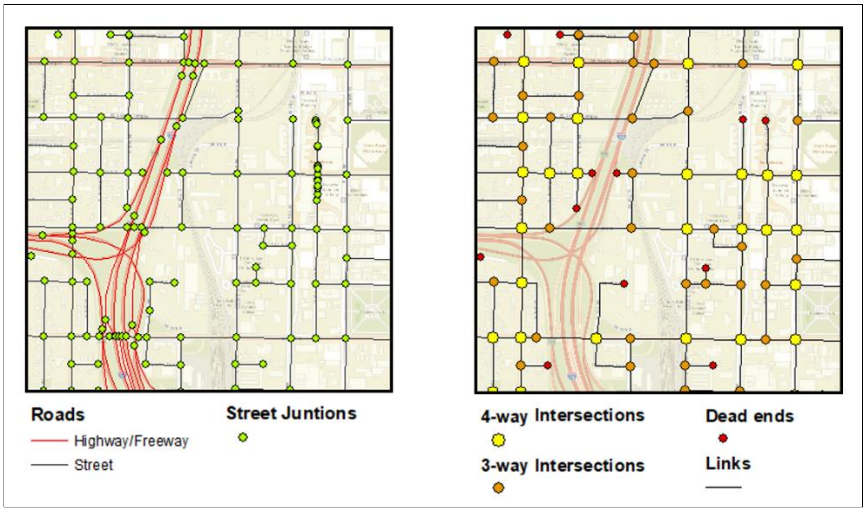


Figure 3.3 Original road network data (left) and modified road network data for measuring street connectivity (right).

Note: Highways or freeways with many pseudo nodes at access points were removed to correctly represent the street network characteristics of neighborhoods.

3.2.2 Matching Variables: Social and Environmental Characteristics

From the literature review, we identified other factors that could affect traffic delay and road safety, including activity density, land use characteristics, income, race, age, schools, and VMT (Alba and Beimborn, 2005; Marshall and Garrick, 2011; Wang et al., 2013; Yu, 2014; Yu, 2015). Activity density was calculated as the sum of population and employment per square mile. The percentage of commercial use refers to the total parcel area of commercial land uses divided by the total areas of all land-use types. The income, race, and age variables were based on the U.S. American Community Survey data (2013-2018 census block group-level data for income; 2010 census block-level data for race and age), calculated as the percentage of non-white population, median household income, and the percentage of older adults (> 65), respectively. Since there are differences in the data unit, all the census data were reapportioned based on the proportion of the source data that overlap with the study unit (grid cell). As VMT data was not available for all the examined neighborhoods, we used the total mileages of major roads (arterials and collectors) as proxy values of VMT. Lastly, we counted the number of schools for grid cells using data from the Utah Automated Geographic Reference Center.

Table 3.1 Data Description, Source, and Descriptive Statistics.

Variable	Description	Data Source	N	Mean	S.D.	Min.	Max.
Street Network Connectivity							
Intersection density	Number of intersections/gross area in square mile	Utah AGRC	297	96	32	25	178
Percentage of 4-way intersections	Number of four-or-more way intersections/number of intersections	Utah AGRC	297	0.18	0.09	0.03	0.69
L-N ratio	Number of links/number of nodes	Utah AGRC	297	1.44	0.12	1.18	1.84
Block size	Median census block area in an acre	US Census Bureau	297	7.49	3.58	2.30	37.63
Social and Environmental Variables							
Activity density	(Population + employment)/(gross area in square mile*1000)	US Census Bureau	297	5.69	2.81	1.51	20.15
Income	Median household income	US Census Bureau	297	161,690	93,305	2,719	524,697
Percent non-white population	Number of non-white population/total population	US Census Bureau	297	0.15	0.11	0.03	0.54
Percent of older adults	Number of older adults (>65)/total population	US Census Bureau	297	0.10	0.05	0.02	0.29
Number of schools	Number of schools	Utah AGRC	297	1.60	1.39	0.00	9.00
Percent of commercial land use	Commercial land use area/gross area	Utah DOT	297	0.06	0.06	0.00	0.35
Major road miles	Total length of major roads (primary/minor arterials, major/minor collectors)	Utah DOT	297	3.31	1.10	2.00	9.25

3.2.3 Dependent Variables: Congestion and Safety

For traffic congestion measures and VMT estimates, we used metrics derived from the InSight ® transportation analytics platform developed by StreetLight Data, Inc. It provided segment-level traffic data down to local streets. There are multiple commercially available traffic data sources, such as HERE, INRIX, StreetLight, TomTom, and Cuebiq. While each supplier tends to focus on one monitoring technique (either Location-Based Service [LBS] data through smartphone apps or Global Positioning System [GPS] data through vehicles with a navigation system), StreetLight Data, Inc. integrates GPS data with LBS to infer contextual details in zonal analyses (Lee and Sener, 2017). StreetLight's Big Data resources include over 110 million unique devices, or roughly one-third of the adult U.S. and Canadian population (StreetLight Data, 2020). The travel time and VMT metrics derived for this study using *StreetLight InSight*, the StreetLight Data Platform, were based on LBS trips exclusively. The large sample size and ability to analyze all needed transportation metrics using a single, consistent software platform drove the decision to use *StreetLight InSight* for this research.

We chose the travel-time index (TTI) to measure congestion. According to Texas A&M Transportation Institute (2019), TTI is calculated as "the ratio of travel time in the peak period to travel time at free-flow conditions," referring to how much longer a traveler needs to drive a road segment in congested conditions than in free-flowing conditions. For example, a TTI of 1.4 means that a 10-minute free-flow trip takes 14 minutes in peak hours. While other congestion measures, such as Level of Service, Planning Time Index, and Volume-to-Capacity Ratio, are commonly employed to estimate the performances of freeway or highway, the TTI can be applied to many different road system elements, including lower functional classes (FHWA, 2004). We identified the morning peak (7-9 am), afternoon peak (4-6 pm), and non-peak periods based on hourly traffic volumes of the weekdays (Monday through Thursday) in the study areas (62 neighborhoods selected for the analysis) [see Figure 3.4]. Due to the possibility of small sample size in the late-night (after 11 pm), we chose 9-11 pm as the non-peak/free-flow period. As freeways with limited access are seldom affected by abutting street network characteristics, the freeway segments and crashes that occurred on the freeways were both excluded in the estimation of crash rates. Lastly, we estimated the average travel times for major roads in each neighborhood to obtain the travel-time index (see Table 3.2).

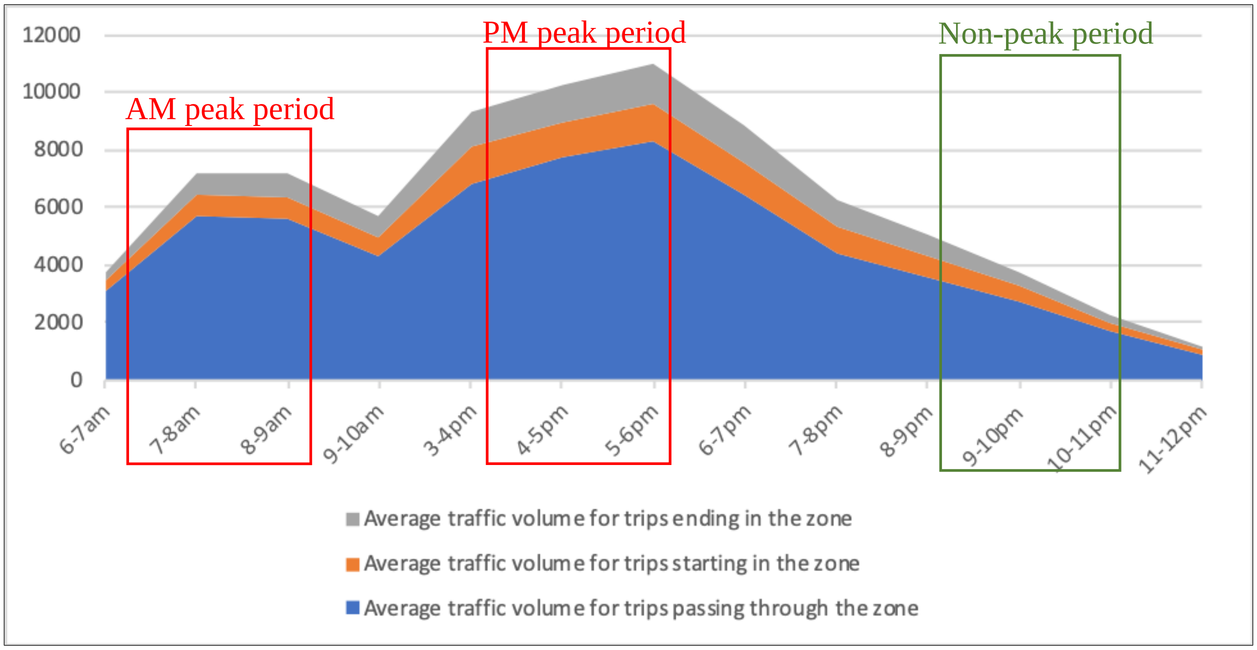
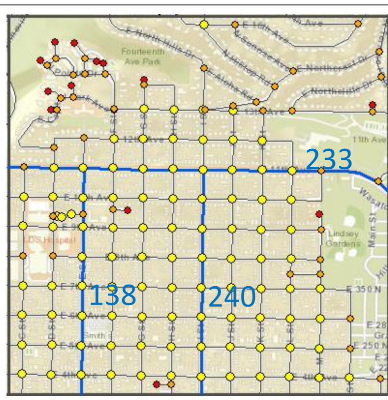


Figure 3.4 Average daily traffic volume in the 62 selected neighborhoods (2019).

Table 3.2 Examples of Travel-Time Estimates: The Avenues and Kearns.



The Avenues				**Kearns**			
Road ID	Morning peak (7-9am)	Afternoon peak (4-6pm)	Non-peak (10-11pm)	Road ID	Morning peak (7-9am)	Afternoon peak (4-6pm)	Non-peak (10-11pm)
138	161s	189s	173s	2017	169s	158s	150s
233	301s	201s	269s	2089	199s	196s	200s
240	151s	162s	176s	-	-	-	-
Avg.	204s	184s	206s	Avg.	184s	177s	175s

We obtained three years of State of Utah Crash Data (1/1/2016 - 12/31/2018) from the Utah Department of Transportation for crash rates. In this dataset, severity level was ranked in five categories—no injury (1), possible injury (2), suspected minor injury (3), suspected serious injury (4), and fatal injury (5). Since the literature revealed differences in the direction of relationships between street connectivity and crash rates depending on the severity, we tested the effect of street connectivity on three different levels of crash rates—all crash rate (1-5), injury crash rate (2-4), and fatal crash rate (5). To control for traffic volume, the number of crashes was divided by total VMT in the neighborhood. The VMT was estimated as the average daily traffic volume of the same data period (1/1/2016 - 12/31/2018) at the grid level (based on the StreetLight Data source), multiplied by the total length of the road mileage and the total days over three years. StreetLight Data provides traffic volume estimates for user-defined areas using traffic data for sampled roads with trips in the pre-defined zones (StreetLight Data, 2019). As freeways with limited access are seldom affected by abutting street network characteristics, the freeway segments and crashes that occurred on the freeways were both excluded in the estimation of crash rates. Finally, using the resulting crash data and VMT estimates, we computed all, injury, and fatal crash rates as the number of corresponding crashes per unit VMT (one million VMT for all and injury crash rates and 100 million VMT for fatal crash rates).

3.3 Analysis Process and Methods

3.3.1 Street Connectivity Index Using Principal Component Analysis

A Principal Component Analysis (PCA) was conducted in SPSS Statistics 26 to build one consolidated street connectivity index representing multiple connectivity measures—link-node ratio, intersection density, percentage of 4-way intersections, and median block size. The PCA is a statistical process converting correlated input variables into a set of uncorrelated outcome variables, called principal components (Jolliffe, 1986). The first principal component accounts for the greatest variance, while other principal components with a smaller variance are extracted in order of the variance size. The PCA approach helps to reduce the number of similar variables in the dataset and thus creates a lower-dimensional picture of the underlying construct of the original variables.

First, pairwise correlation tests were conducted to verify linear correlations between the four connectivity measures. Then, we applied PCA and extracted principal components. The Kaiser-Meyer-Olkin (KMO) scores for all the four variables and individual variables were over 0.5 that verified the sampling adequacy for this analysis based on the acceptable minimum of .5 (Field, 2009). The eigenvalue of the first principal component is 1.815, which is over the widely accepted Kaiser's criterion of 1 (Kaiser, 1958), in combination with 45.46% of variance explained. As anticipated, three connectivity variables loaded positively on the principal component, indicating neighborhoods with higher connectivity index values have a higher link-node ratio, a higher intersection density, and a higher percentage of 4-way intersections. As expected, the median block size was negatively correlated with the principal component, meaning that areas with a higher connectivity index tend to have smaller block sizes (See Table 3.3). Lastly, we standardized the extracted principal components to create the Street Connectivity Index (SCI) that has a mean of 100 and a standard deviation of 25 (as have Ewing and Hamidi, 2017).

Table 3.3 Street Connectivity Index Variables and Factor Loading.

Connectivity Variable	Factor Loading*
link-node ratio	0.840
intersection density	0.423
percentage of 4-way intersections	0.772
median block size	-0.578

*correlation with street connectivity index

3.3.2 Neighborhood Selection Using Propensity Score Matching

We employed Propensity Score Matching (PSM) to select a pairwise sample of neighborhoods (grid cells) with comparable socio-demographic and built-environment attributes but are different in street connectivity. PSM is a statistical matching technique widely applied in non-randomized observational studies to enable proper comparisons by controlling for potential confounding variables (Cao and Fan, 2012; Park et al., 2018). The key outcome variables in this study rely on observational data, such as the number of crashes and average daily traffic, in which the treatment assignment is not often random and rather confounded by residential self-selection or other built-environment characteristics. For example, neighborhoods with better street connectivity may experience less traffic congestion due to less dense environmental characteristics. Accordingly, failure to account for the confounding effects can lead to biased estimates of the treatment effect.

We chose PSM over multivariate regression models for several reasons. First, as we have limited access to granular traffic data due to budgetary constraints, sampling was inevitable. Also, PSM performs successfully with small samples (Pirracchio et al., 2012). Lastly, having comparison groups is more practically straightforward for municipalities to understand the differences and monitor changes caused by future community enhancements.

The PSM was built in R 3.6.3 environment using the MatchIt package. The Propensity Score is a number estimated between zero and one that represents the probability that a case is in a particular group (e.g., neighborhoods with good street connectivity), given the covariates (Resenbaum and Rubin, 1984). First, we selected the top 40 grid cells in terms of street connectivity as the treatment group because these neighborhoods present connectivity values greater than (for block size, smaller than) the local average of most of the connectivity measures. In contrast, the remaining samples were considered as the control group that shows relatively lower street connectivity. Second, we ran a logistic regression to calculate propensity scores. In this logit model, we initially included all seven social and environmental factors that might affect crash rates and congestion levels based on our literature review, of which only activity density and major road mileage were significantly associated with the probability that a neighborhood has better street connectivity. While the PSM can apply to a small sample (Pirracchio et al., 2012), the number of matching variables should be proportional to sample size, and a suggested number of observations per matching variable is 10 (Blackford, 2009). Thus, given the sample size of 40 in this study, we selectively included three variables—two significant variables identified in the initial logistic regression and median household income to control for other potential socio-economic influences—for the final computation of propensity scores.

Third, each neighborhood in the treatment group (better connectivity) was matched with one in the control group based on the propensity score and caliper width of 0.2 standard deviations of the logit of the propensity score. The caliper width refers to a pre-specified search distance from the score of the treatment observation to find a match in the control group. A suggested caliper width to properly remove bias and maximize performance for estimating treatment effects is 0.2 standard deviation (Austin, 2010). Then, t-tests were conducted to identify whether the matching variables are balanced between the matched groups.

The final goal of the PSM is to estimate the true effect of street connectivity on congestion levels and crash rates. Once the matching was complete, we estimated the average congestion levels on major roads and VMT-weighted crash rates for the matched sample and compared the differences.

4.0 DATA EVALUATION AND RESULTS

4.1 Street Connectivity in the Wasatch Front Region

The propensity score match found 31 neighborhood pairs (in total 62) out of 40 initial samples (Figure 4.1). After matching, we evaluated whether the selected neighborhoods are systematically different in terms of street connectivity and whether they are balanced on other attributes. As shown in Table 4.1, t-tests results for the matched samples show that the two types of neighborhoods are statistically different in street connectivity index, having a connectivity index of 97.54 and 146.41 respectively in the control and treatment groups. However, they do not differ in terms of all other variables, including the three covariates used in the PSM (activity density, major road mileage, and median household income). Thus, the 31 matched samples were finally chosen to compare crash rates and congestion levels. In contrast, the unmatched nine neighborhoods in the treatment group (good connectivity) were excluded in our analysis because there were no comparable neighborhoods in the control group within the caliper length we applied.

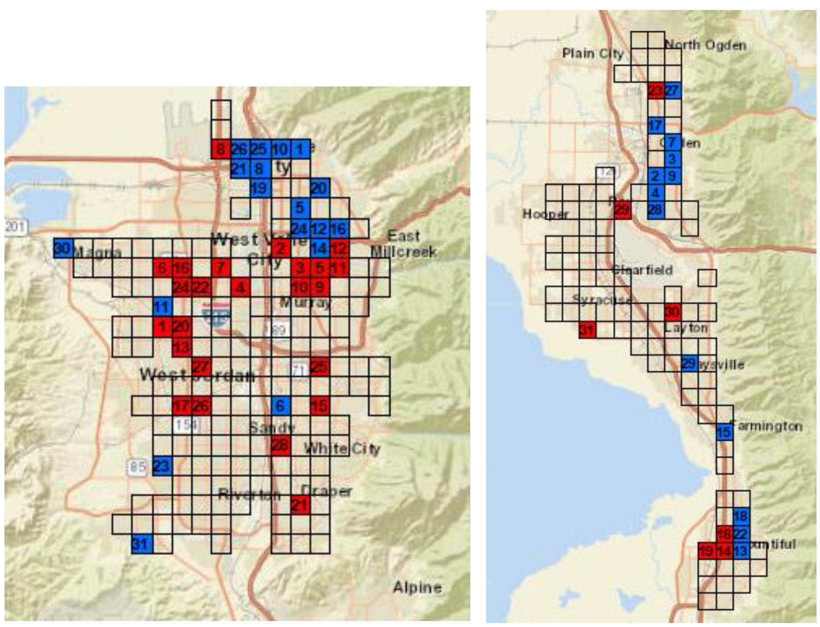


Figure 4.1 Neighborhood samples: 31 neighborhood pairs (left: Salt Lake County; right: Davis and Weber Counties)

Note: Blue cells are neighborhoods that have better street connectivity, whereas reds are matched neighborhoods having relatively poor street connectivity. Numbers are Pair I.D.s.

Table 2.1 Differences in Social and Environmental Characteristics Between Neighborhood Types After Matching.

	Neighborhoods with poor connectivity (control)	Neighborhoods with good connectivity (treatment)	Observed difference	t-statistics	*p-value*
Sample size	31	31		-	
Street connectivity index	97.54	146.41	-48.87	-11.25	<.001
Activity density*	7.49	7.39	0.1	0.14	0.89
Major road miles*	3.77	3.84	-0.07	-0.27	0.79
Median HH income*	197,515	204,813	-7298	-0.29	0.77
Percent non-white population	0.2	0.2	0	-0.17	0.86
Number of schools	1.68	2.19	-0.51	-1.45	0.15
Percent commercial use	0.09	0.06	0.03	1.71	0.09
Percent older adults	0.11	0.11	0	0.11	0.91

*Variable used for matching

4.2 Congestion Level and Crash Rates in Matched Neighborhoods

Based on the matched sample, we calculated crash rates and congestion levels and examined their average differences (Table 4.2). First, two different types of travel-time indices were estimated that represent congestion levels in the morning peak period (7-9 am) and the afternoon peak period (4-6 pm), compared to the same non-peak hours in the night (9-11 pm). Both neighborhood types display no travel delay in the morning peak period, having a travel-time index less than or close to 1. It means the average travel time in the peak hour is similar or a little smaller than the one in the non-peak period, which is attributable to potential commuters driving faster in the early peak than late night, or the suburban neighborhoods in our sample that do not have much traffic volume even in the early peak hours. The difference in the travel-time index in the morning peak hours was statistically significant between the two groups, showing that more connected neighborhoods provide a road system where drivers can travel faster, even with more stopping points (e.g., intersections) in that area.

Table 4.2 Differences in Street Connectivity, Crash Rates, and Congestion Levels Between Neighborhood Types After Matching.

		Neighborhoods with poor connectivity (control)	Neighborhoods with good connectivity (treatment)	Observed difference	t-statistics	*p-value*
Sample size		31	31			
Street Connectivity	**Street connectivity index**	97.54	146.41	-48.87	-11.25	<.001
	Intersection density	105.77	113.87	-8.10	0.01	0.32
	Percent 4-way intersections	0.15	0.34	-0.18	-8.89	<.001
	Link-node ratio	1.41	1.65	-0.25	-10.49	<.001
	Block size	7.14	5.77	1.37	2.79	<0.01
Congestion	**Travel-Time Index 1: morning peak**	1.00	0.92	0.08	2.11	<.05
	Travel-Time Index 2: afternoon peak	1.12	1.02	0.1	3.23	<.001
Safety	**all crash rate[1]**	0.201	0.167	0.034	1.56	0.12
	injury crash rate[1]	0.064	0.057	0.007	1.12	0.27
	fatal crash rate[2]	0.067	0.051	0.016	0.76	0.45

[1] Crash counts per one million VMT; [2] Crash counts per 100 million VMT

In the afternoon peak hours, neighborhoods with better connectivity present nearly no congestion in the peak hours compared to the non-peak hours, having a travel-time index of 1.02. However, communities with less connectivity have a travel-time index of 1.12, meaning 1.12

times more travel time in the peak period compared to the non-peak hour travel time. The difference in the travel-time index between the two neighborhood types appears statistically significant, representing that there was a measurable reduction of congestion in more connected neighborhoods.

In terms of crash rates, better-connected neighborhoods have lower crash rates at the three different severity levels (all, injury crash, and fatal crash) than do poorly connected areas, but not at statistically significant levels. All crash rates particularly show a quite small significant level (0.12), meaning that there is only a 12% probability that the two neighborhood types are not different in terms of their total crash rates. Still, this falls short of the conventional 0.05 significance level.

5.0 DISCUSSION AND CONCLUSIONS

5.1 Summary and Findings

An interconnected street network is considered a critical environmental element of urban and suburban communities. Still, the effects of connectivity on traffic flow and safety have heretofore not been backed by much empirical evidence. In this study, we investigated whether better connectivity is associated with a measurable reduction in congestion levels and crash rates, focusing on the Wasatch Front Region in Utah. Our analysis of 31 neighborhood pairs shows that there are statistically significant lower congestion levels in neighborhoods with better connectivity. This finding is aligned with earlier studies revealing more balanced traffic distributions and greater traffic volume capacity associated with networks with more connectivity (Ayo-Odifiri et al., 2017; Tasic et al., 2015; Zlatkovic et al., 2019).

Unlike earlier studies (Marshall and Garrick, 2011; Rifaat et al., 2012; Zhang et al., 2012), highly connected neighborhoods did not have significantly lower crash rates at three different levels of severity—all, injury, and fatal—compared to less-connected areas. One possible reason for this is the small sample size, where many of the local neighborhoods were not included in the comparison. These results might also be attributable to more 4-way intersections in connected networks. Intersection areas are traditionally understood as the areas where crashes are mostly concentrated (Ewing and Dumbaugh, 2009; Marks, 1957). Even if a 4-way intersection might contribute to lowering vehicle speeds, this area is shared by many different types of travelers and, thus, is more likely to have conflicting movements than anywhere else in a neighborhood. Nevertheless, it is noteworthy that at the neighborhood level, more connectivity, if anything, is associated with fewer crashes, even with a greater number of 4-way intersections in the area.

Taken together, improving street connectivity at a neighborhood level could be considered as a viable community development strategy to mitigate congestion on major arteries without compromising road safety, even while having more intersections at which conflicts occur. Another important finding is that some better-connected neighborhoods display a TTI value less than 1, implying that some drivers might take advantage of less congested roads by driving faster in peak hours. Even though our data show no higher crash rates in better-connected areas, this speeding behavior could lead to other road safety concerns. Thus, street connectivity guidelines might need to include other traffic-calming approaches to maintain road safety, such as speed humps, raised crosswalks, and traffic circles (Ewing and Brown, 2009).

This study advances the literature by overcoming limitations found in earlier studies. First, while many previous studies tend to focus on a single connectivity variable (Guo et al., 2017; Marks, 1957; Rifaat et al., 2012), we developed a street connectivity index incorporating multiple aspects of neighborhood-level network characteristics. This approach produces more widely applicable results by reflecting connectivity variables commonly used in academia and practice. Second, propensity score matching enables us to find the best neighborhood pairs for estimating the unbiased and observed effects of street connectivity on traffic congestion and safety. Previous studies often employed traffic simulation approaches, by which the impact of increased connectivity could be measured for the same sample by testing several scenarios (Ayo-Odifiri et al., 2017; Tasic et al., 2015; Zlatkovic et al., 2019). However, the simulated results might be different from reality, being totally dependent on the underlying assumptions. Lastly, previous studies do not control for observed VMT when calculating crash variables (Guo et al., 2017; Rifaat et al., 2012), even though it would significantly affect the number of vehicle conflicts (Dumbaugh and Rae, 2009). We compare VMT-weighted crash rates, allowing a more fine-tuned comparison of road safety between neighborhoods with different connectivity levels.

5.2 Limitations

One main limitation of this study is the small sample size. Although our sample is much larger than ones in earlier studies that only focus on a handful of street segments or neighborhoods, there are still many other neighborhoods we did not include in our analysis due to budgetary constraints, the nature of the propensity score matching approach, and limited traffic data availability. When granular traffic data become available for most of the road segments, future research might yield more generalizable results by examining a larger sample. Moreover, while we successfully control for neighborhood-level attributes in our matching process, we could not consider temporal, personal, and micro-level environmental characteristics, such as weather, time of day, alcohol usage, speeding, surface conditions, and traffic control device.

5.3 Implications

This study provides empirically-supported evidence on the effect of street network connectivity on traffic safety and congestion. Many local and regional planning agencies, especially those experiencing rapid population growth and community development, create street connectivity ordinances or guidelines to create better community environments, where people have a more flexible travel choice and route options. Example approaches include employing block length or link-node ratio requirements, increasing connectivity between residential areas and main arteries, planning for future connecting points, and restricting the use or length of cul-de-sacs (Handy et al., 2003). Although such different types of effort are implemented in multiple ways by different agencies, they will collectively contribute to increasing overall street connectivity. The street connectivity index developed in this study can efficiently represent these various approaches, and using the index as a performance measure will better inform practitioners of the street network characteristics of local neighborhoods. Furthermore, our neighborhood matching method can be replicated by transportation planning agencies and local municipalities that have access to granular traffic data. Such empirical analysis will provide evidence quantifying the benefits of interconnected streets, and better guide data-driven decision-making for municipalities adopting street connectivity standards.

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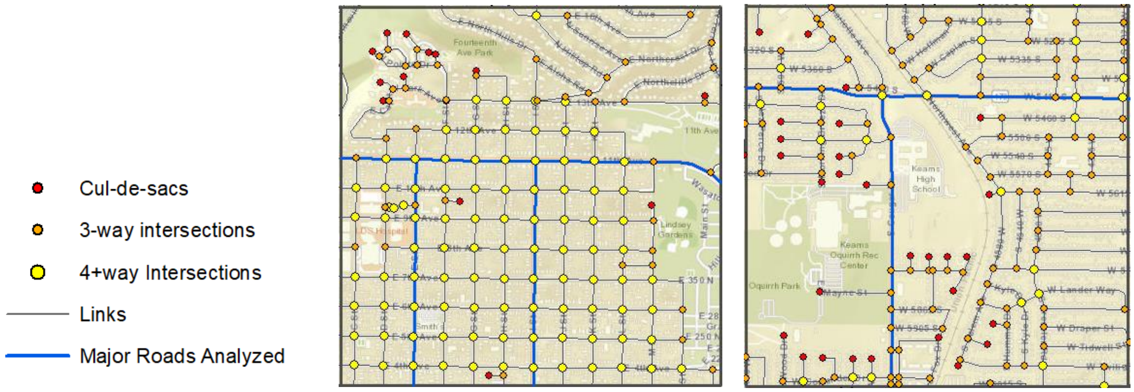
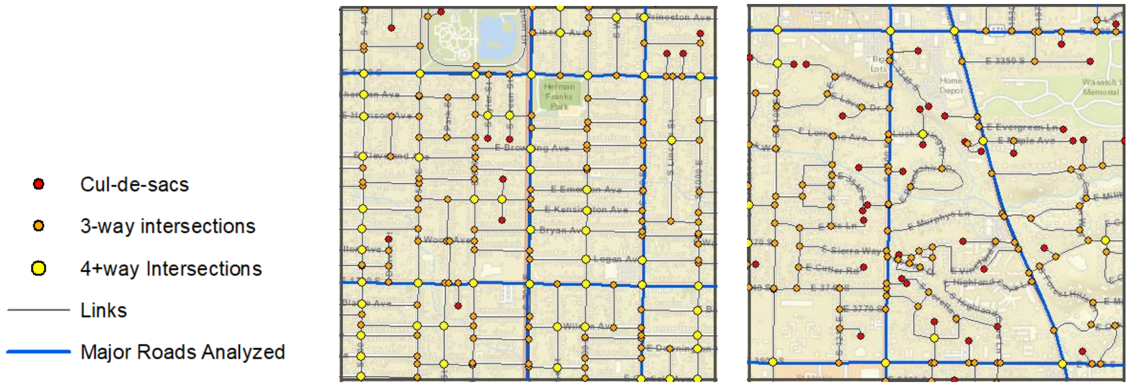
6.0 APPENDIX A: NEIGHBORHOOD-TO-NEIGHBORHOOD COMPARISONS

Table 1. Neighborhood-to-Neighborhood Comparison: The Avenues vs. Kearns.



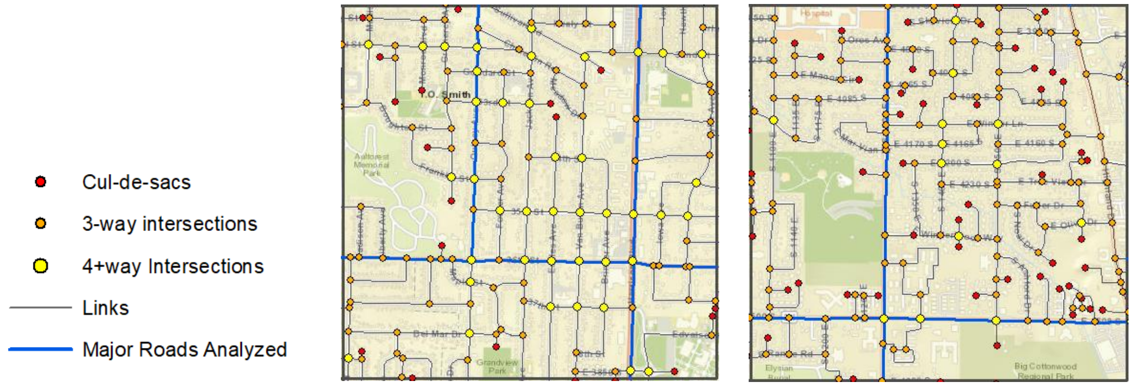
Neighborhood		**The Avenues**	**Kearns**
Street Connectivity	Street connectivity index	209	121
	Intersection density	139	125
	Percent 4-way intersections	0.69	0.19
	Link-node ratio	1.80	1.54
	Block size	3.90	5.82
Congestion	Travel-Time Index 1: morning peak	0.99	1.05
	Travel-Time Index 2: afternoon peak	0.89	1.01
Safety	all crash rate	0.15	0.29
	injury crash rate	0.07	0.07
	fatal crash rate	0	0.10

Table 2. Neighborhood-to-Neighborhood Comparison: The Avenues vs. Kearns.



Neighborhood		Liberty Wells	East Millcreek
Street Connectivity	Street connectivity index	161	94
	Intersection density	178	116
	Percent 4-way intersections	0.3	0.09
	Link-node ratio	1.72	1.41
	Block size	5.44	7.04
Congestion	Travel-Time Index 1: morning peak	0.86	1.01
	Travel-Time Index 2: afternoon peak	0.90	1.18
Safety	all crash rate	0.09	0.32
	injury crash rate	0.04	0.10
	fatal crash rate	0	0.13

Table 3. Neighborhood-to-Neighborhood Comparison: The Avenues vs. Kearns.



Neighborhood		Ogden	Millcreek
Street Connectivity	Street connectivity index	151	91
	Intersection density	117	132
	Percent 4-way intersections	0.35	0.10
	Link-node ratio	1.69	1.34
	Block size	5.82	6.66
Congestion	Travel-Time Index 1: morning peak	0.87	0.96
	Travel-Time Index 2: afternoon peak	0.99	1.14
Safety	all crash rate	0.23	0.22
	injury crash rate	0.08	0.06
	fatal crash rate	0.11	0