UNDERSTANDING PEDESTRIAN INJURIES AND SOCIAL EQUITY

Phase I Analysis (Task 5)

PROJECT SPR 841

RESEARCH

Oregon Department of Transportation

UNDERSTANDING PEDESTRIAN INJURIES AND SOCIAL EQUITY

Phase I Analysis (Task 5)

PROJECT SPR 841

by

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16. Abstract: Past research and planning has highlighted the existence of pedestrian injury disparities throughout the US and some local agencies have performed cursory analysis in Oregon. However, no statewide analysis of pedestrian injuries in Oregon has been completed to see how these injury outcomes differ by race and income. This report aims to help better understand the factors that result in disparate pedestrian injury outcomes for different sociodemographic groups. This report uses data from a variety of sources to understand pedestrian injuries by social equity measures including income, poverty, race, ethnicity, disability and English proficiency. The authors conclude that Black, Indigenous and People of Color (BIPOC) experience a higher rate of pedestrian injury compared to the statewide average. This report also documents pedestrian injuries at the Census tract level and measures factors that influence pedestrian injury risk. Sociodemographic risk factors associated with pedestrian injury risk include race, income, disability, and limited English proficiency. Traffic exposure factors include arterial vehicles miles traveled, miles of roadways with 35 miles per hour posted speed, transit stops, and workers commuting by transit and walking. Built environment risk factors include density of jobs, intersection density, and the density of alcohol establishments. This report concludes that, at both the state and neighborhood level, incorporating social equity measures including race, disability, and income are important to understanding pedestrian injuries and the likely location of these incidents. Race is an important factor in large part due to the relationship with income and the lack of economic opportunities afforded to BIPOC people. Income is important to consider because low-income people are more likely to walk and take transit in neighborhoods with more vehicle traffic moving at higher speeds.

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Social equity, pedestrian injury, FARS, OR-EMSIS data, disparity, ecological analysis, Oregon, Census, tracts. home location, age-adjusted rates, generalized linear regression, mixed effects models

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Symbol	When You Know	Multiply By	To Find	Symbol	Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH					**LENGTH**		
in	inches	25.4	millimeters	mm	mm	millimeters	0.039	inches	in
ft	feet	0.305	meters	m	m	meters	3.28	feet	ft
yd	yards	0.914	meters	m	m	meters	1.09	yards	yd
mi	miles	1.61	kilometers	km	km	kilometers	0.621	miles	mi
		AREA					**AREA**		
in^2	square inches	645.2	millimeters squared	mm^2	mm^2	millimeters squared	0.0016	square inches	in^2
ft^2	square feet	0.093	meters squared	m^2	m^2	meters squared	10.764	square feet	ft^2
yd^2	square yards	0.836	meters squared	m^2	m^2	meters squared	1.196	square yards	yd^2
ac	acres	0.405	hectares	ha	ha	hectares	2.47	acres	ac
mi^2	square miles	2.59	kilometers squared	km^2	km^2	kilometers squared	0.386	square miles	mi^2
		VOLUME					**VOLUME**		
fl oz	fluid ounces	29.57	milliliters	ml	ml	milliliters	0.034	fluid ounces	fl oz
gal	gallons	3.785	liters	L	L	liters	0.264	gallons	gal
ft^3	cubic feet	0.028	meters cubed	m^3	m^3	meters cubed	35.315	cubic feet	ft^3
yd^3	cubic yards	0.765	meters cubed	m^3	m^3	meters cubed	1.308	cubic yards	yd^3
~NOTE: Volumes greater than 1000 L shall be shown in m^3.									
		MASS					**MASS**		
oz	ounces	28.35	grams	g	g	grams	0.035	ounces	oz
lb	pounds	0.454	kilograms	kg	kg	kilograms	2.205	pounds	lb
T	short tons (2000 lb)	0.907	megagrams	Mg	Mg	megagrams	1.102	short tons (2000 lb)	T
		TEMPERATURE (exact)					**TEMPERATURE (exact)**		
°F	Fahrenheit	(F-32)/1.8	Celsius	°C	°C	Celsius	1.8C+32	Fahrenheit	°F

*SI is the symbol for the International System of Measurement

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1.0 INTRODUCTION

Past research and planning has highlighted the existence of pedestrian injury disparities throughout the US and some local agencies have performed cursory analysis in Oregon. However, no statewide analysis of pedestrian injuries has been completed to see how these injury outcomes differ by race and income. This report aims to help better understand the factors that result in disparate pedestrian injury outcomes for different sociodemographic groups. It's important to recognize these disparities and understand the underlying conditions that create them so that targeted and effective action can be taken.

1.1 NATIONAL PEDESTRIAN CRASH AND FATALITY DISPARITIES BY INCOME AND RACE

Although income is not recorded in most crash data, numerous studies have found that areas with lower incomes and higher poverty rates are associated with increased injury and fatality risk (Stoker et al., 2015). A national study utilizing data from the National Highway Traffic Safety Administration (NHTSA) Fatal Accident Reporting System (FARS) from 2008 to 2012 found that Census tracts in metropolitan areas with per capita income of less than $21,559 had pedestrian fatality rates twice as high as in areas with per capita incomes of greater than $31,356 (Maciag, 2014). Another study looking at national data from 2008 to 2017 found that pedestrian fatality rates in neighborhoods with a median household income between $3,000 to $36,000 were more than 2.5 times higher than in neighborhoods with incomes from $79,000 to $250,000 (Smart Growth America & National Complete Streets Coalition, 2019).

Black or African American pedestrians and American Indian or Alaska Native pedestrians are more likely to be struck and killed while walking, than the overall U.S rate (Smart Growth America & National Complete Streets Coalition, 2019). African-Americans and Native Americans are disproportionately likely to be pedestrian fatality victims "the U.S. population was 12% Black in 2000 and 13% Black in 2010, but 17% of pedestrians killed during 2002–2016 were Black. Native Americans were also overrepresented: they made up 0.9% of the population but 2.3% of pedestrian fatalities" (Schneider, 2020).

1.2 PATHWAYS TO PEDESTRAIN INJURY DISPARITIES

National data shows that lower-income and BIPOC households have fewer transportation options and are more reliant on walking and transit, modes that put them at greater risk of pedestrian crashes. For example, data from the 2017 National Household Transportation Survey shows that lower-income households and households with a Black primary household respondent were particularly likely to not have a car (FHWA, 2017). In terms of income, 26% of households earning under $25,000 do not own a car, compared to 5.2% of those earning $25,000 to $49,999, 3.1% of those earning $50,000 to $99,999, and 2.3% of those earning $100,000 or more. In terms for race, only 6% of white households had zero vehicles, while 23.3% of Black households, 15% of American Indian or Alaska Native households, 11.2% of Asian households, and 11.4% of Latino/Hispanic households had zero vehicles. Further, people who are low-income, BIPOC, or immigrants are more likely to have non-standard working hours, commuting in the middle of the day, later in the evening or at night (Sandt et al., 2016), with the non-daylight travel being a particularly dangerous time for pedestrians. A recent study found that people who low income or BIPOC are the most likely to walk for at least 10 minutes per day (Buehler et al, 2020).

Merlin et al. noted that that most studies agree "arterials, multilane streets, and roads with high speed limits are all associated with higher risk and more serious injuries (Merlin et al., 2020). A national study of pedestrian fatalities found that traffic volumes on non-access -controlled principal and minor arterials is strongly associated with increased pedestrian fatalities in urban areas (Mansfield et al., 2018).

Currently, there is limited direct research showing that lower-income and BIPOC individuals are disproportionally exposed to higher volume and higher speed arterials – a gap which this research seeks to partially address. However, there is evidence that lower-income areas have fewer pedestrian facilities to help people navigate traffic threats. For example, a national study found that 89% of streets in high-income areas have sidewalks on one or both sides of the street, compared to only 59% of streets in middle-income areas, and 49% of streets in low-income areas (Gibbs et al., 2012) The study also found that streets in high-income areas are much more likely to have marked crosswalks (13% of streets), compared to 8% of streets in middle-income and 7% of streets in low-income areas; while 75% of streets in high-income areas have street or sidewalk lighting, compared to only 51-54% of those in middle- and low-income areas (Gibbs et al., 2012).

1.3 DISPARITIES IN OREGON

There has been limited studies of pedestrian safety disparities in Oregon; however, those that have touched on the topic suggested that similar disparities exist here. One study found that, for 2008 to 2012, the overall Portland metro area had a pedestrian fatality rate of 5.3 fatalities per 100,000 residents. For tracts with over 25% of residents living in poverty that number was 12.8 fatalities per 100,000 people, while for tracts from 15% to 25% in poverty that number was 7.1 fatalities per 100,000, and for tracts less than 15% in poverty that number was 3.5 fatalities per 100,000 (Maciag, 2014). A report from Oregon Walks examining pedestrian fatalities in Portland from 2017 to 2019 found that Black Portlanders with overrepresented among fatalities, accounting for 17% of pedestrian fatalities but only 5.8% of the Portland population (Oregon Walks, 2021).

1.4 RESEARCH GOALS AND OBJECTIVES

This report seeks to understand pedestrian crash and injury disparities in Oregon using available data sources. However, no one data source provides all the necessary information to understand the extent of how pedestrian crashes, injuries and fatalities affect different Oregon communities and groups, including low-income and BIPOC Oregonians. Therefore, the research pulls from a variety of sources including Fatal Accident Reporting System (FARS) data for Oregon, Oregon emergency medical service data, sociodemographic data from the Census, built environment and traffic exposure data, and data from the Oregon Household Activity Survey (OHAS).

Pulling from these sources, the report documents that fatal pedestrian injury rates are higher for lower-income and BIPOC Oregonians. To better understand some of the reasons behind these disparate rates, and to understand why areas with more low-income and BIPOC Oregonians experience higher rates of pedestrian injury, an analysis of pedestrian fatal and severe injuries is summarized using Census tract measures. This analysis shows that tracts with more low-income people and a higher proportion of people of color have a higher rate of pedestrian injury. Contributing factors include higher vehicle volumes and more people in those communities using public transit or walking to access their work place. We are not able to directly measure the availability of pedestrian safety features, such as sidewalks and crossing improvements, because there is no comprehensive database to track the location of these improvements statewide, but research from other cities has documented the deficiency of these facilities as a contributing factor.

2.0 LITERATURE REVIEW

For a detailed literature review covering factors associated with pedestrian safety, safety disparities, and the impacts of inequity in transportation, see the separate Literature Review document.

2.1 ECOLOGICAL PEDESTRIAN CRASH STUDIES REVIEW

The research team identified 22 studies looking at spatial characteristics of pedestrian crashes published between 2000 and 2020, with priority given for studies published between 2010 and 2020 (earlier studies were included if they were deemed foundational to the topic area based on citations from multiple subsequent studies). An overview of key study and model details is provided in Table 12 of the separate Literature Review document. Of the 22 studies, seven included a focus on some aspect of equity, typically looking at pedestrian crash outcomes and differences by income or race/ethnicity, although age was also considered. However, 18 of the 22 studies included income or race / ethnicity variables in their analysis, allowing for equity-related findings based on those variables to be considered. A full list of significant variables relating to pedestrian crashes is included in Table 13 of the separate Literature Review document.

Select key details of the 22 studies included in the ecological pedestrian crash review are included below.

2.1.1 Zonal vs Network approach

Pedestrian safety analysis has often focused on roadway characteristics, with disaggregation at the intersection and segment level, looking at characteristics that might be associated with increased pedestrian crashes, injuries and fatalities. These usually consider roadway volumes, speeds (speed limit, 85% percentile speed, percent of vehicles travelling 5 or 10 miles over the speed limit, etc.), width (crossing distance, number of lanes, etc.), crossing facilities (presence, spacing, type, quality), medians, sidewalks, lighting and other factors. Some consider adjacent land use, pedestrian volumes (a proxy for exposure), crash records factors (time of day, weather, participants involved), and other factors.

In order to incorporate equity considerations, including the potential influence of income, race, immigration status, age, or other factors, into analyses of pedestrian crash locations, frequency and severity, most studies have turned to census data. This allows for the assessment of whether, for example, lower-income areas are more likely to experience higher rates of pedestrian injury or fatality crashes. The process of connecting the network-based roadway characteristics, crash location data, and the zonal census-derived data (often in census tract or block group formats), requires the decision of whether to employ zonal or network analyses, or a combination.

Although crashes occurring within a zone (e.g. census tract) are not necessarily attributable to residents living within the zone, there is strong evidence that most pedestrian crashes occur nearby where people live. One study (Haas et al., 2015) found that half of pedestrian injuries occur within 1.1 miles from the victim's home, while another found that half of pedestrian injuries occur within 1 mile from home, with 22% occurring in their home census tract, and another 22% occurring in a tract bordering their own (Anderson et al., 2012). For children and those over 65 years of age, over half of pedestrian injury crashes occur within half a mile of their home (Anderson et al., 2012).

2.1.2 Analysis zone level

Most studies used geographic areas as analysis zones, which allowed the overlay of socio-demographic, land-use and certain transportation related variables over crash locations. Most frequently the census tract (CT) was the chosen analysis zone, used by 14 of the 21 studies. Four used block groups (BG), one used transportation analysis zone (TAZ), and one used zip code. One study included the CT, BG and TAZ to compare the effectiveness of each approach. Six studies used the actual crash location and applied either a buffer, or used the nearest intersection or segment.

2.1.3 Modeling approach

The most common modeling approach was to employ a negative binomial regression, employed by 9 of 22 studies, or a Poisson regression, employed by 4 of 22 studies. Other modeling approaches included ordinary least squares (2), binary and ordinal logistic regression (2), multinomial logistic regression, ordered probit, and path models, and colocation quotient analysis.

2.1.4 Dependent Variables

Studies were included on the basis of having some pedestrian safety related dependent variable; however, how the studies specified the variable, and the inclusion of multiple variables differed from study to study.

Nineteen looked at the number or density of pedestrian involved crashes; ten looked at injury-specific crashes, often focusing on severe injury; and eight looked at pedestrian fatalities. Eight studies looked at multiple levels of crashes (e.g. looking at pedestrian crashes and injuries) - of those five constructed separate models for each level, while three studies constructed models that examined tiered crash severity. In addition to these pedestrian crash outcomes, a few included additional outcome variables, including nighttime pedestrian crashes, pedestrian alcohol involved crashes, and walk commute rate.

2.2 PEDESTRIAN SAFETY AND DISPARITY

The remainder of this literature review chapter pulls both from the 22 studies included in the ecological pedestrian crash safety review and other pedestrian safety studies, with a focus on sources of safety disparity.

2.2.1 Exposure, activity and pedestrian crashes

Lower income households are less likely to have a car, which limits their ability to make trips and access economic and social opportunity. People living in households at or below the poverty level are much more likely to have zero cars in the household (about 25%) (*NHTS BRIEF: Mobility Challenges for Households in Poverty*, 2014). Meanwhile, Black Americans are far less likely to own and drive a car (80% compared to 92% of all American households), while American Indians, Latinos/Hispanics, Asian, Pacific Islanders and people of mixed race are less likely to own cars than white Americans (Lucas, 2012).

It is also important to note that, for low-income households, cars represent a financial burden, as they tend to be older, less reliable, and more likely to need expensive repairs (Blumenberg & Manville, 2004). National Household Transportation Survey data from 2017 shows that the cost of travel is a financial burden that influences travel modes, with lower-income and BIPOC residents feeling higher levels of financials burden, and being more likely to choose to walk or take transit to reduce financial burden (NHTS 2017, see Table 4 in the Literature Review for a detailed breakout).

A literature review looking at the relationship between the built environment and walking across different socioeconomic contexts (Adkins et al., 2017) lends support to the notion that, for underserved communities, walking is less of a choice and more of a necessity. The review noted that low-income people walk more than high-income people, on average, in places where the built environment is not conducive or supportive of walking. While both groups had higher levels of walking in a supportive built environment, advantaged groups increased their walking much more than disadvantaged group. This illustrates that, for disadvantaged groups, walking is more of a non-choice or captive mode, while for advantaged groups walking is more of a choice mode.

Another review noted that people who are low-income, BIPOC, or immigrants are more likely to have non-standard working hours, commuting in the middle of the day, later in the evening or at night, rather than at peak commute times (Sandt et al., 2016). Commuting at these times may leave them walking to and from transit outside of daylight hours, which is when a disproportionate number of pedestrian crashes occur, as well as leaving them relying on transit during periods in which transit waits and transfers may take longer and less express service is available.

Of the 22 studies included in the ecological analysis, 4 used the proportion of workers who commute by walking or taking transit, and eight studies used the number of transit stops. Of studies looking at walking or transit commute rates, one found that walking commute rates was associated with increased pedestrian crashes (Abdel-Aty el al 2013), two found that transit commute rates were associated with more pedestrian crashes (Abdel-Aty et al 2013; Dai and Jaworski 2016). Two others found that combined active commute measures (either transit plus biking or transit plus walking) were associated with increased pedestrian crashes (Lin et al 2019; Ukkusuri 2012).

There is evidence to suggest that higher levels of pedestrian activity, on average, result in more, but less severe crashes. However, there are a number of situations wherein further context is needed. For example, while Merlin et al, in a literature review, found that pedestrian crashes increase with more population and employment density, "the relationship between fatalities and density is negative," suggesting that crashes were less severe (Merlin et al., 2020). Guerra et al, in a study of crashes in the Philadelphia region, found different trends in the suburbs than in the city. In the suburbs, higher population densities were generally associated with more pedestrian-involved collisions, but in the city higher population densities were associated with fewer pedestrian-involved collisions (Guerra et al., 2019). Another study found that for block groups, population density was negatively associated with pedestrian crashes, while for counties, population was positively associated with pedestrian crashes - suggesting that lower density areas in higher density counties may be the most dangerous places (Jermprapai & Srinivasan, 2014). The block group and county level effect were similar for income, suggesting that low income areas in higher income counties are most at risk. Seventeen of 22 studies included in the ecological analysis used population density, while 8 of 22 used employment density or a comparable measure. A number of studies have found that, in general, higher population and jobs densities are associated with more vehicle-pedestrian collisions (Loukaitou-Sideris et al., 2016; Merlin et al., 2020; Wier et al., 2009), and in some analyses have used these measures as exposure variables.

Select key findings from the ecological analysis review related to exposure and activity data are shown in Table 2.1.

Table 2.1: Literature Review Pedestrian Crash Findings - Exposure and Activity Related

Variable	Summary of significant findings
No cars in household	• Three studies found higher proportions of household without a car to be associated with increased pedestrian crashes (Chimba et al 2014; Cottrill and Thakuriah 2010; Lin et al 2019).
Walking and Transit Commute Rates	• Of six studies looking at walking or transit commute rates, one found that walking commute rates was associated with increased pedestrian crashes (Abdel-Aty el al 2013), two found that transit commute rates were associated with more pedestrian crashes (Abdel-Aty et al 2013; Dai and Jaworski 2016). • Two others found that combined active commute measures (either transit plus biking or transit plus walking) were associated with increased pedestrian crashes (Lin et al 2019; Ukkusuri 2012). • Two studies considered the variables but did not include them in their final models (Mansfield et al 2018; Wier at al 2009).
Transit Stops	• Three studies found that more transit stops were associated with more pedestrian crashes (Dai and Jaworski 2016; Jermprapai and Srinivasan 2014; Ukkusuri 2012; Yu 2014). • One study found that more transit stops were associated with fewer pedestrian crashes (Clifton et al 2009) and one found decreased pedestrian crash severity (Yu 2015)
Population Density	• 8 studies found population density is associated with more pedestrian crashes (Apardian and Smirnov 2020; Chakravarthy et al 2010; Dai and Jaworski 2016; Dumbaugh and Li 2010; Lin et al 2019; Loukaitou-Sideris et al 2007; Ukkusuri 2012; Yu 2014) • 1 study found population density is negatively associated with pedestrian crashes (Jermprapai and Srinivasan 2014) • 5 studies found population density is associated with a higher number of injury or severe injury pedestrian crashes, or increased severity of pedestrian crashes (La Scala 2000; Lin et al 2019; Moudon et al 2011; Ukkusuri 2012; Yu 2015) • Two studies found that increase population density was associated wither fewer fatalities in cities or urban areas (Guerra et al 2019; Mansfield et al 2018), while one also found it associated increased pedestrian crashes, injury crashes, and fatalities in suburban areas (Guerra et al 2019)
Employment Density	• Three studies found that higher employment density (or more weekly work trips) were associated with more pedestrian crashes (Guerra et al 2019; Jermprapai and Srinivasan 2014; Loukaitou-Sideris et al 2007; Wier at al 2009). Mansfield et al 2018 noted that in particular the employment density of entertainment and food services employees was associated with more pedestrian crashes. Two studies did not find employment density to be significant (Moudon et al 2011; Yu 2015)

2.2.2 Roadway factors and pedestrian crashes

Most studies (though not all) have found that increased intersection density is associated with more crashes, including pedestrian-involved crashes, although a few studies have found that either injury severity is less when crashes occur at intersections (Abdel-Aty et al., 2013; Merlin et al., 2020). For example, one study in Florida found that more road miles and more intersections in a block group were associated with more pedestrian crashes (Jermprapai & Srinivasan, 2014). Another study in Florida found that block groups with more traffic signals and more bus stops per mile were associated with increased pedestrian crash frequency (Lin et al., 2019). Twelve of 22 studies in the ecological analysis looked at the number, density and/or configuration of intersections. Seven specifically focused on roadway density, sometimes in combination with the six that focused on classification. Configurations included the number of 3-way or 4-way intersections, for example.

Numerous studies have found that higher speeds are directly tied to higher injury severity and increased fatality risk for pedestrians (Stoker et al., 2015). Merlin et al. noted that that most studies agree “arterials, multilane streets, and roads with high speed limits are all associated with higher risk and more serious injuries (Merlin et al., 2020). Six studies in the ecological analysis included measures of speed, usually posted speed limits, which were calculated either as an area-wide average speed, or the number or proportion of roads of varying speed limits.

Higher traffic volumes are also associated with more pedestrian crashes (Jermprapai & Srinivasan, 2014). A national study of pedestrian fatalities found that traffic volumes on non-access controlled principal and minor arterials is strongly associated with increased pedestrian fatalities in urban areas (Mansfield et al., 2018). Multiple studies in urban areas have found traffic volume to positively associate with pedestrian injuries (Guerra et al., 2019; Loukaitou-Sideris et al., 2016; Stoker et al., 2015; Wier et al., 2009). Wier et al found that traffic volume was the strongest predictor of pedestrian collisions, while Guerra et al. noted that a doubling of AADT corresponded to 25 to 30% more pedestrian crashes and serious injuries. Assessments looking at vehicle miles travelled, rather than AADT, have also been found to be positively associated with pedestrian crashes (Abdel-Aty et al., 2013; Stoker et al., 2015). Nine of 22 studies in the ecological analysis include measures of AADT, often area-wide calculations of average AADT. Three studies included a measure of the more person-based vehicle miles travel (VMT). Five studies looked at the number of lanes.

Select key findings from the ecological analysis review related to roadway factors are shown in Table 2.2.

Table 2.2: Literature Review Pedestrian Crash Findings – Roadway Factors

Variable	Summary of significant findings
Arterials and Traffic Speed	• Six studies looked at the miles or proportion of arterial roads. Four found that higher proportion of arterials (Wier et al 2009), or more miles of arterial roads (Abdel Aty et al 2013; Dumbaugh and Li 2010; Guerra et al 2019), were associated with more pedestrian crashes. Two others found that higher proportion of lower speed or local roads were associated with fewer pedestrian crashes (Lin et al 2019; Ukkusuri 2012) • Five studies looked at average vehicle speeds, with four finding that higher average speeds were associated with more pedestrian crashes (Chimba et al 2014; DiMaggio 2015; Guerra et al 2019) C and /or increased injury severity (Guerra et al 2019; Yu 2015). One looked at maximum speed limit (Dai and Jaworski 2016) and found it to not be significant.
Traffic Volume	• Of 11 studies looking at traffic volumes, such as VMT or AADT density, seven found that higher average traffic volumes levels were associated with more pedestrian crashes (Cottrill and Thakuriah 2010; DiMaggio 2015; Guerra et al 2019; La Scala 2000; Loukaitou-Sideris et al 2007; Mansfield et al 2018; Wier at al 2009). Four studies did not find volume to be significant (Dumbaugh and Li 2010; Kim 2019; Yu 2014;Yu 2015)

2.2.3 Sociodemographic factors and pedestrian crashes

As noted in the introduction, lower-income and BIPOC pedestrian experience disproportionately high rates of traffic injury. Related factors such as poverty status, education level, language, and age are also associated with disparate pedestrian safety outcomes. All but two of the 22 studies included in the ecological studies review included some socio-economic variables in their analysis; with the most frequently used variables being income, age, race/ethnicity, and education.

Geographic analyses are consistent with national numbers indicating disproportionate pedestrian injury rates among BIPOC residents, with areas of higher BIPOC populations being associated with more pedestrian crashes. For example, a geographic analysis in Florida found that areas with a higher proportion of BIPOC residents are associated with significant increases in pedestrian crashes (Abdel-Aty et al., 2013). A 2010 study in Chicago found that census tracts with higher than average (for the region) proportion of black, Latino/Hispanic or low-income residents had nearly 3 times the number of pedestrian crashes (9.66 crash per 10,000 residents compared to 3.37), including more hit-and-run type crashes (Cottrill & Thakuriah, 2010). A study in Toledo, Ohio found that census tracts with higher proportions of black residents and higher total black population were associated with increased pedestrian crashes (Apardian & Smirnov, 2020). A study in Philadelphia found that increase in proportion of Black residents in a census tract was associated with an increase in pedestrian crashes, though not significant connection to injuries and fatalities (Guerra et al., 2019). Nine of the 22 studies in the ecological analysis looked at race or ethnicity. Some selected a single minority group based on local demographics, for example the proportion of residents who are Black (6 studies), proportion who are Latino/Hispanic (6 studies), or proportion who are Asian (2 studies). Two studies looked at overall proportion of BIPOC population.

Income is strongly correlated with pedestrian crashes and fatalities. Numerous studies have found an inverse relationship between socioeconomic status and injury and fatality risk (Stoker et al., 2015). A literature review of correlates with pedestrian crashes found five studies looking at the connection between income and pedestrian crashes - in each study, higher income levels were associated with fewer pedestrian crashes (Jermprapai & Srinivasan, 2014). For example, in a study of pedestrian crashes in Orange County, California, the percentage of residents living in low-income households was a strong predictor of pedestrian crashes. The quartile of census tracts with the lowest percentage of low-income households, defined as under 185% of poverty line, had 11 pedestrian crashes per 100,000 residents compared to 44 per 100,000 residents in the quartile with the most low-income households (Chakravarthy et al., 2010). A study in Philadelphia found that higher poverty was more associated with pedestrian collisions and injuries than with total (i.e. - non-pedestrian) collisions and injuries. That study found that a 1% increase in poverty led to 0.22 increase in pedestrian crashes, 0.24 increase in injuries and 0.17 increase in fatalities (Guerra et al., 2019). Seventeen of the 22 studies in the ecological analysis considered either income or proportion of residents below or near poverty level, with 12 accounting for median income and 8 accounting for the proportion of residents below (or near) the poverty level. In one case, the income variable was excluded from the analysis due to multicollinearity with another variable.

People who cannot drive, including children, older adults and people with disabilities are more reliant on walking and transit to get around, and are more reliant on high quality facilities to navigate safely (Sandt et al., 2016). Young children are overrepresented in traffic deaths, representing 21% of road traffic deaths, making it a second leading cause of death for young children and a leading cause of childhood disability (Stoker et al., 2015). There is mixed evidence on whether areas with older adults result in more pedestrian crashes. However, there is considerable evidence that such areas are associated more severe pedestrian crashes; elderly individuals are the most overrepresented in traffic deaths (Stoker et al., 2015). Thirteen of the 22 studies in the ecological analysis considered age, with the most frequently used variables being the proportion of residents under or over some age (e.g. under 16 or over 65), while one used median age.

A literature review of correlates with pedestrian crashes found three studies looking at the connection between education and pedestrian crashes - in each study, higher education levels were associated with fewer pedestrian crashes (Jermprapai & Srinivasan, 2014). Eight of the 22 studies in the ecological analysis looked at education, typically including the proportion of the adult population with a high school diploma.

Other socioeconomic demographics included among the 22 studies in the ecological analysis were 5 studies with proportion who do not speak English (or speak it well), 4 studies with proportion of population employed (or unemployed); 4 with proportion of population with a car; as well as gender (3), homeownership (2), housing value (2), and household composition in terms of single or living alone (2). See Table 2.3 for a summary of literature review findings on sociodemographic variables.

Table 2.3: Literature Review Pedestrian Crash Findings - Sociodemographic

Variable	Summary of significant findings
Race / Ethnicity	• Seven studies found that higher proportion of minorities are associated with more pedestrian crashes (Abdel-Aty et al 2013; Apardian and Smirnov 2020; Chimba et al 2014; Guerra et al 2019; Lin et al 2019; Loukaitou-Sideris et al 2007; Mansfield et al 2018), including 5 finding specific connections between higher African-American or Black populations and pedestrian crashes (Apardian and Smirnov 2020; Chimba et al 2014; Guerra et al 2019; Lin et al 2019; Mansfield et al 2018), two findings connections between higher Latino populations and pedestrian crashes (Chimba et al 2014; Loukaitou-Sideris et al 2007), and one finding a connection between higher Asian populations and fatal pedestrian crashes (Mansfield et al 2018). • Conversely, two studies found connections between higher white populations and reduced pedestrian crashes (Chimba et al 2014; Yu 2014)
Income	• Six studies found household income to be associated with FEWER pedestrian crashes (Cottrill and Thakuriah 2010; Dai and Jaworski 2016; DiMaggio 2015; Jermprapai and Srinivasan 2014; Mansfield et al 2018). • One study found household income to be associated with more pedestrian crashes (Chimba et al 2014). • Five studies considered the variable but did not include it in their final models (Abdel-Aty et al 2013; Clifton et al 2009; La Scala 2000; Lin et al 2019; Yu 2015)
Poverty	• Five studies found that higher proportions of household below poverty level were associated with increased pedestrian crashes (Chakravarthy et al 2010; Chimba et al 2014; Guerra et al 2019; Jermprapai and Srinivasan 2014; Wier at al 2009)
Education Level	• Three studies looking at education levels found that the proportion of residents without a high school diploma or equivalent was associated with increased pedestrian crashes (Chakravarthy et al 2010; Lin et al 2019), pedestrian injuries (La Scala 2000) and severe pedestrian injuries (Lin et al 2019). One did not find the variable significant (Apardian and Smirnov 2020).
Non-English Language	• Three studies found connections between higher proportion of non-English speaking residents and more pedestrian crashes (Chakravarthy et al 2010; Dai and Jaworski 2016; Jermprapai and Srinivasan 2014), with Jermprapai and Srinivasan also finding proportion of non-English speaking residents associated with severe pedestrian crashes, fatal pedestrian crashes, and nighttime pedestrian crashes. • Two studies considered the variable but did not include it in their final models (Cottrill and Thakuriah 2010; Lin et al 2019)

Variable	Summary of significant findings
Un-employment	• La Scala 2000 found that higher unemployment was associated with more pedestrian injury crashes. • However, Chimba et al 2014 found that higher labor force participation was associate with more pedestrian crashes.
Age	• Studies looking at average age have found age to be associated with increased severity of crashes (Moudon et al 2011 Yu 2015). • One study found age negatively associated with crashes, severity and nighttime crashes (Jermprapai and Srinivasan 2014). Proportion of 65+: • Of studies looking at the proportion of residents over age 65, five found that to be associated with fewer pedestrian crashes(Chakravarthy et al 2010; Dai and Jaworski 2016; Lin et al 2019; Ukkusuri 2012; Wier at al 2009), and one found it to be associated with more pedestrian crashes (Guerra et al 2019). • Two studies found higher proportions of 65+ residents to be associated with fewer severe pedestrian crashes(Jermprapai and Srinivasan 2014 Lin et al 2019), while three found it to be associated with more severe crashes (Clifton et al 2009; Moudon et al 2011; Yu 2015). Proportion of children: • Studies are mixed on the impact of higher proportion of children on pedestrian crash rates. Three found increases in pedestrian crash rates (Chakravarthy et al 2010; Clifton et al 2009; Ukkusuri 2012), while two found decreases (Apardian and Smirnov 2020; La Scala 2000). • Another study found the proportion of kids in K-12 in a TAZ associated with more pedestrian crashes, while the proportion of kids age 0-15 was associated with fewer pedestrian crashes (Abdel-Aty et al 2013)

2.2.4 Land use

Land use variables are often a potential proxy for the types of interactions that pedestrians or motorists will have on the nearby streets. Eighteen of the 22 studies included land use considerations in their analysis, generally looking at the proportion of land occupied by a certain use, or the presence or number of certain types of destinations, such as school or bars. The most commonly used land use variables were the presence of or proportion of land used by residential purposes (9 studies) and the proportion of land used by commercial purposes (9 studies). Three studies also looked at the proportion or presence of pedestrian-oriented commercial, while three looked at the presence of strip-style commercial, including big-box stores. Six studies looked at the proportion of land devoted to industrial purposes, and five looked at offices. Six looked at the presence of or proportion of land devoted to schools, and five that the presence of or proportion of land devoted to parks, open space or recreation. Five studies included other destination types, such as bars or restaurants, while three studies used measures of land use diversity in their models. Of studies looking at alcohol sales locations, locations with on-site sales, and bars or pubs in particular, were deemed to be more correlated with pedestrian crashes or injuries than off-premise sales locations, such as stores that sell beer, wine or liquor to go.

In general, land uses that are significant attractors of pedestrian activity are associated with higher pedestrian crash risk. A national study found that, in both urban and rural areas, higher employment in the retail sector was associated with higher pedestrian fatality rates (Mansfield et al., 2018). Merlin et al found that commercial and mixed-use areas, along with areas nears schools, are associated with higher crash risk (Merlin et al., 2020). A study in San Francisco, CA, found that areas with a higher percentage of land area zoned for neighborhood commercial and residential neighborhood commercial, both potential pedestrian attractors, were associated with more vehicle-pedestrian collisions (Wier et al., 2009). A study in Los Angeles found more pedestrian collisions in areas of more concentrated commercial and retail land uses, and fewer pedestrian collisions in areas of vacant land, industrial use or office land uses (Loukaitou-Sideris et al., 2016).

While denser urban areas experience more pedestrian crashes, there is evidence that they are on average less severe. A Florida statewide pedestrian crash analysis found that census block groups in urban areas had more pedestrian crashes, but fewer fatal crashes than rural areas (Jermprapai & Srinivasan, 2014), possibly due to the lower speeds and more walking activity - proximity to medical care may be related as well. Another study notes that, when controlling for miles walked, pedestrian fatality rates are higher in rural (and small urban) areas than in urban and suburban areas (Jamali & Wang, 2017).

Consistent with the notion that higher density zones with lower density larger areas are more prone to pedestrian crash risk, there is considerable evidence that land uses such as strip malls and areas associated with arterial style big box commercial areas are connected to higher crash risk. A literature review of pedestrian risk factors found that rural areas and sprawling urban areas have higher pedestrian crash and fatality rates (not necessarily absolute numbers), which may be due to higher vehicle miles traveled (VMT) per capita and higher speeds (Stoker et al., 2015). More specifically, they found that characteristics associated with urban sprawl, including more arterials and strip malls, and big box stores are associated with higher traffic injury rates, while denser street networks are associated with fewer crashes (Stoker et al., 2015). A study in Florida found that density of discount stores, convenience stores and fast food stores was also associated with increased pedestrian crash frequency (Lin et al., 2019).

Some studies have found that alcohol sales locations (including bars, liquor stores, restaurants, and grocery stores) are associated with increased pedestrian crash risk. One study in New York City looked at the presence or absence of alcohol outlets in a census tract, and found that the presence of such an outlet in a tract increased the risk of an alcohol-related pedestrian or bicycle crash by 47%, although the authors noted that many such tracts had concentrations of outlets, such as entertainment districts (DiMaggio et al., 2016). A pair of studies in Baltimore found that each additional alcohol outlet in a census tract was associated with a 12-14% increase in pedestrian injury risk (Nesoff et al., 2018, 2018). These studies attempted to control for confounding factors; however, it should be noted that other studies have found that alcohol outlets tend to be concentrated in underserved communities (LaVeist & Wallace, 2000; Pollack et al., 2005).

2.2.5 Pedestrian infrastructure

Notably, there was limited inclusion of pedestrian-oriented transportation infrastructure among the 22 studies included in the ecological analysis review, with 6 studies including sidewalk completeness measures, and 2 studies including crosswalk presence or absence information.

There is evidence that underserved communities are less likely to have safe, accessible and high-quality pedestrian facilities (Sandt et al., 2016). A University of Illinois at Chicago study conducted street fields audits in a nationally representative sample 154 communities around the U.S., and found that 89% of streets in high-income areas ($57k+ on average) have sidewalks on one or both sides of the street, while only 59% of streets in middle income ($45-57k) areas do, and only 49% of streets in 51-54% in low income (less than $45k) areas do (Gibbs et al., 2012).

The literature is mixed on the relationship of the presence of sidewalks on crash risk for pedestrians, with some studies finding decreased risk and others finding increased risk - the latter may be due to the presence of sidewalks being correlated with higher pedestrian activity, and therefore higher exposure (Merlin et al., 2020).

Having access to safe crossing features is a core requirement for a safe pedestrian network, particularly for higher volume and wide roads. A study in Los Angeles, CA, found that 40% of pedestrian collisions occurred in marked crosswalks at intersections, while 28% took place while crossing outside marked crosswalk; 12% while a pedestrian was walking along the side of the road (not crossing), and 20% in other locations such as on a sidewalk, in parking lot, or other non-road locations (Loukaitou-Sideris et al., 2016). A Florida study found that 57% of pedestrian crashes and 65% of pedestrian fatalities occurred outside of intersections, and recommended mid-block crossing signals, high visibility crosswalks, median islands, and appropriate landscaping (Lin et al., 2019). State roads may pose a particular threat to pedestrians. A 2011 study in King County, WA, found that, for state routes, crossing at an unsignalized intersection was associated with an increased likelihood of a severe or fatal injury, though this was not true on city streets (Moudon et al., 2011). There is evidence that lower-income neighborhoods are less likely to have crossing features. A 2012 study found that streets in high income areas are much more likely to have marked crosswalks (13% of streets), than middle income (8%) or low income (7%) (Gibbs et al., 2012). In terms of traffic calming features such as pedestrian medians and islands and curb extensions, 8% of streets in high income areas have such features, compared to 4% in middle income areas and 3% in low-income areas (Gibbs et al., 2012).

Two-thirds of fatal pedestrian collisions occur at night or in low light conditions, with twilight or the first hour of darkness having the highest frequency of such collisions (Stoker et al., 2015). Lack of adequate street lighting is also associated with pedestrian crashes and fatalities. A study in block groups in Broward and Palm Beach counties, Florida, found that a "dark-not lighted condition," particularly in higher speed limit locations, was the most influential variable relating to severe pedestrian crashes (Lin et al., 2019). In that study 72% of pedestrian fatalities occurred at night, and 22% of nighttime fatalities were on streets without lighting. Loukaitou-Sideris et al found that, of a dozen pedestrian high-crash intersections in Los Angeles, half lacked pedestrian lighting (Loukaitou-Sideris et al., 2016). A University of Illinois at Chicago study found that 75% of streets in high-income areas have street or sidewalk lighting, while only 51-54% of those in middle- and low-income areas have such lighting (Gibbs et al., 2012).

2.2.6 Driver Yielding and Bias

Several studies in recent years are uncovering bias in driver yielding behavior. A 2015 study of driver yielding behavior in Portland, Oregon, found that Black male pedestrians waiting to cross at a marked midblock crosswalk "were passed by twice as many cars and experienced wait times that were 32% longer than White pedestrians" (Goddard et al., 2015). Although the study did not test whether this difference was due to explicit or implicit bias, the authors suggest that split second decisions about safety related behaviors are likely representative of implicit assumptions. A study of driver yielding in Las Vegas had four crossing participants, including one Black male, one white male, one Black female and one white female. The study found that "cars yielded more frequently for females (31.33%) and whites (31.17%) compared to males (24.06%) and non-whites (24.78%)." Further, more expensive cars were associated with decreased odds of yielding, with decreased 3% per $1000 increase in car value (Coughenour et al., 2020). A related study of driver yielding behavior in Las Vegas, which had one white female and one Black female crossing participant, found that yielding in the nearside lane was lower for the white participant, while yielding in the next lane, while the participant was already in the street, was lower for the Black participant (Coughenour et al., 2017). That study also found that yielding rates were lower in a high-income area than in a low-income area, though the authors speculate this may have been related to pedestrians being less common in the high-income neighborhood, as well as the street having higher speed limits.

3.0 DATA DESCRIPTION

It is important to utilize information and data from a variety of sources to understand the role that race and income play in pedestrian injury outcomes. This chapter documents the data sets utilized in this report, along with any transformations or calculations performed on the data before analysis. Basic data descriptive and / or high-level summaries of the data are included to help inform other sections of this technical report.

This technical report evaluates multiple elements of pedestrian traffic injury outcomes, identifying disparities by social equity factors such as income and race. To corroborate findings from any individual analysis, multiple analyses are performed to build confidence in any specific findings. The datasets used in this research are summarized in Table 3.1 below.

Data for the crash injury related analysis comes from three sources including ODOT, National Highway Traffic Safety Administration (NHTSA) and Oregon Health Authority's (OHA) Oregon Emergency Medical Service Information System (OR-EMSIS). ODOT's Crash Data System (CDS) crash data file is Oregon's traffic crash database of record and represents the best available data on pedestrian traffic injuries in Oregon. NHTSA's Fatal Accident Reporting System (FARS) database collects fatally injured traffic participants and has the advantage of collecting the race of the participant which is not collected in the ODOT data allowing for population-based injury rate analysis. OR-EMSIS data is collected by EMS providers, and generally includes the home and incident location of crashes. US Census data is used for a number of socio-demographic variables, including race, income and commute mode; however, this dataset is for an area (e.g. Census Tract or Block Group) rather than point data – steps to address this discrepancy in data formats is discussed later in this chapter and elsewhere in the report. Built environment and traffic exposure variables that have been documented to impact pedestrian safety, such as vehicle miles travelled, speed, and alcohol sales, are derived from ODOT and other state data sources like Oregon Liquor Control Commission (OLCC) and Open Streets Map (OSM). Finally, additional travel activity is derived from the Oregon Household Activity Survey (OHAS).

Table 3.1: Dataset Purpose and Source Summary Table

Dataset	Agency	Data Purpose					Report Chapter
		Index Analysis	Ecological Analysis	Population-based Rates	Home/Crash Location Analysis	Travel Activity	
Crash Data System (CDS)	Oregon DOT	✓	✓				Chapter 3, 6, 7, & 8
Fatal Accident Reporting System (FARS)	NHTSA			✓			Chapter 5
Oregon Emergency Medical Service Information System (OR-EMSIS)	Oregon Health Authority				✓		Chapter 7
Census	Census	✓	✓	✓	✓		Chapters 3, 6, 7, & 8
Built Environment & Traffic Exposure	ODOT; OSM; OLCC	✓	✓		✓		Chapters 3, 6, & 8
Oregon Household Activity Survey	ODOT					✓	Chapter 4

3.1 OREGON DEPARTMENT OF TRANSPORTATION CRASH DATA SYSTEM DATA (CDS)

ODOT CDS data is the authoritative source of crash incidents in Oregon and is developed and maintained by the department's Crash Data Section. These data are derived from police records and driver self-reports of incidents that happen on city streets, county roads, and state highways. Data is available at different spatial resolutions depending on the year of interest with low spatial resolution for years the earlier years of data, spanning years 2002 to 2006 with higher spatial resolution for years 2006 to 2018. For the earliest data, the low spatial resolution allows for confident location in an urban area but precise geographic coordinates are not present so exact location is unknown making these data less useful. The 2002-2006 data has street name which may be geocoded but that may introduce some error into any analysis that used those derived coordinates. For the purposes of this analysis, only pedestrian injuries on non-access controlled (functional classifications: arterials, collectors, and local) roads are used since pedestrian injuries on interstates and expressways likely have little to do with surrounding sociodemographic and built environmental characteristics.

The point location of the pedestrian injury is used to locate the injury crash within Census tracts using a spatial overlay function from the *sp* package (Pebesma & Bivand 2005; Roger et al. 2013) in the open-source statistical computing platform R. This calculation uses the spatial precision of the crash point and Census tract spatial data to decide on a single polygon (tract) to locate the pedestrian injury point. The challenge of accurately assigning crash points that fall on Census tract boundaries was raised by Curtis (2017) and is examined in more detail in section 2.4 below.

The specific location of a crash point is derived from the source data which includes either a police report or the DMV report filed by the driver(s) involved in a collision. There is potential for these documented points to not fall exactly where the crash occurred, especially with the reports from DMV where the driver filing out the report is untrained in this documentation process or might misremember various details of the incident.

3.2 NHTSA FATAL ACCIDENT REPORTING SYSTEM (FARS) DATA

FARS collects traffic fatality data through state data files, with the police traffic crash report as the primary source. Additionally, FARS analysts use other state data, such as driver records, vehicle records and medical records. Trained personnel interpret and code data directly from the police traffic crash reports onto an electronic file. Race of the fatality injured crash participant is derived from the death certificate.

These data are available at the location of the incident for data starting in 2002 but are only available at the city and county level for data prior to this year. Data for this project were accessed from the NHTSA FTP site and downloaded and formatted using the R statistical computing platform. These data will be used to calculate age-adjusted population based pedestrian injury rates by race in order to understand pedestrian injury disparities in Oregon.

3.3 OREGON EMERGENCY MEDICAL SERVICES INFORMATION SYSTEM (OR-EMSIS) DATA

ODOT crash data tracks the crash location of the incident but no information is available on the home location of the pedestrian crash participant. Knowing more about the home location of pedestrian crash participants can help with how to best interpret findings in featured in this report. The OR-EMSIS data will be used to answer three questions raised by TAC members in this research and include:

- What is the typical distance from home that pedestrian incidents occur?
- How often are people in the tract in which they reside or a neighboring tract?
- How does the race, ethnicity and income composition of their home tract compare with race, ethnicity and income composition of the incident tract?

OR-EMSIS data is derived from crash incidents where an EMS provider responded to a traffic crash. These data are reported to a centralized repository managed by Oregon Health Authority's EMS and Trauma Systems unit. Reporting by EMS agencies in Oregon became mandatory on January 1st 2019 as per Oregon Senate Bill 52 (2017) making these data useful for crash injury analysis. These data are acquired through a data sharing agreement between OHA and ODOT Research unit.

OR-EMSIS data are not a replacement for the ODOT crash data since they do not go through the same rigor of quality assurance and data element construction. However, these data contain useful information such as race of crash participant, user type (pedestrian, bicycle, motorist), home location, in addition to the incident location, which are of use to this research. Specifically, these data can provide a clearer understanding of the home location of pedestrian relative to the location of the incident. Chapter 6.0 uses an ecological approach to understand the role of zonal (Census tract) measures of residential sociodemographic factors on counts of pedestrian injuries measured in ODOT crash data.

To better understand the changes in the reporting of the OR-EMSIS data the chart is provided in Figure 3.1 below. The figure shows the number of injuries reported to ODOT and are grouped by fatal (K), severe (A), moderate (B) and minor (C) in represented by one line and another line that represents just fatal, sever and moderate (KAB). The chart shows that in 2017 and 2018 the number of EMS records compared to ODOT injury counts for bicycle, pedestrian, and transit incident participants are fewer but in 2019 the recorded count of these non-driving modes nears parity and is even exceeded by the EMS data. More EMS records compared to ODOT data might suggest that ODOT data are underreporting bicycle and pedestrian injuries which has been found in other crash databases where crash records start with police reports or self-reports (Winters and Branion-Calles 2017; Shinar et al. 2018; Langley et al. 2003) ODOT injury counts in the comparison below include all injuries along the KABCO index specifically injury severities K, A, B, and C. The KABCO index is a scale of traffic injury where K, A, B, and C correspond to fatal, incapacitating (severe), moderate (visible) and complaint of pain (minor) respectively.

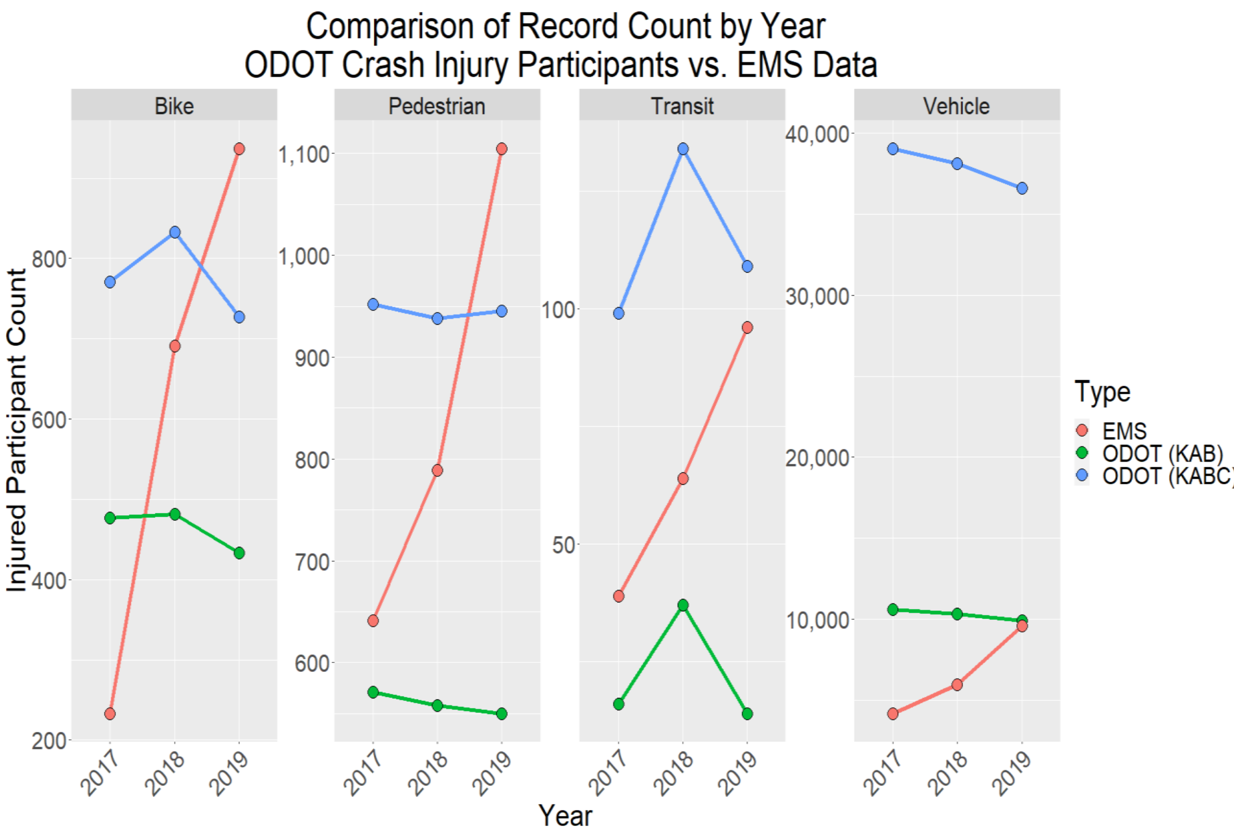

Figure 3.1: Number of ODOT records compared to OR-EMSIS records by year

The location of the home and incident are included as addresses in the OR-EMSIS data and therefor need to be geocoded for spatial analysis. Geocoding was performed on all EMS traffic incident records with a valid address, city, state, and zip code for both the home and incident locations. For addresses within Oregon, the Department of Administrative Services (DAS) geocoding service was used which includes a complete database of addresses in Oregon. For home addresses outside of Oregon, a third-party geocoding service was needed. Of the 27,220 traffic incident home addresses geocoded, 21,060 were geocoded using DAS's geocoding service and 6,120 were geocoded using the third-party geocoding service. Addresses that were matched on zip code and city were not included in the analysis as that level of precision was not good enough to answer the questions these data are being leveraged to answer. OR-EMSIS record were also discarded if the home address indicated the crash participant was homeless and without a home address. Home addresses with P.O. Box addresses were also removed.

For the pedestrian home and incident location analysis, only crash types that would be included in ODOT crash data are included. Pedestrian-involved incidents were selected based on the codes detailed in Table 3.2 and were selected based on review of codes in the National NEMSIS data standard data dictionary (NHTSA 2014). Incidents that are removed but would include pedestrians include clips, trips and stumbles (NEMSIS codeW18.4) and any incidents including both a pedestrian and other non-motorist including bicycles since ODOT data does not consider these traffic-related incidents.

Table 3.2: OR-EMSIS Incident Type Codes for Pedestrian-involved Incident

OR-EMSIS Incident Type Codes	Record Frequency	% Total
Pedestrian injured in collision with heavy transport vehicle or bus(V04)	3	0.3%
Pedestrian - Collision with railway train or railway vehicle(V05.9)	5	0.6%
Pedestrian - Collision with heavy transport vehicle or bus(V04.9)	7	0.8%
Pedestrian injured in collision with railway train or railway vehicle(V05)	7	0.8%
Pedestrian - Collision with two- or three-wheeled motor vehicle(V02.9)	9	1.0%
Pedestrian - Collision with other non-motor vehicle(V06.9)	13	1.5%
Pedestrian - Unspecified transport accident(V09.9)	29	3.3%
Skateboard accident(V00.13)	32	3.6%
Pedestrian on foot injured in collision with car, pick-up truck or van in traffic accident, initial encounter(V03.10XA)	129	14.5%
Pedestrian - Collision with car, pick-up truck or van(V03.9)	183	20.6%
Pedestrian - Collision with car, pick-up truck or van - Traffic(V03.1)	471	53.0%
Total	888	100.0%

Once all geocoding is performed and data is filtered based on incident type 888 pedestrian incidents are available for analysis. This is close to a year's worth of pedestrian injuries that ODOT records which averages about 965 pedestrian injuries per year.

3.4 CENSUS TRACT LEVEL DATA

A number of useful datasets for this research project will be gathered from the U.S. Census which tracks population counts and characteristics such as demographics data each year using a long form survey. Nearly 3.5 million surveys are completed each year, about 1% of the U.S. population which can be aggregated across years to derive meaningful statistical representations at smaller geographic scales with the smallest being the block group with data available for more aggregated geographies including tract, zip code, urban area, and county. Data elements collected from Census population data will include residential and job location data.

3.4.1 Sociodemographic Data

In addition to sociodemographic and job location information traffic exposure and built environment data will be utilized in the statistical analysis featured in Chapter 6. The below offers a summary of the data and calculation process used to derive the measure. The data summarized in Table 3.3 includes two periods of data including 2008 to 2012 and 2014 to 2018 for 520 urban area tracts. Rural tract models were explored as a part of this research but have not been fully developed.

Table 3.3: Urban Area Tracts Summary Statistics

Urban Area Tract Data Elements	Urban Tracts (n = 1040)		
Pedestrian Injury	**Mean**	**Median**	**Sd.**
Fatal & Severe Injury	1.21	1	1.56
Total Injury	6.83	5	7.77
Sociodemographic & Population			
Median Income (thousand)	58.96	54.58	24.57
% Black	0.03	0.01	0.04
% Asian	0.05	0.03	0.06
% Latinx	0.13	0.09	0.11
% BIPOC	0.22	0.2	0.11
% Hhs Limited English Proficiency	0.07	0.04	0.06
% Hh Disability	0.25	0.24	0.09
Average Daily Population	5328	4278	4038
Traffic Exposure & Built Environment			
VMT on Major Arterials (million)	1.33	1.01	1.62
Miles of Non-Interstate Roads w/ 45 mph+	0.05	0	0.12
Miles of Non-Interstate Roads w/ 35 mph+	0.13	0.1	0.16
Mean Width of Arterials	9.58	12	5.05
Sidewalk Miles (ODOT System)	2.78	0.77	4.85
Sidewalk Rated Poor (Mi.) (ODOT System)	0.19	0	1.07
Sidewalks Rated Substandard (Mi.) (ODOT System)	1.98	0.44	3.35
Low Wage Jobs Density (thousands per sqmi.)	0.61	0.31	1.2
Less than College Job Density (thousands per sqmi.)	0.54	0.47	0.36
% Walk Commute	0.05	0.03	0.06
% Transit Commute	0.06	0.04	0.06
Transit Stops	32.16	30	20.65
% Households with Zero Vehicles	0.09	0.07	0.08
Total Jobs Density (thousands per sqmi.)	2.73	1.13	7.26
Alcohol Establishment Density (per sqmi.)	107.8	44.25	232.3
Intersection Density (per sqmi.)	0.36	0.27	0.29
Tract Land Area (sqmi.)	1.61	1.11	1.56

Fatal, severe and total pedestrian injury counts by tracts come from ODOT's CDS crash data file. These data are assigned to the census tract in which they are located with no manual adjustments. For the demographic measures such as percent Black and percent Asian the total number of people in these Census categories are divided by the total population in the tract to calculate the proportion. In the statistical modeling featured in Chapter 6 a measure of daytime population is used as an offset which enables the models to account for population along with the other covariates. The calculation of daytime population is shown in equation 2-1 below. The calculation for commuter-adjusted or daytime populations comes from U.S. Census Bureau recommended calculation and is represented below by the variable Pop_t. This value is aimed at representing an estimate of people who are present in an area during normal business hours (U.S. Census Bureau 2017).

$$\boldsymbol{Pop_t = ResPop_t + (Workers\ WAC_t - Workers\ RAC_t)}$$

(3-1)

Where:

Pop_t is the average daily population in tract t

$ResPop_t$ is the residential population in tract t

$WorkersWAC_t$ is the number of workers working in tract t

$WorkersRAC_t$ is the number of workers living in tract t

3.4.2 Built Environment and Traffic Exposure

Information on the VMT and roadway speeds data are derived from data maintained by ODOT's Transportation System Monitoring Unit in the Table of Potential Samples (TOPS) dataset and are reported to the Federal Highways Administration on an annual basis through the Highway Performance Monitoring System (HPMS). These data are available at a disaggregate level for all streets with a functional classification of minor collector and above for years 2011 through 2019. Since the scale of these data is at the network level these data were aggregated to Census tracts for use in analysis. Since many roads run along tract boundaries VMT is equally apportioned to any tract that intersects with the tract boundary. The TOPS data also features measure of posted speed and if a traffic median is present the width which are also summarized to the tract level.

Information on sidewalks is derived from a database of sidewalk data that ODOT maintains for the state system and does not include non-state owned roads or adjacent sidewalks. These measures are aggregated to the tract level based on their location within the tract with no double counting for being near a Census boundary. Two attributes of the ODOT sidewalk system are used including the condition and whether or not the sidewalk adheres to the agency standard. Condition is a statement of the physical condition of the pavement and includes three ratings summarized below (ODOT 2020):

- Good (G): Smooth, new pavement. Only to be used for new construction.

- Fair (F): Reasonably smooth pavement, safe to walk on.
- Poor (P): Pavement that is cracked, heaved, eroded, etc. Pavement which is dangerous to walk on or is impassable by a wheelchair or stroller.

Employment data, including worker employment location comes from the Longitudinal Employment-Household Dynamic (LEHD) program database. These data allow for assessments of employment location down to the Census block but were aggregated to the tract level for this analysis. Disaggregate measures of job type by industry and wage are available and used in the analysis featured below.

Data on the percent of workers that commute by walk and transit comes from the U.S. Census and is available at the block group level but for this research these measures were aggregated to the tract but otherwise used as is with no calculations. Similarly, the number of vehicles per household was taken as is from Census for use in this analysis. Transit stop information is derived from statewide database of General Transit Feed Specification (GTFS) based data. The location of stops are available for the entire state because ODOT's Public Transit Division has spent resources and staff time making sure all relevant transit providers in Oregon collect their service information and submit it using this data standard. Ideally ridership data at the stop location would be available but unfortunately transit agencies have not yet adopted the related GTFS ridership component GTFS-ride to standardize these data so ridership data at the stop level is not available statewide. Lastly, the number of alcohol establishments was determined by using data from the Oregon Liquor Control Commission (OLCC) which tracks the count and address of liquor licenses. These data were geocoded using a statewide address database from the Department of Administrative Services (DAS) geocoding service. Addresses that were not able to be matched at the address level were discarded. On average the total number of addresses that were discarded was 632 to 774 or 7% to 8% of the total records. Table 3.4 summarizes the geocoding results below.

Table 3.4: Oregon Statewide OLCC Address Geocoding Results

Year	Address Geocode Match Result		Acceptable Match %	Total Addresses
	Acceptable	Unacceptable		
2008	7,495	632	92%	8,127
2009	7,699	642	92%	8,341
2010	7,750	642	92%	8,392
2011	7,952	645	93%	8,597
2012	8,086	663	92%	8,749
2013	8,296	703	92%	8,999
2014	8,592	700	93%	9,292
2015	8,798	709	93%	9,507
2016	9,084	726	93%	9,810
2017	9,168	765	92%	9,933
2018	9,503	774	93%	10,277

3.5 OREGON HOUSEHOLD ACTIVITY SURVEY (OHAS)

The OHAS data includes 17,941 households in Oregon where all the people in the household were asked to keep a diary of all travel-related activities for an assigned 24-hour period. Travel periods were evenly distributed throughout the weekdays when school was in session and respondents were asked to complete logs by mail and telephone. Results were compiled into a statewide database which are used to inform travel models among other descriptive uses. The survey documented daily weekday household travel patterns of 17,941 households randomly sampled from among the 1.5 million Oregon households (Bricka 2019). The survey design focused on acquiring data that would allow for the generation of travel activity summaries by some sociodemographic groups like income and number of workers. Census data were used to create statistical weights to ensure the data are demographically representative but ODOT reported that because of lower participation rates by BIPOC groups and young adults the ability to generalize results is limited. The major implication for the lack of participation by certain race and ethnicity groups is that disaggregate measures of race and ethnicity are aggregated to improve reliability of the travel activity measures. Even with the aggregation of low income populations and BIPOC participants, measures should be considered estimates with some measure of error. Additionally, the OHAS survey collected income and race for the household, and not for the specific individuals within the household. This level of data collection is aimed at informing household based travel demand models and is sensible for income but is problematic for race. It's not unusual for people of different races to live in a single household together so categorizing all individuals in a household as one race creates additional error when reporting findings on race. For summaries below Asian, Black, Native Hawaiian, Pacific Islander, Native American and Alaskan Native and Latinx survey participants were all grouped into the BIPOC category to increase the statistical precision of summaries below. For the reasons described, since the survey was not structured to be representative for each disaggregate racial group some groups have too few trips to reliably document travel behavior.

3.6 USING CRASH POINTS AND CENSUS TRACT POLYGONS

Statistical analysis methods, described in Chapter 7, model factors associated with pedestrian crashes at the Census tract level. One potential concerns about linking crashes (points) and tracts (polygons) is that traffic crashes occurring on the boundaries of Census tracts might present problems for subsequent analysis. The potential issue would be that points on boundaries could be double counted or erroneously assigned to a neighboring Census tract. In order for this issue to impact the study findings, several factors would need to be true – first, characteristics of neighboring tracts (such as income or racial breakdown) would have to be significantly different; second, there would have to be a significant bias pushing the erroneous assignment of points to polygons in as specific direction. This section explores this concern and documents relevant literature on the topic.

Analysis of the Census tract data is performed below, and demonstrates the following key findings:

- Assigning points on boundaries to one tract versus its neighbor likely has minimal impact due to significant autocorrelation, or the tendency of neighboring tracts to resemble one another.

- We have no reason to believe that there is a particular bias by which a point get assigned to a polygon, which limits the likelihood of any systematic bias being introduced into the analysis.

- The Race, Ethnicity and Income Index method reduces the point-on-boundary issue by dissolving boundaries of many tracts creating 'super' polygons based on index value.

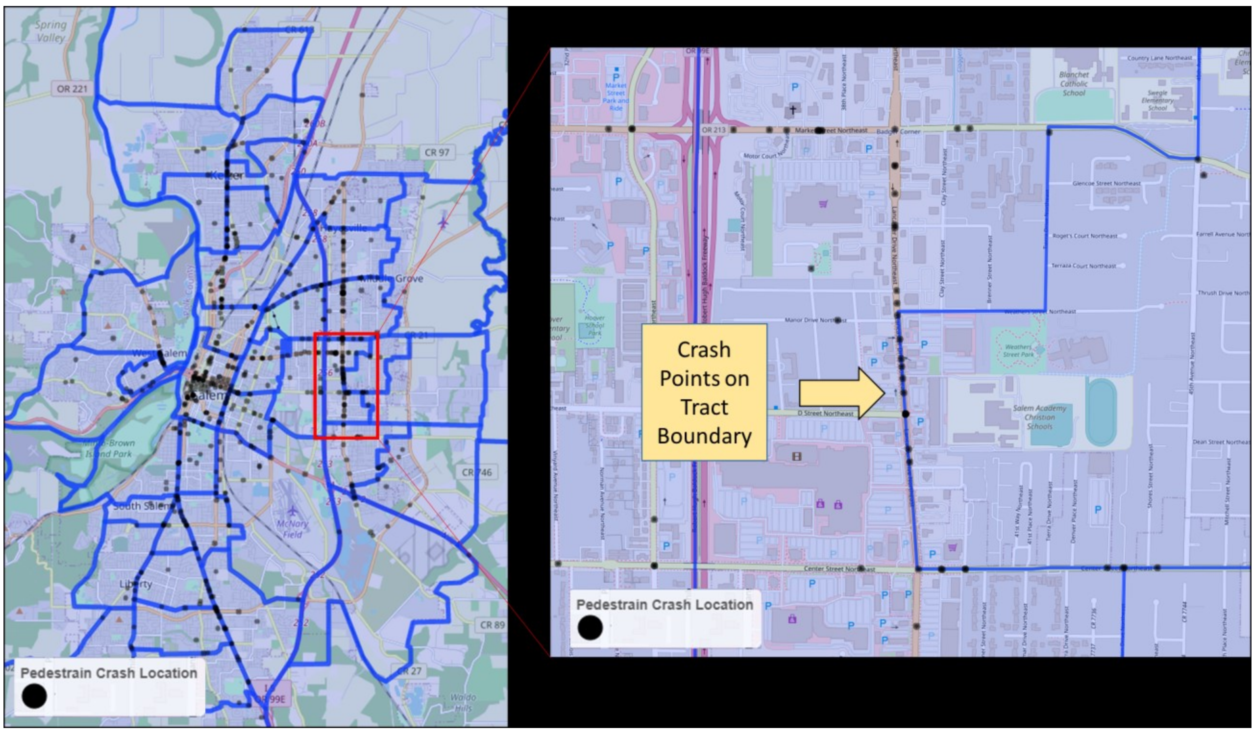

Figure 3.2: Crash point on census boundary example

For all the pedestrian injury data available from ODOT's crash data file, which includes 8,851 pedestrian crashes between the years 2008 and 2018, 60% of pedestrian injury crashes are placed farther than 5m from a Census boundary and are therefore not on any Census tract boundary while 35% are on a boundary of two tracts, 4% on a boundary of three tracts, and 1% on a boundary of four tracts (see Table 3.5). Because 40% of pedestrian injury crashes occur on a Census tract boundary the examination below is worthwhile.

Table 3.5: Summary of Instances that Pedestrian Injuries Fall on Census Tract Boundaries (2008-2018 Data)

Intersecting Tract Boundaries	Records	%
1	5,343	60%
2	3,066	35%
3	345	4%
4	97	1%
Total	8,851	100%

There is no established literature that this report's authors are aware of that preclude the use of joining information from polygons to points, which is standard practice in many ecological analyses. As described in the literature review, the project team reviewed at least 20 studies that analyzed factors associated with pedestrian crashes by assigning crash points to geographic polygons (typically tracts or polygons) to explore the relationship between crashes and factors such as Census-derived population level data. We reviewed these papers to see if they noted the challenge of assigning crashes that occurred on polygon borders. Of the 20 papers, 16 did not address this potential concern. Two noted the potential issue, but indicated that they felt the issue was of minimal concern. Chakravarthy et al (2010) noted that while "collisions occurring near census tract boundaries may have been assigned to the wrong census tract," they "we would expect this misclassification to be nondifferential with respect to poverty and other population characteristics and to diminish measures of association." Similarly, Wier et al (2009), noted that there could be "erroneous census-tract assignment for some collisions that fall on census-tract boundaries," but that they did "not have reason to believe that there would be systematic bias in this error." Two studies took small steps to reduce the potential error that could be introduced through this issue, with one assigning the mean value of both tracts to crash points when crashes occurred on borders (Dai and Jaworski 2016), while another, which was assigning crash counts to block groups, buffered the block groups by 200 feet, generally resulting in crashes on border roads being included in both block groups (Dumbaugh and Li 2010).

We identified another paper that looked at the potential for double counting points (traffic incidents) when the points fall on a polygon (Census tract) boundary (Curtis 2014). The author concludes: "*there is no reason to question the standard GIS practice of aggregating points to polygons*" but offers that the joining methods should be well-understood so that scholars are aware of the methods their technology is using to compute the results.

3.6.1 Spatial Autocorrelation of Census Tract Level Information

At the heart of the point-on-polygon boundary issue is whether bias is injected into subsequent analysis because of a miss-assignment of the point to the tract. However, because neighbor tracts typically reflect values of the 'home' tract the risk of bias is low. This concept, known as spatial autocorrelation, is a well-known phenomenon in geospatial analysis. Spatial autocorrelation describe the existence of systemic spatial variation in a given variable (Haining 2003) and arises when adjacent observations exhibit similar values. This phenomenon can present issues in statistical analysis and should be investigated though do not necessarily introduce bias (Diniz, Bini, & Hawkins, 2003).

We will explore autocorrelation for the Census tract data used in this research to help understand the potential of bias being introduced by assigning crash points to one tract versus a neighbor tract. Spatial autocorrelation is computed using Moran's I which defines the ratio between the local and the global coherence (Schmal et al. 2017; Gao et al. 2019) using the following formula:

$$\boldsymbol{I} = \frac{\mathbf{1}\ \sum_{ij} w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_{ij} w_{ij} N^{-1} \sum_{i}(X_i - \bar{X})^2}$$

(3-2)

Where:

N describes the number of observations locations

X_i and X_j are the values of observation at location i and j respectively

$\bar{X}$ describes the mean value of all observations

Using this formula, we find that Census tract information is spatially auto correlated for most key variables using in the analysis, meaning that tract level characteristics are typically similar to nearby tracts. To compute spatial autocorrelation we first compute the values of the nearest neighbors for each Census tract and assign equal weight to each tract that touches the queen (noted as tract$_i$). For example, Figure 3.3 shows how BIPOC % for select tracts are used to compute Moran's I. In the example, Census tract 41047001602 represents Tract$_i$ (queen tract) while the other tracts represent Tracts$_j$. Since we are giving equal weight to Tracts$_j$ we can simply average their BIPOC values which include 49.7%, 44.6%, 44.9%, 43.3%, and 36.4%. The mean of these values is 43.8% which compared to 46.1% is very similar. For Moran's I, do this calculation for all Census tracts and the composite measure, the slope between the composite neighbor values and the queen tract is Moran's I. For the BIPOC % measure the results reveal a Moran's I of 0.52 which suggests strong positive autocorrelation. This can also be observed in the chart featured in Figure 3.4 where the spatial lag variables are compared with the queen tract (Tract$_i$) values.

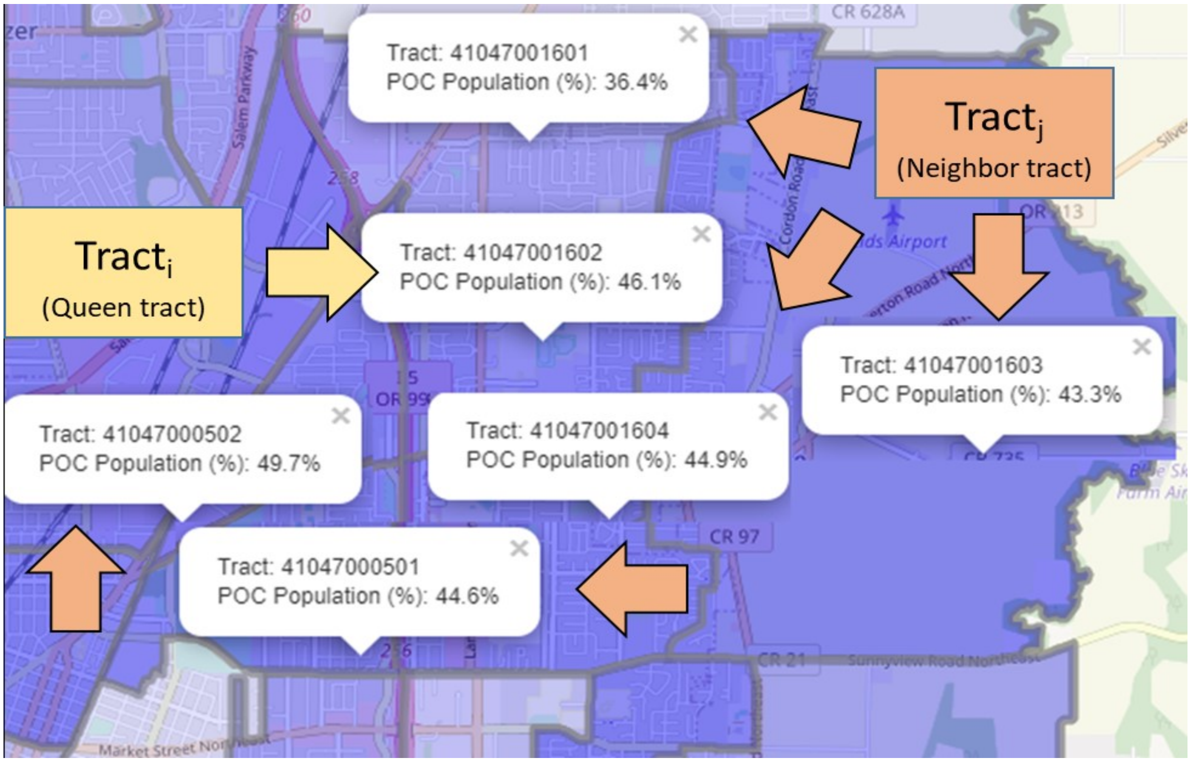

Figure 3.3: Example of spatial autocorrelation and Moran's I calculation– Salem, OR urban area

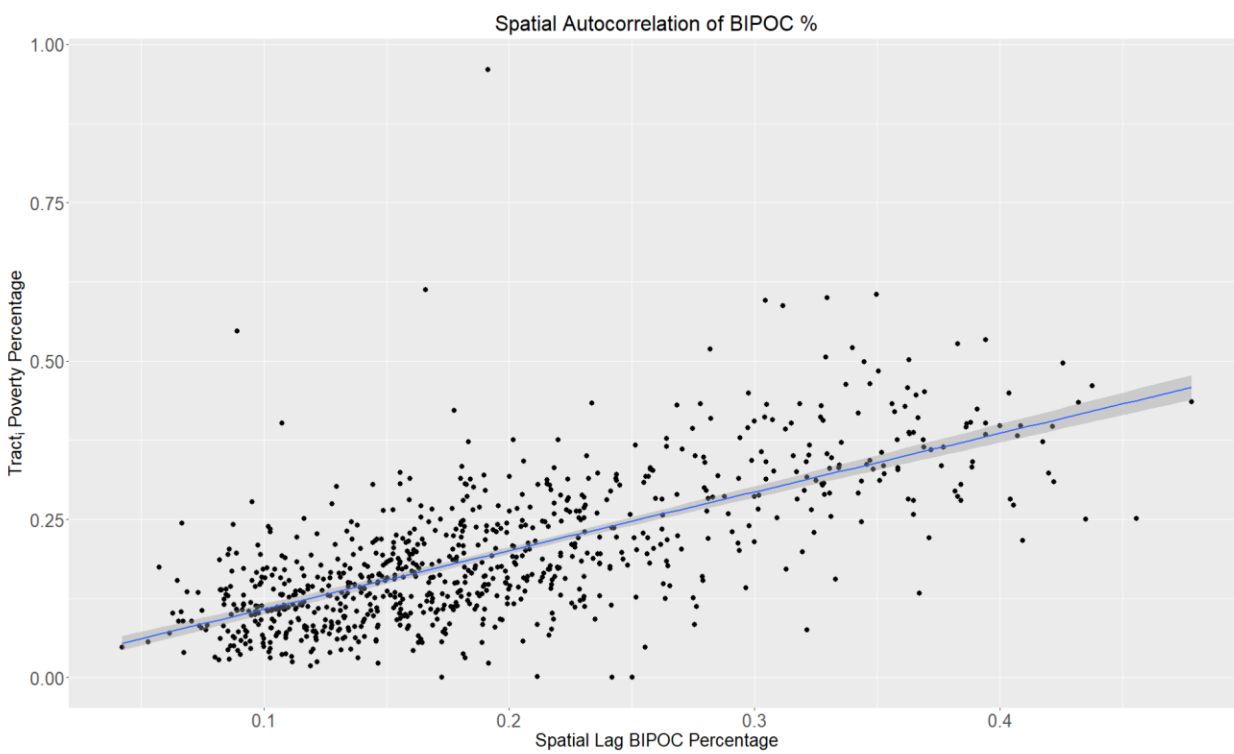

Figure 3.4: Correlation between spatial lag and tract BIPOC % values

Using variables from models featured in Chapter 7 below Moran's I is calculated for multiple sociodemographic, built environment, and traffic exposure variables and presented in Table 3.6. This summary shows a range of Moran I values from 0.107 to 0.745 with the majority of values showing significant positive autocorrelation. Higher values indicate a greater amount of spatial autocorrelation compared to values closer to zero.

Table 3.6: Summary of Moran's I Values for Select Variables

Variable	Moran's I
Asian %	0.627
Black %	0.609
Latinx %	0.560
BIPOC %	0.521
Median Income	0.527
Poverty %	0.360
Disability %	0.556
Limited English Proficiency %	0.608
VMT on Major Arterials	0.107
Miles of Roadway 45 mph+	0.541
Miles of Roadway 35 mph +	0.514
Mean Arterial Width	0.351
Total Sidewalk Miles (ODOT System)	0.589
% Households with Zero Vehicles	0.450
Mean Transit Stops	0.554
% Workers Commute by Walk	0.411
% Workers Commute by Transit	0.745
Less than College Education Job Density	0.703
Total Job Density	0.415
Alcohol Establishment Density	0.525
Intersection Density	0.684
Miles of Sidewalk in Poor Condition (ODOT System)	0.182
Miles of Sidewalk in Substandard Condition (ODOT System)	0.551
Low Wage Job Density	0.475

The implication of this autocorrelation is twofold. First, when crash points are on a boundary of multiple Census tracts, the risk of biasing the overall analysis is low since tracts near one another typically exhibit similar values. Second, the analysis needs to account for the presence of spatial autocorrelation otherwise standard errors may be biased giving a false assessment of precision. More description of how this is handled is available in Chapter 7 below.

3.6.2 Point-on-polygon Boundary Issue with REII Analysis

Even if Census tracts were not auto correlated (we find that they are) and if there were a bias pushing points toward particular polygons in a systemic way that could cause bias (we don't have reason to believe there is), analysis conducted in Chapter 5 of this study suggests that the pedestrian safety disparities could not be caused by point assignment error or bias. This section documents instances in which points are present on polygon boundaries when using the REII index approach featured in Chapter 5. The analysis in that chapter uses a standardized scoring method to assign an index value based on the percent of the population that is BIPOC or lives under the poverty line. The REII index, which is described in more detail in Chapter 5, uses index categories including Lowest, Low, Moderate and High concentration of BIPOC and poverty. Partially explained by the autocorrelation demonstrated in section 2.5.1 above, significant clustering of these index values occurs especially in Oregon's large urban areas. An example of this REII clustering is presented in Figure 3.5 below. This figure shows that index values tend to cluster into larger groups (super polygons) of similar values as exhibited by the large number of contiguous High (blue) REII tracts.

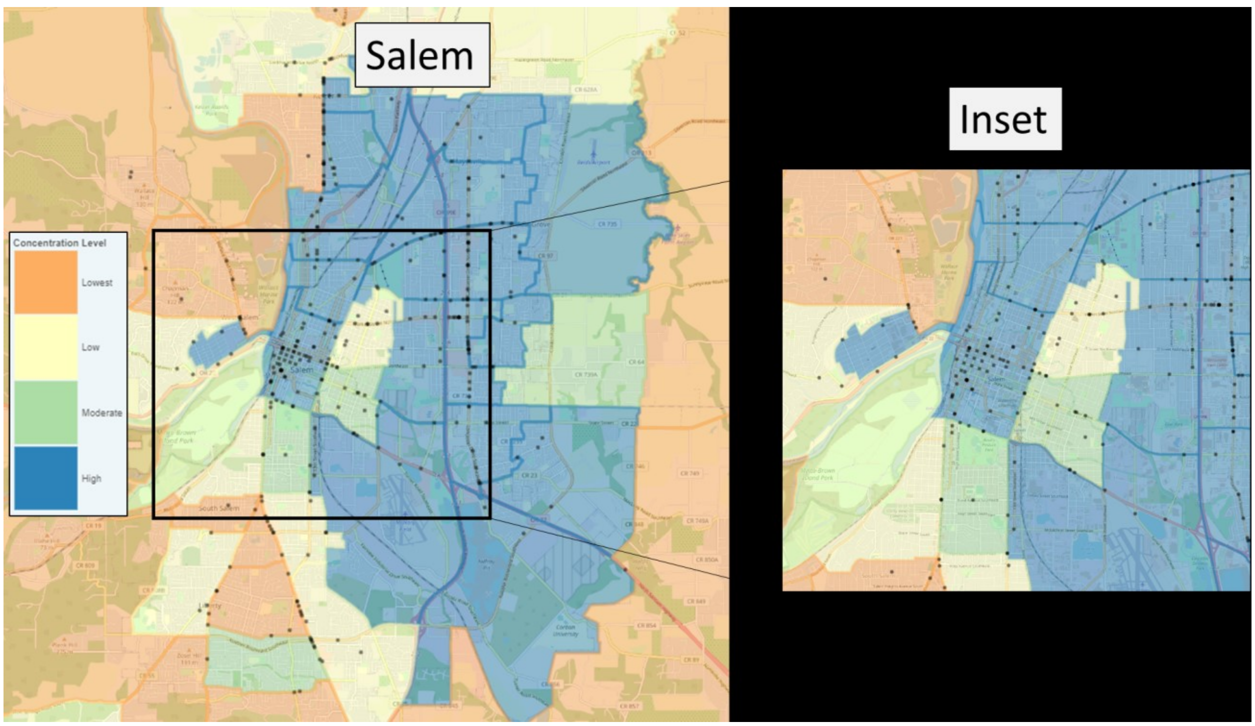

Figure 3.5: Example of spatial clustering of REII values – Salem, OR urban area

This figure also highlights how the point-on-boundary issue diminishes since points previously on Census tract boundaries are no longer on boundaries of these larger agglomerations of Census tracts. The diminishing instances of points on polygon is further highlighted in Figure 3.6 below where tracts are dissolved on the REII index values.

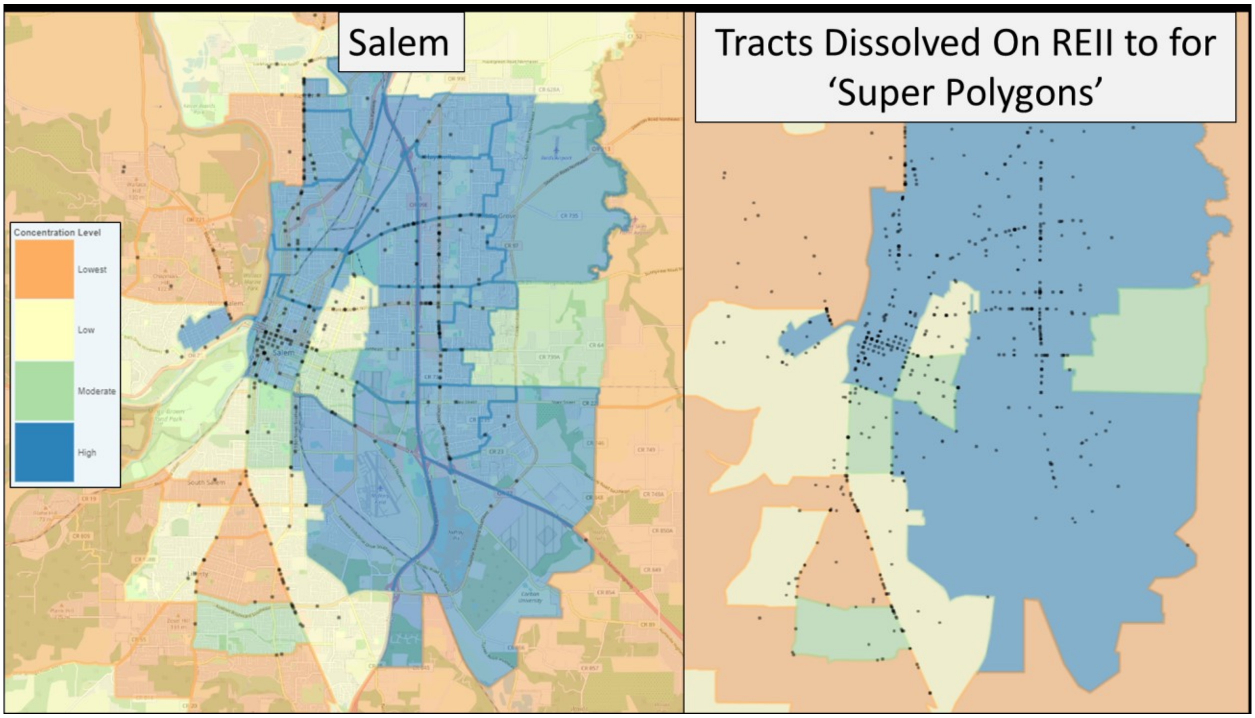

Figure 3.6: Tracts dissolved by REII index value – Salem, OR urban area

Figure 3.6 shows the tracts dissolved by REII value to highlight how the point-on-boundary issues dissipates when these super polygons are used to aggregated pedestrian injuries as is done in Chapter 4 analysis. Using these 'super polygons', for years 2008 through 2018, the number of pedestrian injuries that are located on a boundary is just 23%. The implication of this outcome is that the uncertainty of appending a pedestrian injury point is diminished when using the REII approach.

Table 3.7: Summary of Instances that Pedestrian Injuries Fall on Census Tract Boundaries (2008-2018 Data)

Intersecting REII Super Polygon Boundaries	Records	%
1	6,802	77%
2	1,953	22%
3	96	1%
Total	8,851	100%

4.0 TRAVEL ANALYSIS BY RACE AND INCOME

This section analyzes travel behavior with a specific focus on race and income in order to provide contextual information for the crash related analysis in latter chapters. Primary findings from this chapter include the following:

- People in households living at or below the poverty line travel more miles by walking compared to people living above the poverty line.
- People living in households classified as BIPOC travel more miles by walking than people in households classified as White. This is likely because the average household income of BIPOC households is less than White households.
- People in households living at or below the poverty line travel more miles by transit compared to people living above the poverty line.

This travel behavior analysis uses available data from the most recent household travel survey conducted in Oregon. The household travel survey data is derived from the 2009 to 2011 Oregon Household Activity Survey (OHAS).

4.1 OHAS TRAVEL ANALYSIS BY INCOME AND RACE

The table below summarizes by race category and poverty status the total trips and persons surveyed in the 2009-2011 OHAS travel survey and includes measures that characterize the weighted and unweighted measures of trips and person. For all modes of travel, the weighted number of trips include 13.5 million (157,000 unweighted) trips for 3.74 million (42,208 unweighted) people. For the state as a whole the average number of trips taken by all modes (drive, passenger, walk, transit, bike, motorcycle, etc.) was 3.6 trips per weekday. This statewide trip rate 3.6 is roughly one trip more per weekday than the 2.5 trips per weekday measured for people living at or below the poverty line. For BIPOC survey respondents, the average trip rate is 2.7 trips per weekday. For all race/ethnicity categories, poverty status is a strong predictor of total trip making with differences between people living below the poverty line and those above the poverty threshold existing in all racial categories. Poorer BIPOC households also take fewer trips than poor White households with BIPOC households living in poverty taking 2.0 trips per weekday compared to 2.8 trips for White households.

Table 4.1: All Mode Trip Rate by Poverty Status and Race

Poverty Status	Aggregate Race/Ethnicity Category	Total Trips (Expanded Survey)	Trips (Unweighted)	Persons (Expanded Survey)	Persons Surveyed	Trip Rate (Weighted)
Above Poverty	BIPOC	718,764	6,598	207,550	1,866	3.5
At or Below Poverty		428,196	2,137	210,619	724	2.0
Refused		50,473	420	21,252	140	2.4
Statewide		1,197,433	9,155	439,421	2,730	2.7
Above Poverty	White	10,061,950	126,099	2,593,585	33,360	3.9
At or Below Poverty		1,101,274	8,490	390,967	2,513	2.8
Refused		720,018	8,504	183,348	2,271	3.9
Statewide		11,883,242	143,093	3,167,900	38,144	3.8
Above Poverty	Other	154,377	1,413	42,221	369	3.7
At or Below Poverty		28,663	207	19,496	62	1.5
Refused		20,589	160	4,340	39	4.7
Statewide		203,630	1,780	66,057	470	3.1
Above Poverty	Refused	166,840	2,401	47,515	655	3.5
At or Below Poverty		49,375	213	12,036	64	4.1
Refused		46,761	540	11,552	145	4.1
Statewide		262,976	3,154	71,103	864	3.7
Above Poverty	Statewide	11,101,931	136,511	2,890,872	36,250	3.8
At or Below Poverty		1,607,508	11,047	633,118	3,363	2.5
Refused		837,841	9,624	220,493	2,595	3.8
Total		13,547,280	157,182	3,744,483	42,208	3.6

The figure below uses the OHAS travel survey data to calculate miles of travel by select modes. These per capita miles of travel by mode are broken out by poverty status of the household. Figure 4.1: Figure 4.1 shows that for people living in poverty, there average weekday miles of travel as a pedestrian is 0.18 miles compared to 0.12 miles for people living above the poverty line. Transit use is also higher for people living in poverty with average weekday per capita miles of travel of 0.8 miles compared to 0.47 for people living above the poverty line. Conversely, people living in poverty drive less with just 6.3 miles per person compared to 16.8 miles for people living above the poverty line.

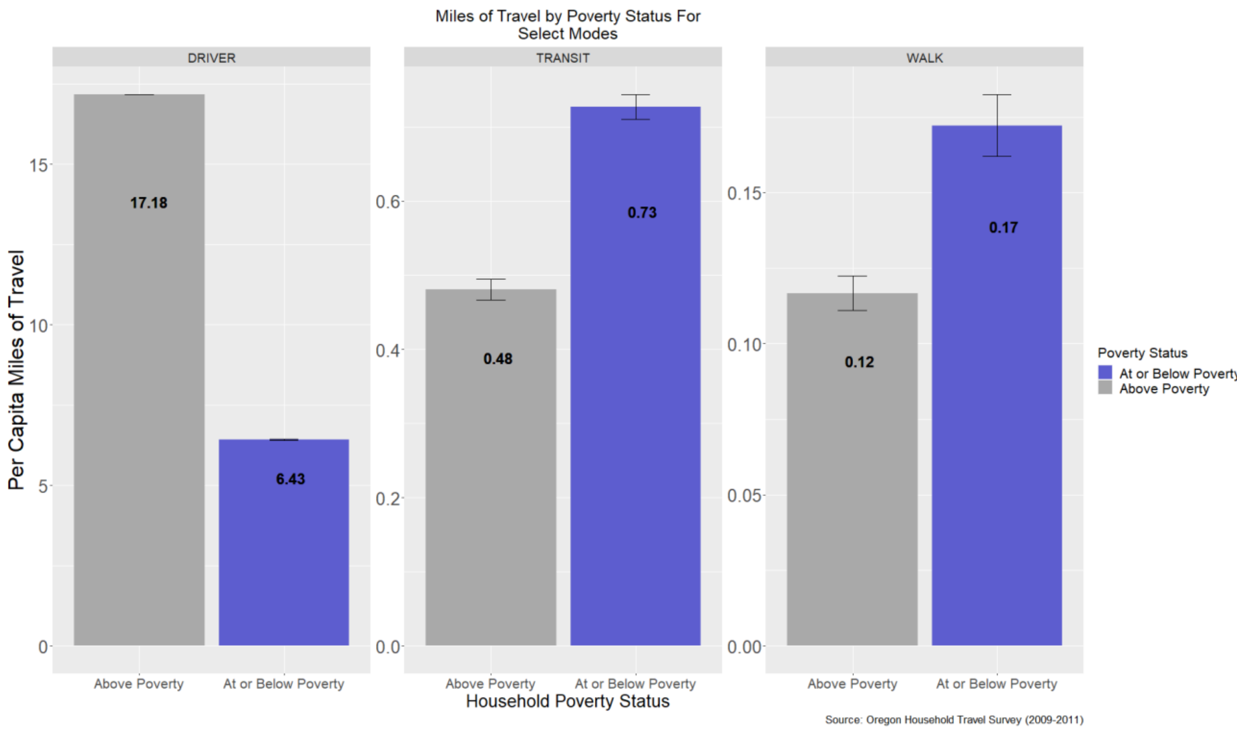

Figure 4.1: Miles of travel by poverty status for select modes

Figure 4.2 below summarizes per capita travel by select modes by race category including White and BIPOC. Because BIPOC households were more likely to be lower income than White households ($48,000 vs. $54,000) the figure above reflects similar outcomes shown in Figure 4.1. In Figure 4.2 people living in a household designated as BIPOC walked 0.17 miles compared to 0.12 miles for survey respondents in households that are White. Miles of travel by transit also showed some difference with people in BIPOC households traveling 0.57 miles compared to 0.52 for people in White households. This figure also shows the miles of travel by driving displaying 8.3 miles of per capita travel for people living in BIPOC households compared to 16 miles of driving per person in households classified as White.

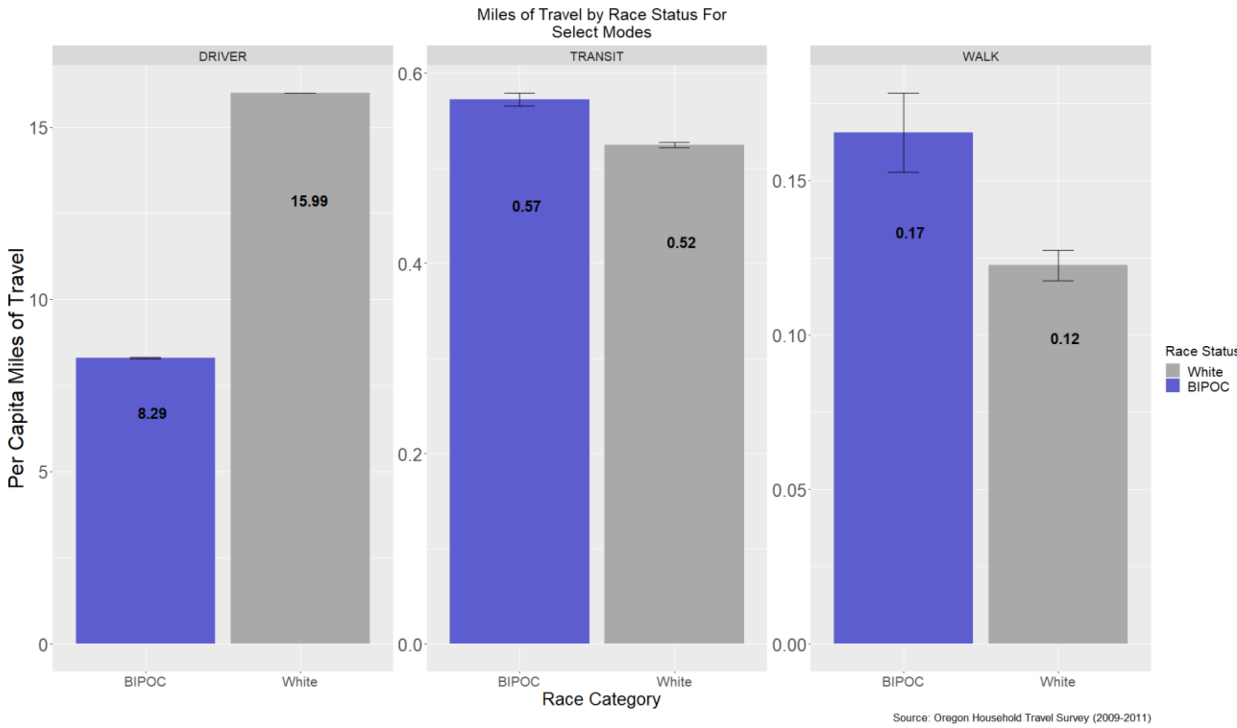

Figure 4.2: Per capita travel by race category

Figure 4.3 below shows per capita miles of travel for select modes broken out by both poverty status and race category. Because of the intersection of poverty and race this chart attempts to show how even after controlling for poverty status some travel behavior differences persist. For walk miles of travel, BIPOC households living at or below the poverty line travel 0.22 miles of travel per person compared to 0.17 miles per person for households that are classified as White. Both of these measures of walk miles appear significantly different than the state average. For transit miles, BIPOC households living in poverty do not appear to travel more miles than BIPOC households living above the poverty line when considering the margins of error. Households classified as White that are living below the poverty line appear to travel significantly more miles by transit than BIPOC households (living under the poverty line) and more than the average household classified as White. For driving miles, per capita miles driven by BIPOC households living in poverty is just 4.2 miles per person compared to 12.5 miles for BIPOC households living above the poverty line. This is less driving compared to households classified as White where for people living below the poverty line drive 7.7 miles per person.

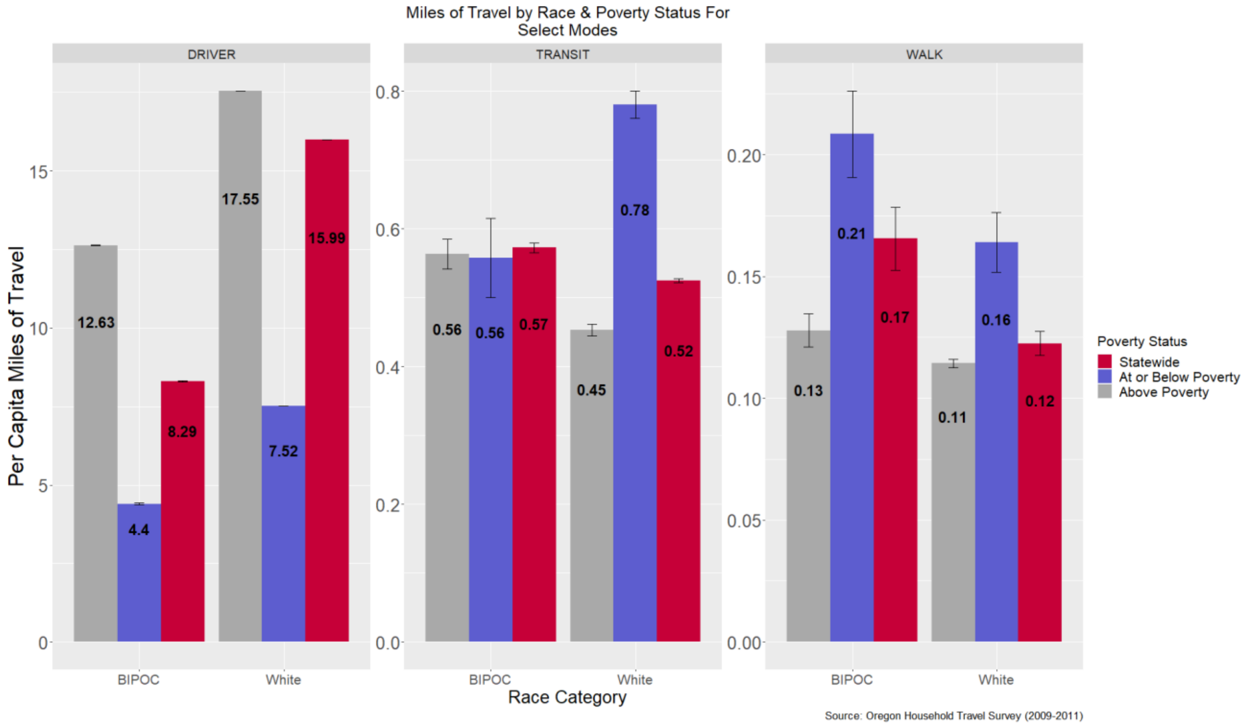

Figure 4.3: Per capita miles of travel by poverty status and race category

4.2 OHAS TRAVEL ANALYSIS SUMMARY

Figures presented in this chapter highlight the increased pedestrian exposure faced by low income people and BIPOC populations. Income is a significant predictor of walk miles but there is some residual differences even after controlling for poverty as shown in Figure 4.3 though income is certainly the main effect. Transit usage by race category showed no significant difference but instead is primarily a function of poverty status. These findings should inform findings documented in Chapters 4 and 7 where disparities of pedestrian injuries shown to exist based on race and income. It is logical to conclude that people who walk more are more likely to be involved in a pedestrian traffic incident, all else being equal. Transit miles are a related exposure considering many people access transit by walking.

5.0 FATAL ACCIDENT REPORTING SYSTEM (FARS) ANALYSIS

This section details analysis of the Fatal Accident Reporting data in order to understand fatal pedestrian injury rates by race. A summary of findings in this chapter include:

- Pedestrian injury rates for the most recent period of data show that Black, Indigenous and People of Color (BIPOC) experience a higher burden of pedestrian injury compared to the state average. (2.8 deaths per 100K for BIPOC compared to 2.1 deaths per 100K for all people in Oregon)

- In the most recent period of data, Black people experience the highest rate of pedestrian injury followed by American Indian and Alaskan Native, Latinx, and Asian.

- Pedestrian injury disparities vary over time with earlier periods of data exhibiting smaller disparities between BIPOC populations and the state average.

5.1 FATAL INJURY RATES CALCULATION METHODS

These data are the only data that directly measure the race of the pedestrian involved in a fatal crash and when paired with population data from Census are valuable to understand disparate injury outcomes. Fatal injury burden is measured using age-adjusted rates (Anderson & Rosenberg 1998) and is calculated using the counts of fatal injuries combined with population counts of people by age cohort for each race adjusted by using the US population as the standard population. Age-adjusted rates are important tools in the epidemiology because they account for the variability of age-specific mortality rates and make comparisons across geographies possible. These rates are calculated using the following equation:

$$\boldsymbol{\frac{D}{N} = \frac{\sum d_i}{N} = \frac{\sum n_i\,(d_i/n_i)}{N} = \sum(n_i\,/N)(d_i/n_i) = \sum w_i(d_i/n_i)} \qquad \textbf{(5-1)}$$

Where:

D = deaths (fatally injured pedestrians)

N = population (Oregon)

i = age-stratum

d_i = age-stratum specific deaths

n_i = age-stratum specific population

w_i = weights from standard population

These calculations are equivalent but when comparing Oregon-specific rates to other states for instance, the age-adjusted result should be used to account for age differences in the populations being compared. The results reported in this chapter present rates using person years which uses the total population over multiple years as opposed to the population for any one year. This principle of epidemiology aims to more accurately capture the time people are exposed to a given disease or health outcome, in this case pedestrian injuries. Compared to a single year of population, rates using person years will be lower but differences between groups, in this case race, will remain relatively stable.

Since most of Oregon's population is white, the number of pedestrians in BIPOC categories can be small for some time periods so rates are an important normalizer to help understand disparate outcomes. This research utilizes guidance that Oregon Health Authority's Health Promotion and Chronic Disease Prevention unit developed titled *Guidelines for Reporting Reliable Numbers* (2018). This guidance recommends that for individual strata at least 12 observations are available to report without a notice of caution for statistical reliability. Additionally, this guide recommends that if the calculated standard error exceeds 30% that readers are notified of the potential unreliability of the reported quantity (OHA 2018). This chapter follows that guidance by including the three instances where the standard error threshold is not met. These instances include the rates calculated for both periods of data for Native Hawaiian and Pacific Islander where counts of pedestrian injuries are very low. The third instance of unreliable estimates occurs for Black pedestrian rates in the 2009-2013 period where counts of pedestrian deaths are too small to accurately determine statistically significant differences compared to the state average. Margins of error are also shown which can help readers see where the precision of the calculated rate makes meaningful comparisons problematic.

Age-adjusted population-based rates are a measure of the burden on the population of a given health outcome, in this case the burden of fatal pedestrian traffic injury. Using FARS pedestrian injuries and population data from the Census for each age cohort, these rates can be calculated to understand whether disparities exist based on race. In addition to the age-adjusted rates, margins of error are presented which describe the confidence intervals of the fatal injury rates. Confidence intervals are measures of uncertainty associated with the age-adjusted injury rates (Burruss and Bray 2005). A large standard error and confidence interval reflect a less certain estimate. The size of these measures depends on the number of deaths (numerator) and the base populations (denominator) for each group. Large numbers of deaths and large base population lead to greater certainty in estimating age-adjusted death rates. These measures do not incorporate uncertainty associated with age misreporting or inconsistencies in racial and ethnic identification and do not attempt to handle issues of underreporting.

5.2 FATAL INJURY RATES BY RACE CATEGORY

The results presented in Figure 5.1 document the five-year fatal injury rates and highlight the disparate pedestrian fatal injury outcomes of BIPOC populations, with Black people facing the highest disparities in this period of data with 4.7 pedestrian fatalities per 100,000 people. Native Hawaiian and Pacific Islander (NHPI) people have a high rate but the low number of fatalities and base population results in a statistically unreliable rate. The next highest rate is for American Indian and Alaskan Native (AIAN) followed by Latinx and then Asian people with 3, 2.7, and 2.4 pedestrian fatal injuries per 100,000 people respectively. An aggregate rate was also calculated that aggregates all BIPOC fatalities and base population and shows that overall the pedestrian injury rate for BIPOC is 2.8 pedestrian fatal injuries per 100,000. The rates for all BIPOC populations (except for NHPI) are significantly (considering the confidence intervals) higher than the state average and higher than the rate for White people.

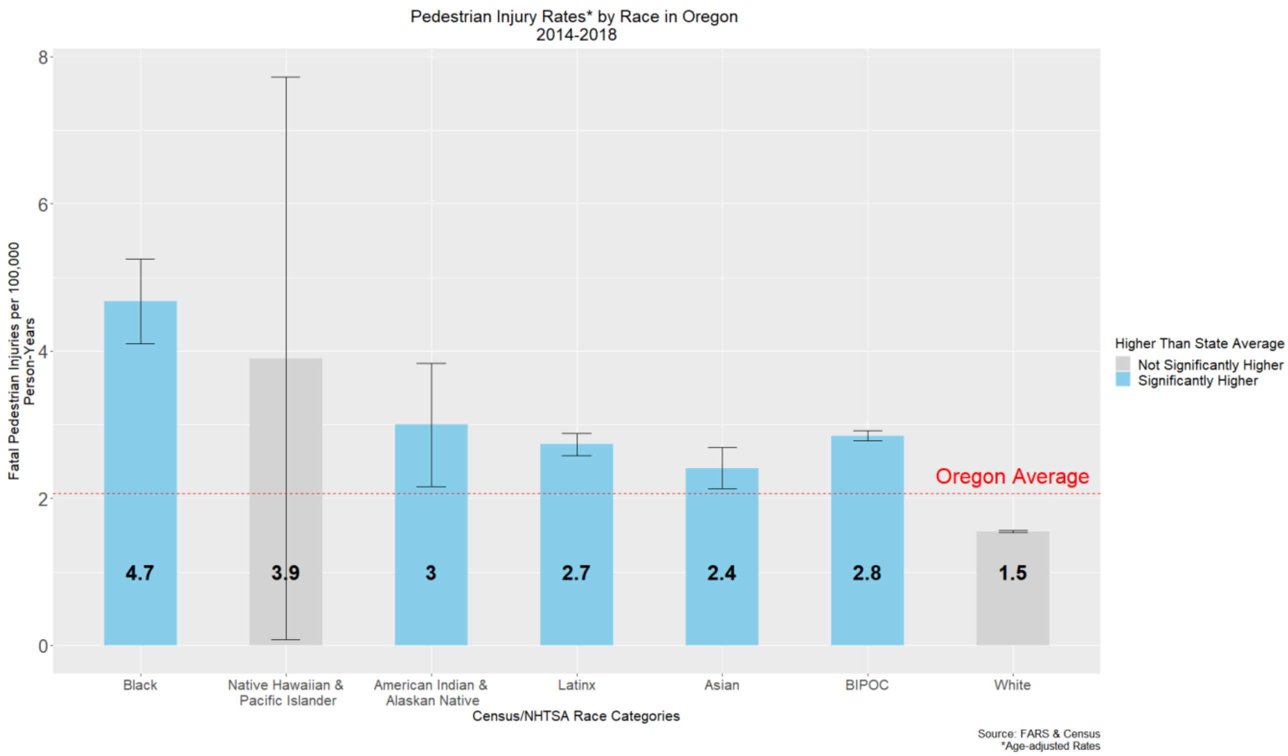

Figure 5.1: Age-adjusted fatal injury rates per 100,000 people 2014-2018

Though the rates show a significant disparity in the most recent data these rates vary over time. Figure 5.2 below shows two five-year periods including the years from 2009 to 2013 and 2014 to 2018. The mid-point for the rate is shown as text in the chart for clarity. American Indian and Alaskan Native populations exhibit a higher burden of pedestrian death in both periods with the disparity shrinking between periods. The pedestrian fatal injury rate for Asian populations was slightly lower (though not significantly) than the state average in the first period but increased in the second period to be higher than the state average. The rate for Black populations was at or near the state average for the first period but then increased too over two times the state average. The rate for Latinx populations was 33% higher than the state in the first period and increased to 75% higher than the state average the latter period. For Native Hawaiian and Pacific Islander populations there were no recorded pedestrian traffic deaths in the first period and so no reported rate and therefore this population has been masked from the figure. The rate for BIPOC population as a composite group 10% higher than the state average in the earliest period of data but then increases in the second period to be 15% higher in the latter period. The rate for White populations slightly lower than the state average in the first period with the difference growing into the second period.

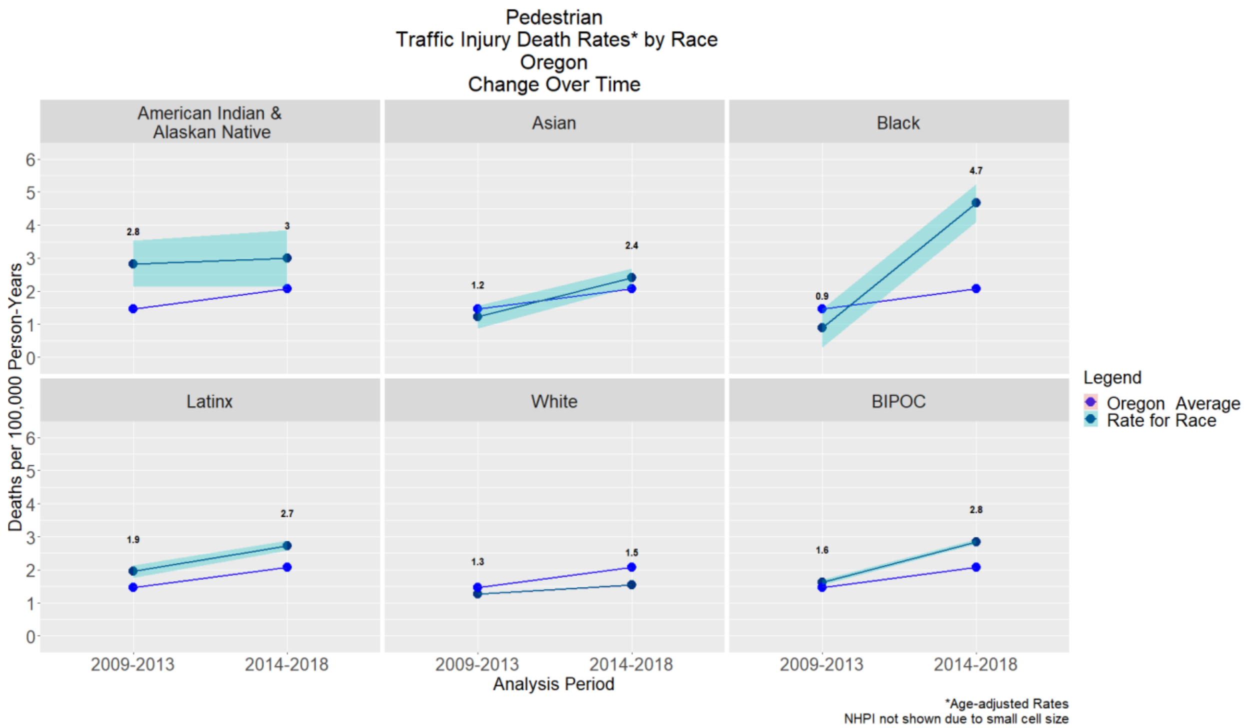

Figure 5.2: Age-adjusted fatal injury rates per 100,000 people over time

6.0 RACE, ETHNICITY AND INCOME INDEX ANALYSIS

This section uses a social vulnerability index to assess whether areas with higher proportions of low-income and / or BIPOC residents are subject to higher levels of pedestrian injury and fatality. The analysis also looks at whether these areas have differing built environment or traffic characteristics, such as higher speed and volume arterials, that are associated with pedestrian crashes. Key findings in this chapter include:

- Some Census tracts have significantly higher rates of poverty and BIPOC population
- Tracts with higher concentrations of poverty and BIPOC populations experience higher rates of pedestrian fatal and severe injury.
- Tracts categorized as High represent 25% of the state's population (1.002 million people) but 40% of the fatal and severe injuries and 45% of the total pedestrian injuries.
- The rates of pedestrian injury in tracts classified as Moderate and High have increased by 18% and 13% compared to 1% and 7% for tracts classified as Lowest and Low poverty and BIPOC population.

Many versions of composite indices exist that collapse multiple factors into a single index value with an aim to simply measures of social disadvantage or social vulnerability. The Centers for Disease Control (CDC) have constructed a Social Vulnerability Index (SVI) that employs 14 variables from the Census including proportion of people 17 years of age and below, people 65 years of age and above, single parent households with children 17 years of age and below, racial/ethnic minorities, and people living in group quarters, proportion of people below poverty level, unemployed, no high school diploma among people 25 years of age and above, people who have limited English proficiency, housing infrastructure with 10 or more units, households that have more people than rooms, mobile homes, no vehicle access, and per capita income.

The variables are used in the Race/Ethnicity and Income Index (REII) for this work and include the following measure:

- Poverty Rate - Percent of the population living at or below the poverty line
- BIPOC % - Percentage of the population that are American Indian or Alaskan Native, Asian, Black, non-White Hispanic, and Native Hawaiian or Pacific Islander

These population factors are used to calculate z-scores, or standardized scores to determine if the given measure is higher or lower relative to the mean of that value, in the case the statewide average. Z-scores are helpful tools for locating individual observations that differ significantly from the mean. Z-scores are based off of population metrics, meaning they represent where a particular value falls relative to the entire population, not the sample of interest. A positive Z-score means that a particular corresponding raw score fell above the population mean or average. A negative Z-score represents a raw score that falls below the population mean. The numerical value of the Z-score is actually the number of standard deviations above or below the mean, depending on the sign of the score. A Z-score in the middle of the normal distribution has a mean of 0 and a standard deviation of 0, meaning that the score falls in the exact center of the normal distribution (Frey 2018). Because Z-scores standardize the values for individual metrics (e.g. Poverty, % BIPOC, etc.) multiple metrics can be combined into an index. Z-scores are calculated for each metric using the following equation.

$$\boldsymbol{Z_{id}} = \frac{\boldsymbol{x_d - \mu_d}}{\boldsymbol{\sigma_d}} \tag{6-1}$$

Where:

Z is the standardized score for tract I for REII measure d

x is the REII measure for tract I for element d

μ is the average statewide value of REII measure d

σ is the standard deviation of the REII measure d

The index represents the composite score of the combined metrics by adding each z-score together. The resulting index measure shows how the select measures compare relative to the mean of the population (the state average). Based on the number of standard deviations from the mean, these composite index values are then grouped into lowest, low, moderate, and high social vulnerability based on their distance from the mean. For this research the thresholds for the low and moderate category were set slightly below the standard deviations to ensure these categories has adequate population and pedestrian injuries. Figure 6.1 shows where those cut points fall and how many census tracts are included in each of the REII categories.

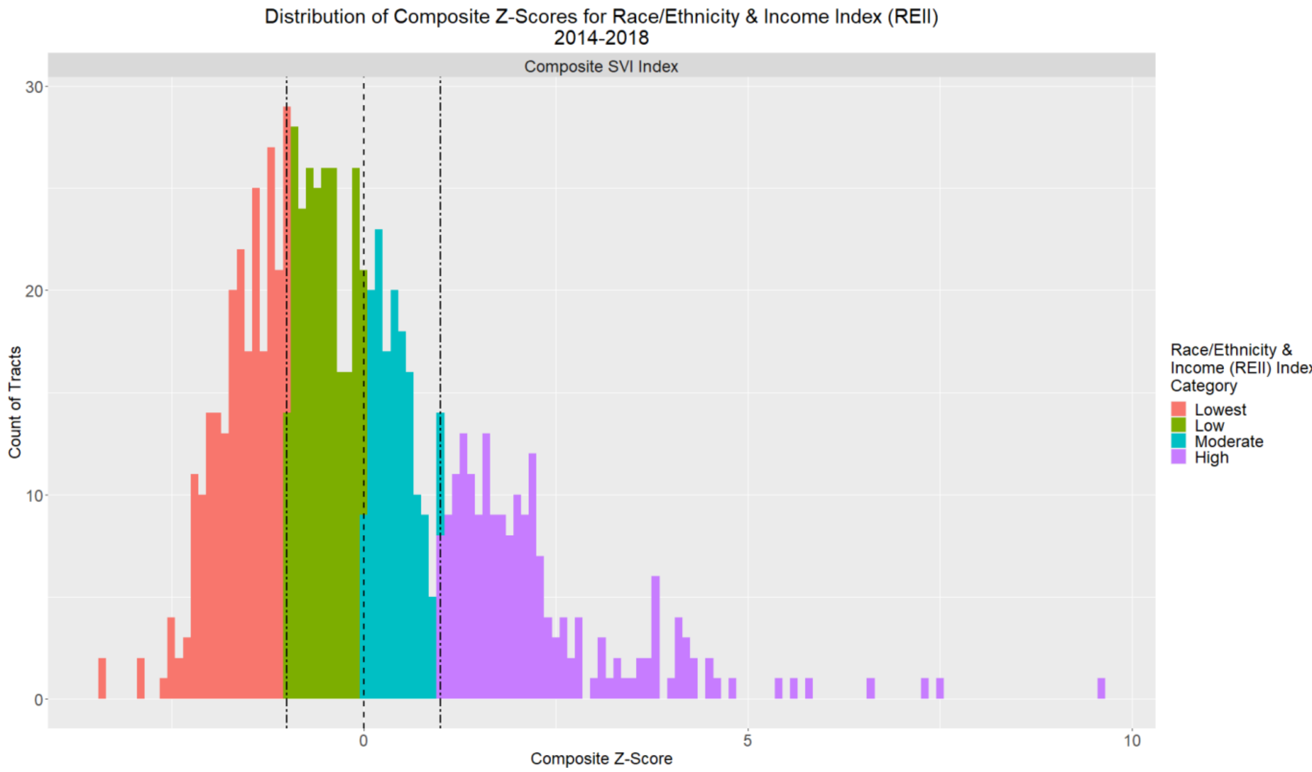

Figure 6.1: Distribution of composite Z-scores for social vulnerability index 2014-2018 data

Using the REII to categorize Census tracts in this way simply reveals where there are concentrations of people above and below the state average for the selected socio-demographics. Using these categories, relevant injury, travel, and built environment measures are summarized in Table 6.1 and shows how the REII elements relate to the overall categories. For instance, in the lowest REII category the average percentage of the population living in poverty, for all the tracts included in this REII category, is 8% while the average for the tracts designated as low, moderate, and high is 12%, 15% and 23% respectively. Compared to the statewide average poverty rate of 14% it is simple to see how the Z-score method uses the various data elements to categorize the tracts. For the BIPOC percentage by REII index, the average percentage of the population that is BIPOC in all tracts categorized as lowest, low, moderate, and high is 10%, 16%, 22% and 33% respectively compared to the state average of 20.

Table 6.1: Race/Ethnicity & Income Index Measures and Related Metrics Summary

Data Category	Measure	Race/Ethnicity & Income Index				Statewide
		Lowest	Low	Moderate	High	
Socio-Demographic & Population	% People Living in Poverty	8%	12%	15%	23%	14%
	% BIPOC	10%	16%	22%	33%	20%
	Population	1,139,724	1,165,118	774,907	1,002,194	4,081,943
Pedestrian Injury	Fatal & Severe Injury Rate	12.8	15.5	27.0	35.7	21.9
	All Injury Rate	54.4	78.9	129.3	203.8	112.3
	Fatal & Severe Injuries	146	181	209	358	894
	All Injuries	620	919	1002	2042	4583
	Average Fatal & Severe Injury	0.6	0.8	1.4	1.8	1.1
	Average Pedestrian Injury	2.6	3.8	6.5	10.5	5.5
Travel & Built Environment	Arterial VMT Density (Millions VMT per Sq. Mi.)	493,726	634,285	1,052,054	1,459,501	865,363
	Miles of 45 MPH Roadway per 100 Sq. Mi.	0.52	0.48	0.90	1.05	0.70
	Transit Stops per Sq. Mi.	12	18	28	42	24
	% Household without Vehicle	3.7%	5.9%	8.2%	12.3%	7.2%
	Walk, Bike and Transit Commute %	5.8%	9.0%	12.3%	16.3%	10.5%

Pedestrian injury data and data summarizing the travel and built environment of the tracts are also summarized in Table 6.1. Fatal and severe pedestrian injuries, as well as all injuries, are included. Even though only 25% of the total state population lives in the tracts designated as High in the REII, 40% of the fatal and severe injuries and 45% of the total pedestrian injuries occur in those tracts. These pedestrian injury outcomes are also expressed as a rate normalized by the total population in the tract. These rates show that for both injury categories (fatal & severe/ all injuries) rates are significantly higher in Moderate and High REII categories.

The travel and built environment data summaries shed some light as to why these disparities in pedestrian injury outcomes may be occurring. Arterial vehicle miles traveled (VMT) density and miles of roadway with a posted speed limits of 45 miles per hour (MPH) or greater are shown in order to describe the vehicle travel exposure that people living and working in these tracts experience. The arterial VMT density is significantly higher in the tracts classified as High in the REII compared to the Lowest and Low REII categories and also higher than the statewide average. The number of miles high speed roadway is also higher in the Moderate and High REII tracts compared the Lowest and Low tracts. Together these measure of VMT and speed suggest that tracts designated as Moderate and High in the REII experience more arterial VMT and that VMT is typically higher speed compared to tracts in the other REII categories.

Other ecological studies we reviewed for the literature review confirm that areas with more arterial roads, higher speeds, and higher volumes are associated with more and higher severity pedestrian crashes. Six studies looked at the miles or proportion of arterial roads. Four found that higher proportions of arterials (Wier et al 2009), or more miles of arterial roads (Abdel -Aty et al 2013; Dumbaugh and Li 2010; Guerra et al 2019), were associated with more pedestrian crashes. Two others found that higher proportions of lower speed or local roads were associated with fewer pedestrian crashes (Lin et al 2019; Ukkusuri 2012). Five studies looked at average vehicle speeds, with four finding that higher average speeds were associated with more pedestrian crashes (Chimba et al 2014; DiMaggio 2015; Guerra et al 2019) C and /or increased injury severity (Guerra et al 2019; Yu 2015). One looked at maximum speed limit (Dai and Jaworski 2016) and found it to not be significant. Of 11 studies looking at traffic volumes, such as VMT or AADT density, seven found that higher average traffic volumes levels were associated with more pedestrian crashes (Cottrill and Thakuriah 2010; DiMaggio 2015; Guerra et al 2019; La Scala 2000; Loukaitou-Sideris et al 2007; Mansfield et al 2018; Wier at al 2009). Four studies did not find volume to be significant (Dumbaugh and Li 2010; Kim 2019; Yu 2014;Yu 2015).

The number of transit stops, percent of households without a vehicle, and the percentage of workers using walk, bike, and transit to commute to work are summarized by REII in Table 6.1 to demonstrate that people living and working in these tracts are more exposed to the high volume, high speed traffic conditions. The number of transit stops is nearly double the state average in tracts designated as high in the REII, as and nearly four times higher than in tracts classified as Lowest in the REII. Additionally, 16.3% of workers in tracts classified as High in the REII commute to work by walking, biking or using transit compared to just 5.8% in the lowest category and 10.5% statewide. Lastly, the percentage of households without a vehicle in the High REII category is 12.3% compared to just 3.7% in the lowest category and 7.2% statewide. Vehicle-less households are more likely to use other modes of travel such as walking and transit. Taken together these data summaries demonstrate the likely amount of pedestrian exposure in tracts within each of the REII categories. Tracts categorized as High in the REII have higher number of transit stops and workers using either walk, transit or a bike to commute meaning they are likely more exposed to vehicle traffic and contributes to higher numbers of pedestrian injuries in these tracts.

A key objective of this research seeks to know if pedestrian injury disparities are growing or shrinking. In order to measure these outcome changes over time, we use the REII approach to compare two separate period of data, including the 2008 to 2012 five-year period and the 2014 to 2018 five-year time period. Population based injury rates are calculated for each REII category the fatal and severe injury rates are shown in Figure 6.2 while the total pedestrian injury rates are shown in Figure 6.3.

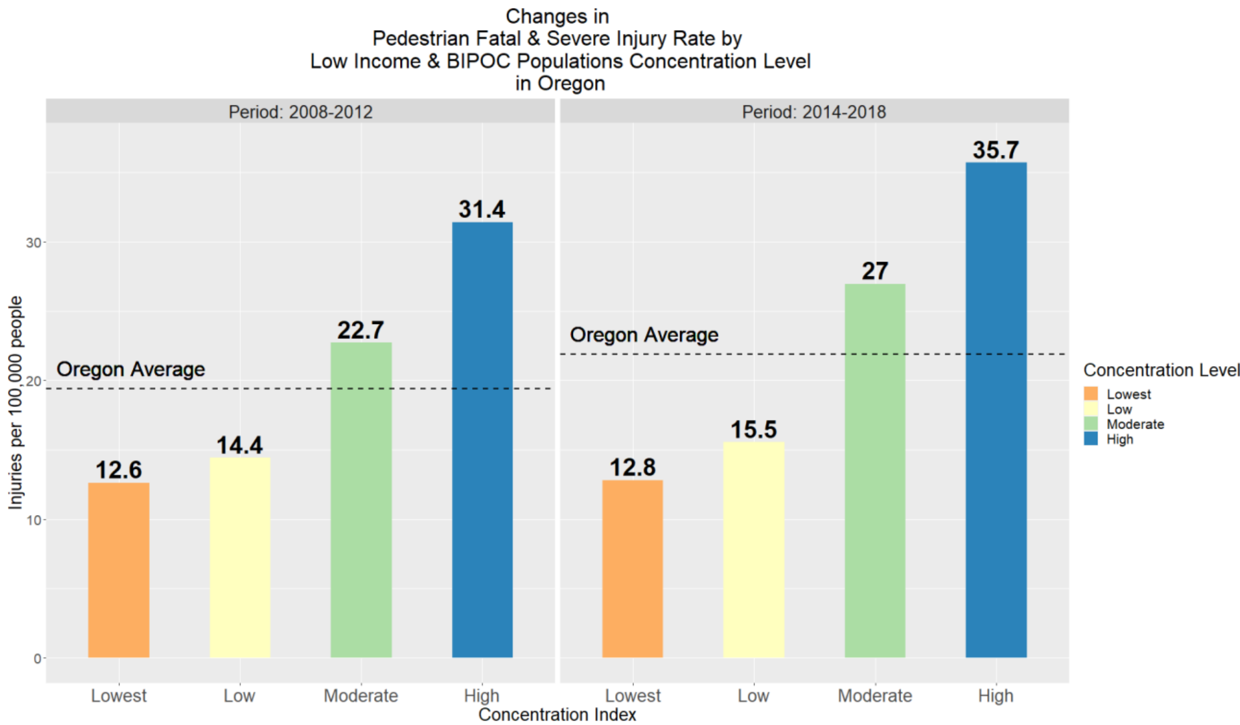

Figure 6.2: Pedestrian fatal & severe injury rate period comparison

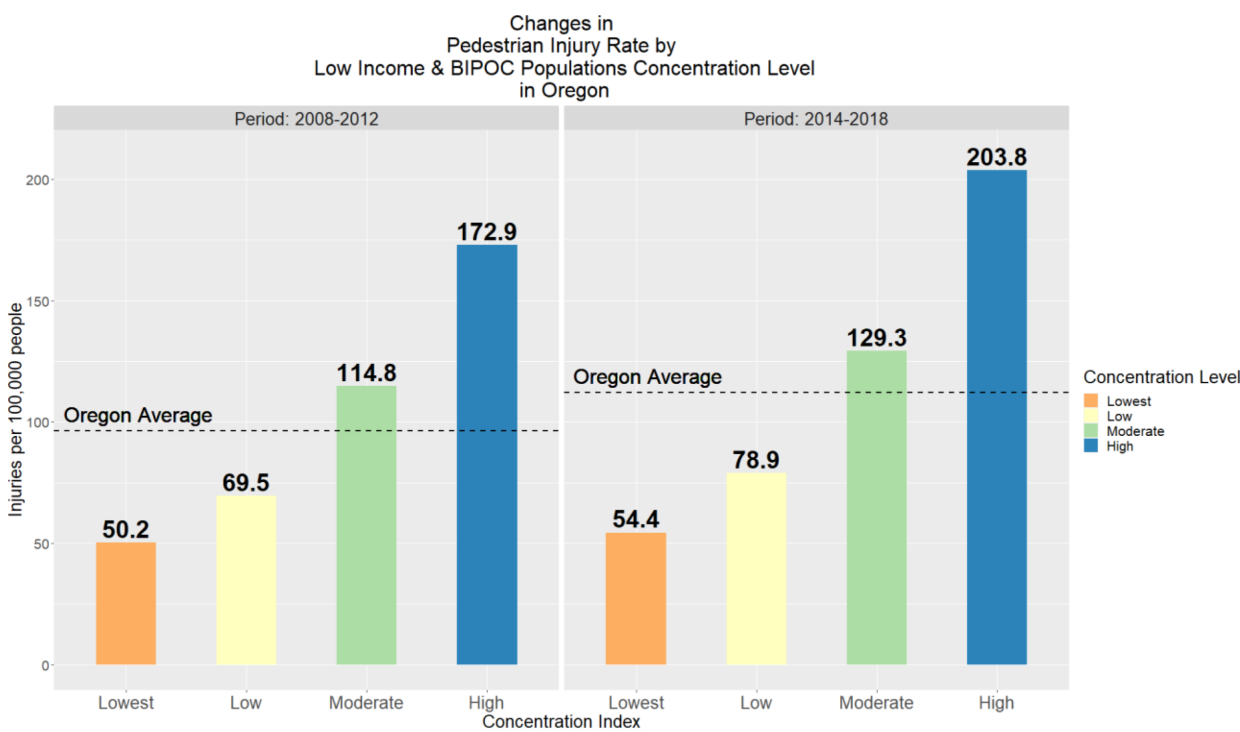

Figure 6.3: Pedestrian total injury rate period comparison

Figure 6.2 and Figure 6.3 show that for all REII categories, and for both injury severity categories, the injury rate has increased over the two time periods. The rate of increase has not been equal across REII categories however, with the fatal and severe injury rate increasing by 14% in the High REII while the Lowest REII category only increased by 2%. For the total injury rate the tracts categorized as High REII increased by 18% while the Lowest REII tracts only increased by 8%. So even though the pedestrian injury rate grew across the state the increase was higher in High REII tracts compared to the Lowest REII tracts.

The analysis featured in this section informs the analysis in Chapter 7.0 that will use a variety of statistical analysis tools to better capture the effects of built environment, traffic exposure, race, ethnicity, and income on pedestrian injury outcomes. The results presented above show that tracts with higher concentrations of people of color and low-income people have higher rates of pedestrian injuries for all injury severities. Likely contributors to these disparate outcomes are that BIPOC communities and low-income communities have more exposure to high vehicle volumes moving at higher speeds. Based on the REII summaries above, people and workers in these High and Moderate REII tracts also travel by foot, transit, and bicycle at a higher rate which increases their exposure to the high volume, high speed roads. The analysis in Section Chapter 7.0 analyzes the relationships between the built environment, traffic exposure, race, ethnicity, and income to more precisely understand the role these factors play in pedestrian injury outcomes.

7.0 OREGON EMERGENCY MEDICAL SERVICES INFORMATION SYSTEMS (OR-EMSIS) ANALYSIS

This chapter utilizes traffic crash incident data collected by Emergency Medical System (EMS) providers in Oregon to understand pedestrian incidents and the dynamics between home and incident location. Key findings in this chapter include:

- Based on Oregon EMS traffic incident data, half of pedestrian incidents occurred within 1.06 miles from the crash participants home. This result is consistent with past findings in Hass et al (2015) and Anderson et al. (2012).
- Half of pedestrians 15 years of age or younger are involved in a traffic related incident within 0.32 miles from their home
- Half of pedestrians 65 years of age or older are involved in a traffic related incident within 0.82 miles from their home
- Based on the Oregon EMS traffic incident data, 60% of pedestrian incidents occur within their home tract (38%) or a neighboring tract (22%).
- For pedestrians that live in a Census tract with high poverty and concentration of BIPOC population, 70% are struck in a tract that is also high poverty and high BIPOC concentration.

These data are reported to a centralized database called Oregon Emergency Medical Service Information System (OREMSIS). These data represent a sample of the crashes since it doesn't represent the universe of crash data in Oregon. However, since these data include the home address of the crash participant they are useful data for answering questions about the distance from home that pedestrian injuries occur and the likelihood that a pedestrian injury participant is injured in their home tract, a neighboring tract, or a tract more distance from their home.

7.1 DISTANCE BETWEEN HOME AND INCIDENT LOCATION

The OR-EMSIS data include 9,278 records that have reliable incident and home location information to use in the analysis featured in this chapter. These include 888 records where the traffic incident participant was a pedestrian which comprises 12.3% of the total EMS records. These incidents occurred in the years 2017 through 2019. The distance between the incident and the home location are calculated using the Euclidean distance and is presented in miles. Incidents from crash participants that lived outside the state are included. A map of the of the incident location, home location, and straight -line distance for the Salem urban area are featured in Figure 7.1 below to show how this calculation process looks spatially.

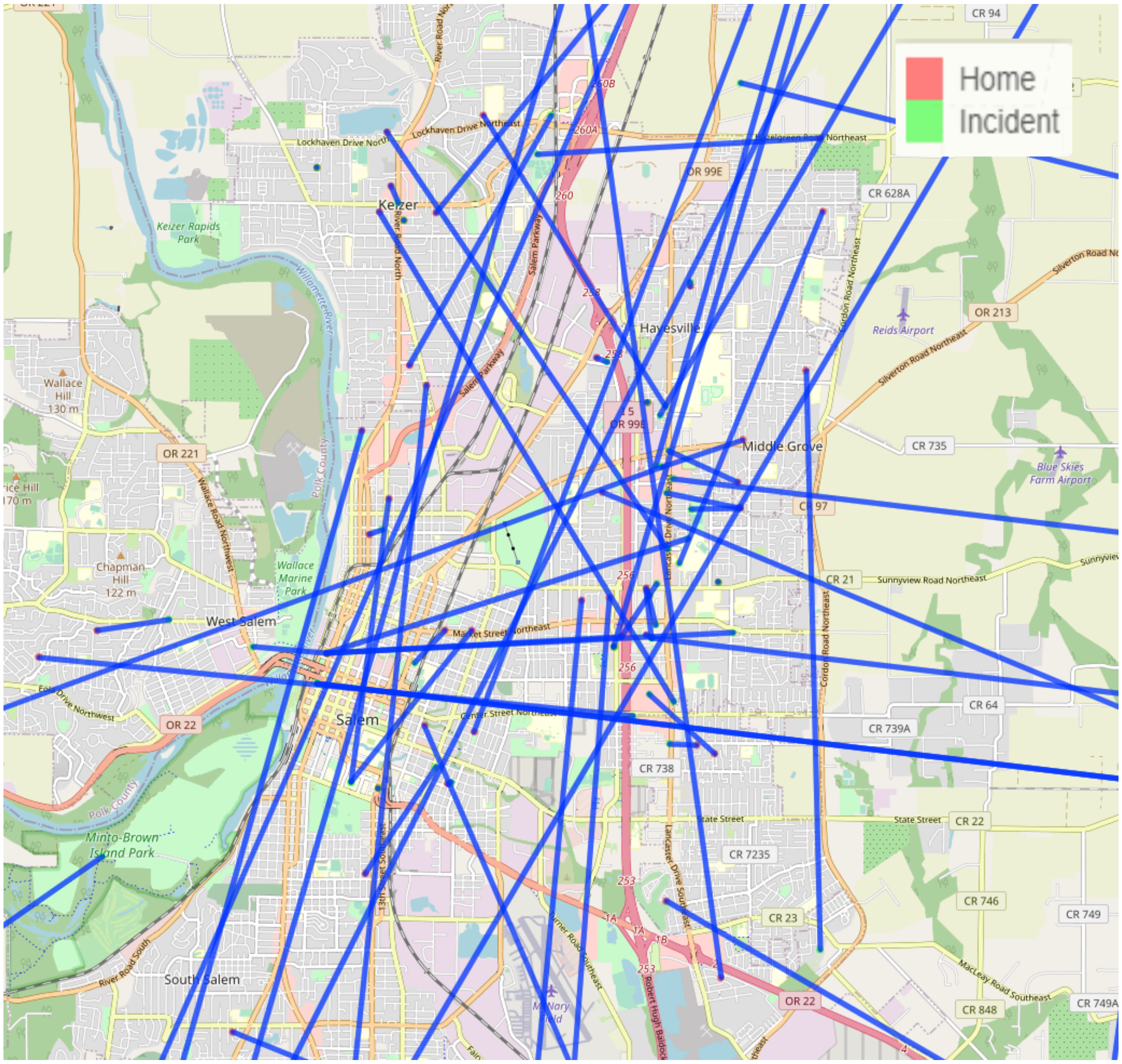

Figure 7.1: Incident and home locations for pedestrian incident participants – Salem, OR urban area

Using these calculated distances for all modes the table below summarizes the distance from that incidents occur for each mode included in the dataset. For pedestrian participants the median distance from home is 1.0 miles meaning that half of all pedestrians in these data are injured 1.06 miles from their home. This result is similar to what past research has found where one study (Haas et al., 2015) found that half of pedestrian injuries occur within 1.1 miles from the victims home, while another (Anderson et al., 2012) found that half of pedestrian injuries occur within 1 mile from home. Anderson et al. found that for children and the elderly, the injury distance from home was even shorter with half the injuries occurring within a half-mile of the victim's home. The distances for the other modes seem reasonable with heavy vehicle (freight) users showing the longest distance from home across most summary statistics followed by motorcycle, transit, all-terrain vehicle (ATV), and finally vehicle. For bike participants, half of all incidents occurred within 1.7 miles of the participant's home.

Table 7.1: Summary Statistics for Incident Distance from Home by User Type

				Distance Summary			
User Type	**Records**	**1st Quartile**	**Median**	**3rd Quartile**	**Mean**	**Max**	**Std. Dev.**
ATV	529	0.51	4.4	20.8	59.0	2429	221
Bike	741	0.32	1.7	5.7	55.1	2683	275
Heavy vehicle	42	2.12	20.8	100.3	208.5	2351	520
Motorcycle	624	1.72	6.3	20.4	43.6	2453	172
Pedestrian	888	0.12	1.06	4.6	34.5	2710	211
Transit	43	1.36	5.0	13.2	16.1	187	37
Vehicle	4541	1.07	3.6	10.5	37.3	2599	194

As was noted in Anderson et al. (2012), the distance from home varies by age of traffic incident participant. The distance between home and incident location by age of incident participant is summarized in Table 7.2. This table shows that for people ages 15 and under, half of all crash participants are involved in an incident within 0.3 miles from home while 16-24 year olds are higher with median distance of 1.45 miles. The next age group, 25-64 the median distance is 1.2 miles and for seniors aged 65 and older 0.8 miles.

Table 7.2: Summary Statistics for Incident Distance from Home by Age for Pedestrian Users

				Distance Summary			
Age Group	**Records**	**1st Quartile**	**Median**	**3rd Quartile**	**Mean**	**Max**	**Std. Dev.**
0-15	98	0.03	0.32	2.18	22.1	1643	167
16-24	151	0.33	1.45	4.10	39.0	2710	263
25-65	506	0.12	1.18	6.77	43.5	2319	228
65+	122	0.06	0.82	2.54	4.1	119	13.7
Unknown	11	0.00	1.25	3.04	2.6	10.2	3.47

The last summary of the home and incident location distance data is presented in Table 7.3 and shows the summary statistics for urban areas that recorded at least 10 participants. This table also includes participants with home locations outside Oregon urban areas and are titled 'Rural/Non-Oregon Home' in the table below. These records are for Bend has the shortest median distance of 0.02 and 3rd quartile distance of 0.90 miles while Salem has the longest median distance of 1.52 miles. The participants living in rural areas have the longest distances from home of 3.85 miles with significantly higher 3rd quartile and maximum values of 1,760 miles. These longer distance are due to five incident participants that lived outside of Oregon with one participant residing as a far as Illinois. For context, the mean and median land area for urban Census tracts is 1.6 and 1.1 square miles respectively.

Table 7.3: Summary Statistics for Incident Distance from Home by Urban Area

				Distance Summary			
Home Urban Area	**Records**	**1st Quartile**	**Median**	**3rd Quartile**	**Mean**	**Max**	**Std. Dev.**
Albany	12	0.00	0.24	0.60	1.0	7.71	2.19
Bend	16	0.00	0.02	0.90	1.3	15.5	3.82
Corvallis	11	0.38	0.99	2.27	7.3	68.1	20.2
Eugene	19	0.08	1.25	2.84	4.5	48.8	11.1
Grants Pass	30	0.25	0.46	1.33	1.0	8.03	1.55
Hermiston	11	0.50	0.93	3.46	5.5	42.7	12.5
Medford	26	0.00	0.86	2.64	12.2	156	36.2
Portland	475	0.12	1.10	3.93	4.6	193	15.7
Redmond	11	0.54	1.29	4.70	4.3	18.1	6.16
Salem	47	0.31	1.52	5.15	11.6	174	29.8
Rural/Non-Oregon	96	0.11	3.85	14.9	44.4	1,760	211
All Pedestrians	888	0.12	1.06	4.6	34.5	2,710	211

7.2 TRACT TO TRACT ANALYSIS - HOME AND INCIDENT LOCATION DETAILS

The ability to know the home and incident location also allows for understanding how often people are involved in a crash in their tract in which they reside or a tract that they don’t reside in but is nearby. With half of all pedestrian injuries occurring within 1.0 miles from home it would be expected that many injuries happen in a neighbor tract. The table below shows that for the 888 pedestrian incident participants, 38% are injured in their home tract and 60% are injured in their home tract or a neighboring tract. The other modes are shown for context and show motorcycles and heavy vehicle participants are the least likely EMS incident participants to be in their home tract when involved in a crash. For bicycle incidents, 32% of participants were in their home tract when they reported the incident and 53% were injured in their home tract or a neighboring tract.

Table 7.4: Summary of Tract Location of Incident

User Type	Incident in Home Tract		Incident in Tract Neighboring Home Tract		Incident in Home Tract or Tract Neighboring Home Tract		Total Incidents
	Count	%	Count	%	Count	%	
ATV	171	33%	82	16%	172	48%	523
Bike	239	32%	148	20%	241	53%	738
Heavy vehicle	9	23%	4	10%	9	33%	40
Motorcycle	122	20%	121	20%	122	39%	617
Pedestrian	336	38%	198	22%	350	60%	888
Transit	16	39%	9	22%	16	58%	41
Vehicle	1,116	25%	1,112	25%	1,130	50%	4502

The Census tract for the home and incident location is obtained by spatially overlaying the 2010 Census tract boundaries for Oregon. In order to highlight how the tracts classified in the REII Index form groups of tracts within the same category which then makes people residing in any one designation likely to be in a similar index value when involved in an EMS report traffic incident. The table shows that of the 835 pedestrian EMS incidents 318, or 37%. These results are similar to those presented in Chapter 4 where ODOT pedestrian injury data was used and showed that 40% and 45% of fatal and severe injuries and all pedestrian injuries respectively, occur in high poverty, high BIPOC communities.

The strength of the data summary below is to show what the REII designation is for the home and incident tract. We would expect that because half of pedestrians are injured within 1.0 miles of their home and the REII index tracts cluster spatially there would be more similarity between home REII and incident REII values. Table 7.5 shows that the most common home and incident tract pair is to live in a home tract with high poverty and BIPOC and to be struck in a tract with High REII index value tract with 26% of the total 854 incidents. In fact, of the 318 incidents in tracts classified as High, 223, or 70% had both lived in a home tract that is classified as High and were struck in a census tract classified as High by the REII Index. The next highest home and tract combination is Moderate home and Moderate Incident location with 13% of the total pedestrian incidents. For pedestrian incident participants living in tracts classified as Moderate Poverty and BIPOC concentration, 22% were involved in an incident in a tract classified as High.

The other categories show a strong tendency toward being struck in a tract that is similarly designated as the home tract. Of the pedestrian incidents in tracts classifies as Lowest (8% Poverty & 10% BIPOC), 55% occurred in tracts classified as Lowest while for pedestrian incidents in tracts classified as Low (12% Poverty & 16% BIPOC), 56% also live in a tract classified as Low.

Table 7.5: Summary of REII Index Value of Home and Incident Location

Race. Ethnicity & Income Index					
Home Tract	**Incident Tract**	**Count**	**% of Total incidents**	**% of Home Tract Total**	**Total for REII Index**
Lowest	Lowest	88	10%	55%	159
	Low	26	3%	16%	
	Moderate	19	2%	12%	
	High	26	3%	16%	
Low	Lowest	15	2%	9%	174
	Low	98	11%	56%	
	Moderate	22	3%	13%	
	High	39	5%	22%	
Moderate	Lowest	20	2%	10%	203
	Low	29	3%	14%	
	Moderate	109	13%	54%	
	High	45	5%	22%	
High	Lowest	18	2%	6%	318
	Low	25	3%	8%	
	Moderate	52	6%	16%	
	High	223	26%	70%	

The chart in Figure 7.2 attempts to represent the frequency of the home and incident tract REII pairs. This figure shows for instance, how many of the 854 EMS pedestrian incidents have participants that reside in tracts classified as High (Poverty and BIPOC) and are involved in an incident in a tract classified as High. As described in the table above, 223 pedestrian incidents have a participant that resides in a census tract classified as High and are involved in an incident where the tract is classified as High.

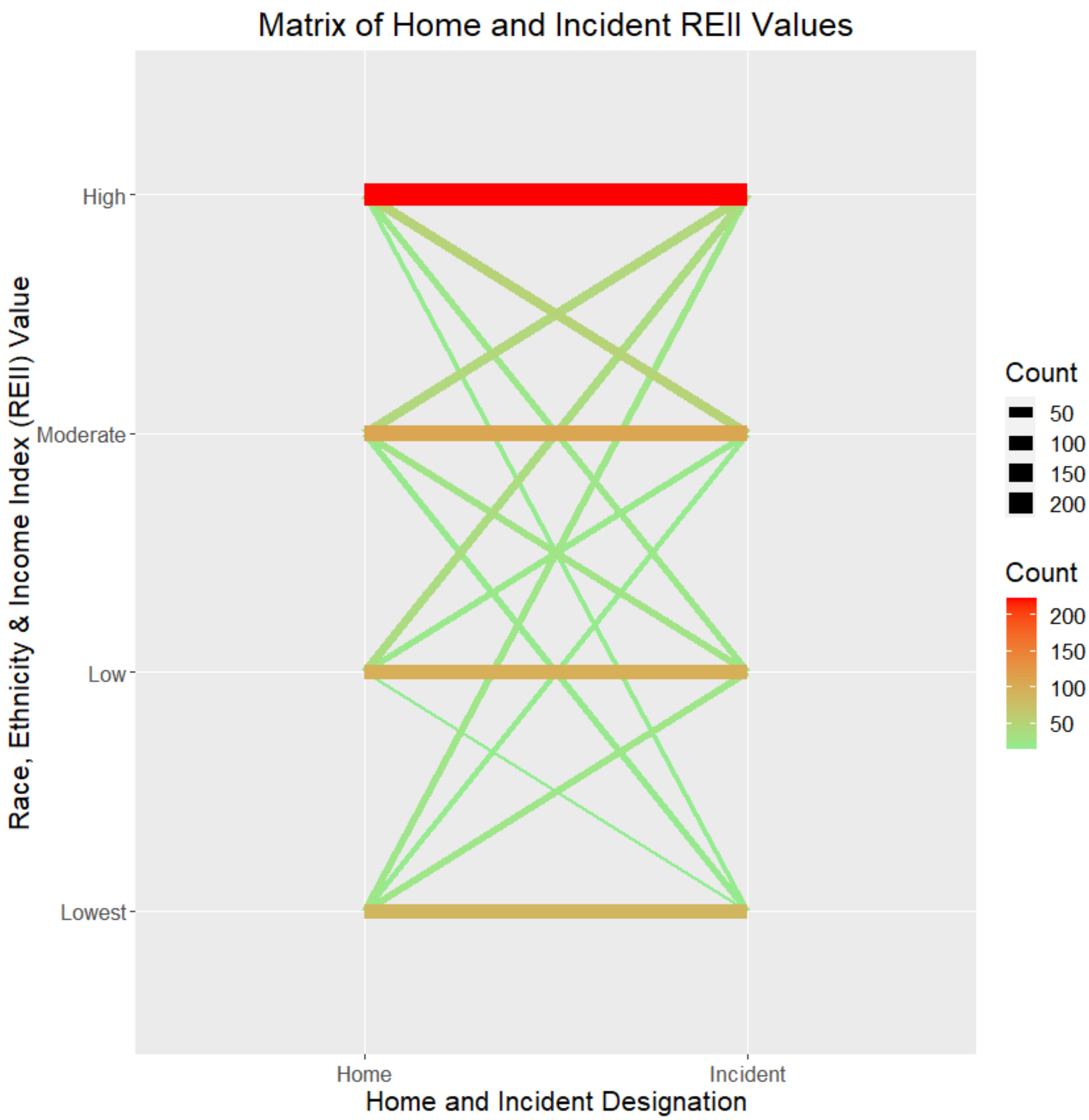

Figure 7.2: Matrix of home and incident location REII index values

7.3 OR-EMSIS DATA ANALYSIS DISCUSSION

This chapter is meant to address questions that TAC members have raised about the relationship between the home and incident locations of pedestrian injury participants. These questions include:

- What is the typical distance from home that pedestrian incidents occur?
- How often are people in the tract in which they reside or a neighboring tract?

- How does the race, ethnicity and income composition of their home tract compare with race, ethnicity and income composition of the incident tract?

In summary, based on pedestrian incidents reported to OR-EMSIS database, half of all pedestrians are struck within 1.06 miles of their home which is within the distance measures reported in the literature. The tracts level analysis shows that 38% of pedestrians are struck within their home Census tract while another 22% are struck in the neighboring Census tract. Using the REII index values, this chapter highlighted that for pedestrians struck in high poverty tracts with high concentrations of BIPOC, 70% also live in a high poverty, high BIPOC Census tract.

8.0 URBAN CENSUS TRACT STATISTICAL ANALYSIS

This section develops statistical models to better understand the association of sociodemographic, built environment, and traffic exposure factors with pedestrian injury counts at the Census tract level in Oregon. The analytic approach featured in this chapter uses Census tracts as the unit of analysis and measures various built environment and traffic exposure measures as independent variables in a statistical model where pedestrian injuries are the response variable. Both rural and urban models were considered but this report only documents the results for Census tracts considered urban. In addition to the built environment and traffic exposure variables, various measures of race, ethnicity, disability status, English proficiency, and income will be included to determine whether there are measureable effects from these variables even when controlling for the other contributing factors. Two measures of pedestrian injury are analyzed including the count of fatal and severe injuries in a tract as well as the total count of pedestrian injuries of all severities including fatal, severe, moderate, and minor injuries.

Key findings in this chapter include:

- Median income of the Census tract is negatively associated with pedestrian injuries, meaning that the lower the tract's income the higher the number of pedestrian injuries. These results are consistent with findings from Mansfield et al. (2018), Dai and Jaworski (2016), DiMaggio (2015), Jermprapai and Srinivasan (2014), and Cottrill and Thakuriah (2010).

- Percent of the tract population that is BIPOC is positively associated with pedestrian injuries, meaning that the higher the percentage of the population that is BIPOC the higher the number of pedestrian injuries. These results are consistent with findings with findings from Apardian and Smirnov 2020, Lin et al 2019, Guerra et al. (2019), Mansfield et al. (2018), Chimba et al. (2014), Abdel-Aty et al(2013), and Loukaitou-Sideris et al (2007).

- When disaggregate measures of race and ethnicity were used, variation in the risk factors were measured with percent Asian exhibiting a bigger positive effect on pedestrian injuries than percent Latinx, albeit with greater range of effect as measured in the confidence intervals.

- Race and ethnicity were less stable for the fatal and severe models but consistent predictors of pedestrian in total pedestrian injury models.

- Arterial vehicle miles traveled density and miles of roadway with a posted speed limit of 35 mph or greater are correlated with higher pedestrian injuries. These results are consistent with findings from Abdel -Aty et al (2013), Dumbaugh and Li (2010), Guerra et al. (2019).

- The percentage of workers using transit and the number of transit stops are both correlated with an increase in pedestrian injuries. These results are consistent with findings from Chimba et al. (2014), Cottrill and Thakuriah (2010), Lin et al. (2019) and Mansfield et al. (2018).

- Low wage job density is correlated with higher pedestrian injuries but total job density was associated with fewer pedestrian injuries. These results are consistent with findings from Guerra et al. (2019), Jermprapai and Srinivasan (2014), Loukaitou-Sideris et al (2007) and Wier et al (2009) and Mansfield et al. (2018).

- Alcohol establishment density was found to be positively associated with an increase in pedestrian injury. These results are consistent with findings from DiMaggio et al. (2016), Nesoff et al. (2018), Nesoff et al. (2018).

- Mixed effects and fixed effects models are evaluated using 10-fold cross validation and show mixed effects specifications have higher predictive accuracy.

8.1 MODEL SPECIFICATION AND VARIABLE SELECTION

Multiple regression model approaches have been used in past research to assess the relationship between pedestrian injury and Census tract characteristics. This section describes the process used to determine the model forms used in this chapter. Because the pedestrian injury counts are overdispersed and zero counts are not excessive, this research utilizes a negative binomial model with random effects parameters though tests a fixed-effects form as well.

Selection of the appropriate model depends on the nature of the data. Ordinary least squares (OLS) regression is appropriate when data are normally distributed but most crash data are not-normally distributed and typically reflect a Poisson distribution with overdispersion. Overdispersion exists when the response variance is larger than the mean. If overdispersion is not properly accounted for standard errors can be deflated and predictors may appear statistically significant when in fact they are not significant (Hilbe 2011). The pedestrian fatal and severe injury counts and total pedestrian injury counts data are charted below in Figure 8.1 and Figure 8.2 in order to visually inspect the distributions of pedestrian injuries. The charts have two panels, one for tracts classified as rural and the second panel are showing tracts classified as urban.

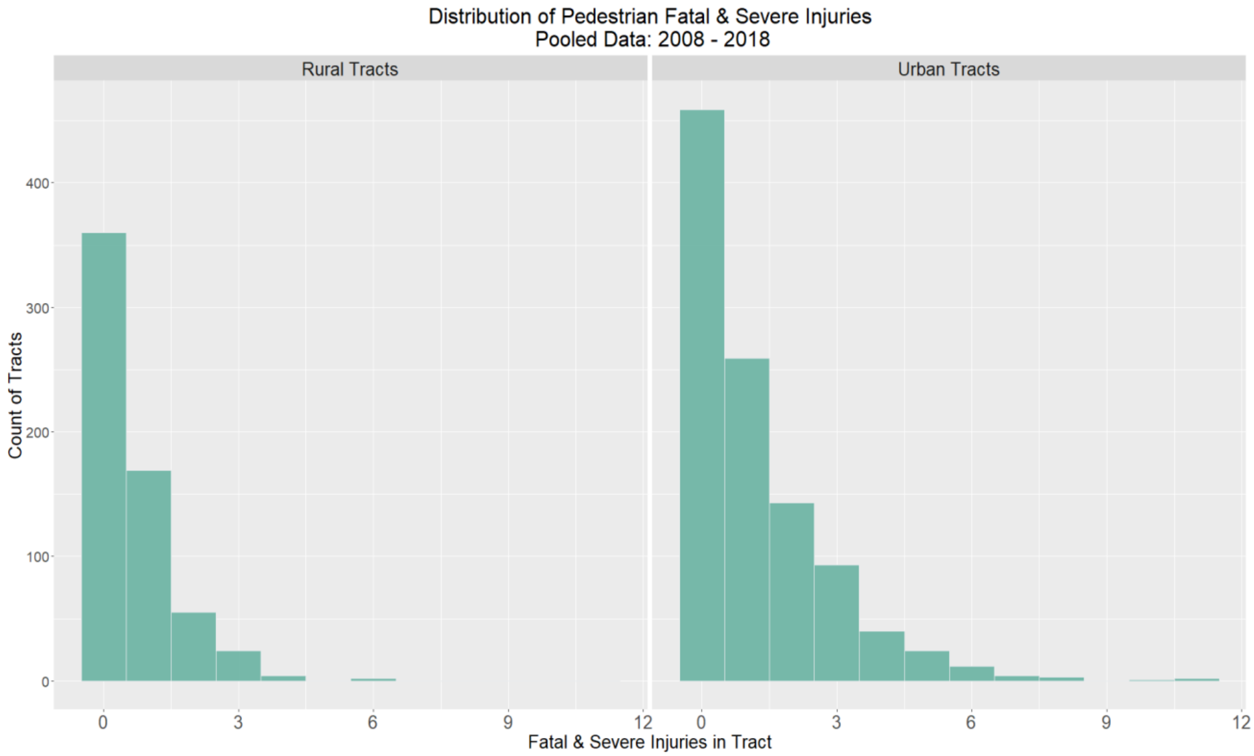

Figure 8.1: Pedestrian injury rate period comparison

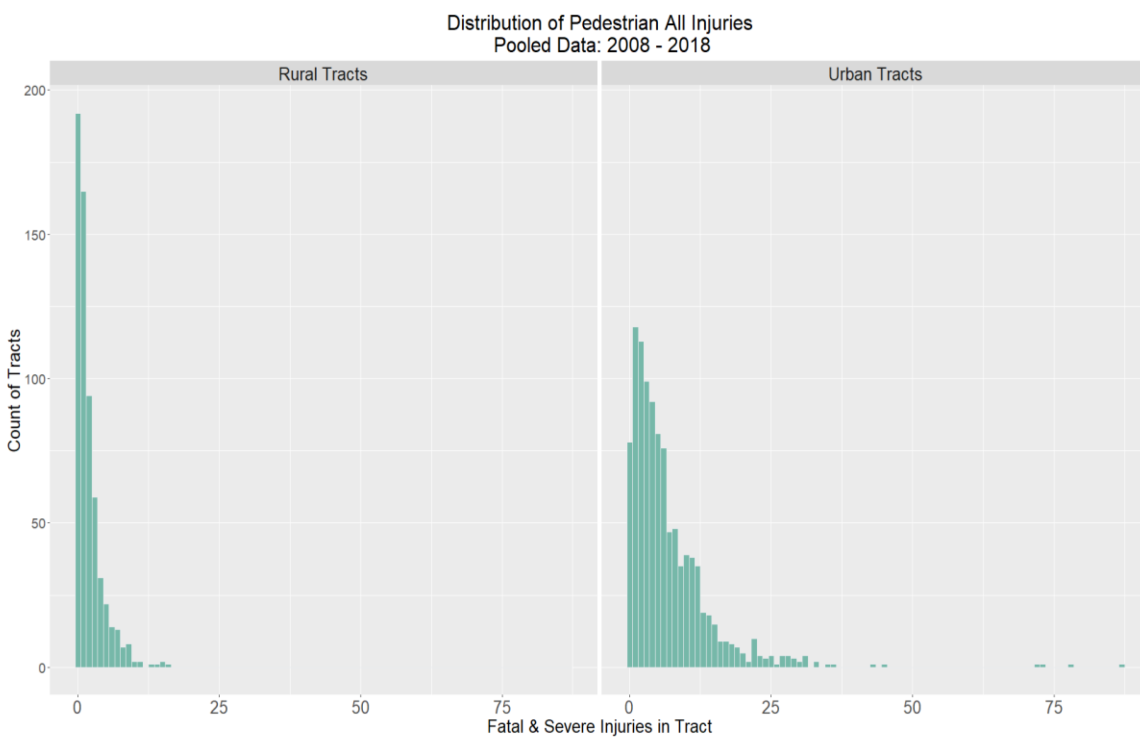

Figure 8.2: Pedestrian injury rate period comparison

In addition to visual inspection of the pedestrian injury data, the mean and variance as well as the overdispersion parameter are summarized in Table 8.1 below. The overdispersion parameter is calculated using the method developed by Cameron and Trivedi (1990) where the null hypothesis of equidispersion is tested in a Poisson model against the alternative of overdispersion and/or underdispersion. Values significantly larger than one are considered overdispersed. The R function *dispersiontest* from the AER (Kleiber & Zeileis 2008) package are used to calculate this quantity and to test for significance at the 0.05 level. For urban tracts, all periods of data for both injury severity categories reveal overdispersion but for rural tracts, equidispersion was measured for fatal and severe injuries in the 2008-2012 and 2014-2018 periods. This research report only models urban tracts but if rural tract models are estimated using these periods of data and injury severity, a Poisson model may be more appropriate than the negative binomial model.

Table 8.1: Pedestrian Injury Variance, Mean and Overdispersion Parameter Measures by Period and Urban/Rural Designation

Urban/Rural Tracts	Variance	Mean	Overdispersion Parameter	Severity	Period
Urban	1.86	1.06	1.19	Fatal & Severe Pedestrian Injury	2008-2012
	3.00	1.36	1.44		2014-2018
	2.45	1.21	1.37		Pooled
	49.60	6.03	2.96	Total Pedestrian Injury	2008-2012
	70.10	7.63	3.32		2014-2018
	60.42	6.83	3.40		Pooled
Rural	0.83	0.63	1.02*	Fatal & Severe Pedestrian Injury	2008-2012
	0.83	0.60	1.14*		2014-2018
	0.83	0.62	1.12		Pooled
	5.33	1.84	1.64	Total Pedestrian Injury	2008-2012
	6.39	2.01	1.91		2014-2018
	5.86	1.93	1.85		Pooled

Since crashes are rare events another potential issue in crash counts data is an overabundance of zero counts in the data. Negative binomial regression models underperform when the data features an excessive number of zeroes in which case a zero-inflated negative binomial should be considered. Dong et al. (2014) suggests that if 65% or more of the data's observations are represented by zeros, then a zero-inflated model should be used.

Table 8.2 below summarizes the number of tracts that experiences zero pedestrian injuries summarized by urban and rural designations as well as by analysis period. The table shows that no analysis period or urban and rural designation meets the 65% threshold for employing a zero inflated model. Because of the overdispersion featured in this data and because there is not an overabundance of zeroes in the data, a negative binomial specification will be used in the analysis of these data below.

Table 8.2: Count of Tracts with Zero Pedestrian Injuries

Urban/Rural Designation	Analysis Period	Tracts with Zero Counts of Injury		Total Tracts	% of Tracts with Zero Counts of Injury	
		Fatal & Severe	All Injury		Fatal & Severe %	All Injury %
Rural	2008-2012	179	101	307	58.3%	32.9%
	2014-2018	181	91	307	59.0%	29.6%
Urban	2008-2012	236	43	520	45.4%	8.3%
	2014-2018	223	35	520	42.9%	6.7%

Many crash analyses using count data assume that the parameters have fixed effects and do not address unobserved heterogeneity across analysis units by incorporating a random-parameter. In the presence of unobserved heterogeneity, past research suggests using a count model with a random parameter to handle the potential bias in fixed-parameter estimates (e.g. Anastasopoulos and Mannering, 2009; EI-Basyouny and Sayed, 2009; Anastasopoulos et al., 2012). Without a random parameter, fixed effect parameters may be biased (Amoh-Gyimah et al., 2016; Anastasopoulos, 2016), and estimated model coefficients will result in improper inferences. To account for the potential unobserved heterogeneity, a mixed-effects model will be tried along with a fixed-effects model. The specification below also uses Pop_t as an offset which converts the injury counts into population-based rates. The mixed effect model is described in the equation below:

$$\boldsymbol{\lambda_t = exp(ln(Pop_t) + \beta X_t + \varepsilon_t + \theta_g)}$$

(8-1)

Where:

λ_t is the expected number of pedestrian injuries in tract t,

X_t is a vector of explanatory variables,

β is a vector of model parameters, ε_t is an error term,

θ_g is a random effect for group g.

Random-effect parameters will include the urban area and the year for models using multiple years of data. In order to measure the performance of model results multiple measures will be used including Akaike Information Criterion (AIC), marginal and conditional R^2 values, and Root Mean Squared Error (RMSE). The formula for AIC is presented in Equation 2 below:

$$\boldsymbol{AIC = 2k - 2\ln(L)}$$

(8-2)

Where:

k = number of free parameters in the model,

n = sample size,

L = maximized value of the likelihood function

AIC is a common measure of prediction error and lower values indicate a model with a better fit and penalizes models with more estimated parameters. AIC measures are not standardized to remove units like more commonly reported coefficient of determination or R^2 but are still useful metrics to compare models against one another. In addition to AIC criteria, model selection will also evaluate marginal and conditional R^2 using the formulation suggested by Nakagawa and Schielzeth (2012). Because the model specifications in this research include both fixed and mixed effects both the marginal and conditional R^2 will be reported. Marginal R^2 measures the variance explained by the fixed effect parameters while the conditional R^2 measures the variance explained by both the fixed and random effects parameters. These R^2 measures are calculated using the *tab_model* function from sjPlot library in R (Lüdecke D 2020).

The last performance measure used in model assessment includes RMSE which is a common measure deployed in cross validation. Cross-validation assesses the predictive capability of a statistical model by testing the model on an out-of-sample dataset, comparing the estimated values to the observed. RMSE is the standard deviation of the prediction errors (observed compared to predicted) and measure how far from the spread out these predictions are compared to the observed values. For this work RMSE is calculated using the rmse function in the Metrics (Hammer and Frasco 2018) package and utilizes the equation below:

$$\boldsymbol{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{8-3}$$

These performance measures will be used to determine whether models using different variable specifications are improving or degrading the overall model performance. Over 500 variables were constructed for this research, so a stepwise variable selection process was chosen as a way to start to narrow down variables to use in selected models. A forward and backward stepwise algorithm was employed (Venables and Ripley 2002) using AIC as the performance measure selection criteria. No algorithm exists in the R statistical computing platform for doing stepwise feature selection for generalized linear regression mixed models, so the process was applied using a fixed effects negative binomial model specification. Following variable feature selection using the stepwise approach, other variable specifications were tried using various combinations of sociodemographic, traffic exposure, and built environment variables. For each new model developed, the AIC, R^2 and RMSE performance measures were checked to see if overall model performance was being impacted. Additionally, since a primary objective of this research is to determine if any effect from income or race and ethnicity remains after controlling for available traffic exposure and built environment factors, some of the latter variables were held in models if they mitigated the impact of income, race and ethnicity variables. Final models were also selected based on parsimony aiming to remove variables that are collinear. All models were fit using the glmmTMB (Brooks et al. 2017) function, with results presented as incident rate ratios.

Incidence Rate ratios (IRR) are used to understand the rate of an outcome (pedestrian injury) of an exposed population given exposure to the variable of interest (e.g. sociodemographic, traffic exposure, built environment) compared to the rate of outcome for the unexposed population. The IRR values can be interpreted using the following guidelines:

- IRR = 1 Exposure does not affect pedestrian injury outcomes
- IRR > 1 Exposure associated with higher frequency of pedestrian injury
- IRR < 1 Exposure associated with lower frequency of pedestrian injury

In addition to presenting the model results as IRRs this report assist readers in interpreting model coefficients by using marginal effects. Marginal effects summarizes how changes in a variable of interest, like income or race, affect the response variable, in this case pedestrian injury, while holding other variables at the specific values, typically the mean of the observed data. This report specifically uses the representative values method (RVM) defining the start and end values based on observed data ranges for the variable of interest (Mize et al 2019). This method is formulated using the following equation:

$$\boldsymbol{RVM_{x_k} = \eta(x_k = end, x_{-k} = x^*) - \eta(x_k = start, x_{-k} = x^*)}$$

(8-4)

Adjusted risk ratios (ARR) can be derived from the models above by predicting injury outcomes using marginal effects that include specific exposures and comparing to marginal effects without that exposure. ARR is the ratio of the average predicted risk conditional on all observations being exposed, to the average risk conditional on all observations being unexposed to the covariate (Kleinman and Norton 2009). This calculation can be formalized as the following:

$$\boldsymbol{ARR = \frac{\frac{1}{n}\sum_{i=1}^{N} risk_i(X_i | as\ if\ exposed)}{\frac{1}{n}\sum_{i=1}^{N} risk_i(X_i | as\ if\ unexposed)}}$$

(8-5)

N is the risk for individual *i* is the probability that the outcome variable equals one, conditional on the covariate *X*. Using measures derived from the RVM and ARR methods can help to summarize the modeling result in more intuitive ways. Following the presentation of modeling IRR in the modeling results section, marginal effects and subsequent adjusted risk ratios will be presented for select sociodemographic variables to highlight the role these variables play in pedestrian injury outcomes all else being equal.

8.2 VARIABLE EXPLORATION

A primary objective of this research is to understand and isolate the potential role of race and income as factors in predicting pedestrian injury outcomes when taking into account built environment and exposure variables. The relationship between the factors used in the statistical analysis are visualized below in order to show the strength and direction of correlation between relevant variables using the calculated Pearson correlation coefficient. Pearson's correlation is one of the oldest and most common measures to describe the linear dependence between two variables (Pearson 1901) and range from -1 to 1 with negative values indicating a negative correlation and positive values indicating a positive correlation. A value of -1 or 1 indicate a perfect correlation while 0 represents no relationship. Pearson's correlation is denoted as r and is given by the equation below (Mukaka 2012). Variable cross-correlation will be explored for data within tracts classified as urban using this measure.

$$r = \frac{\sum_{i=i}^{n}(x_i - x)(y_i - y)}{\sqrt{[\sum_{i=i}^{n}(x_i - \overline{x})^2]\,[\sum_{i=i}^{n} y - \overline{y})^2]}} \tag{8-6}$$

8.3 URBAN AREA TRACTS VARIABLE EXPLORATION

This section will explore the cross-correlations of each variable used in the modeling section below in order to demonstrate the various interactions between each factor. Figure 8.3 indicates Pearson correlation coefficient values using both the numeric values and color to aid in visualizing the myriad relationships between the pedestrian injury counts and other possible covariates. The color purple indicates a positive correlation with darker colors indicating stronger positive relationships. Similarly, the color orange indicates a negative correlation with darker colors indicating a stronger negative relationship. As mentioned above, two measures of pedestrian injury will be analyzed and are denoted as *Ped_KA* for fatal and severe pedestrian injuries and *Ped_KABC* for all pedestrian injuries including fatal, severe, moderate, and minor.

The figure shows how all pedestrian injuries (*Ped_KABC*) are correlated with various sociodemographic, built environment, and traffic exposure measures. The top two rows (*Ped_KABC & Ped_KA*) in Figure 8.3 allow readers to assess the relationship between pedestrian injuries and included variables.

- For race and ethnicity variables there is a measured positive correlation with pedestrian injuries though some race categories like percentage of the population in a tract that are Asian (*Asian_Prop*) is relatively weak.
- Percentage of households that have people with limited English proficiency (*Limited_English_Prop*) living in them or disabled persons (*Disability_Hh_Prop)* are positively correlated pedestrian injuries.
- Income is negatively correlated with pedestrian injuries.

- Motor vehicle exposure variables are almost all positively associated with pedestrian injuries including vehicle miles traveled (VMT) on all arterial (*Vmt_All_Arterial*) and VMT on major arterials (*Vmt_Major_Arterial*). Three of the four speed variables are positively correlated with pedestrian injuries, though the variable representing the miles of non-interstate roadway with posted speed limits of 45 miles per hour (mph) or more is negatively correlated with pedestrian injuries.

- Pedestrian exposure measures include the number of transit stops in the tract (*Mean_Transit_Stops)*, number of households and percentage of households in a tract with zero vehicles (*Vehicle_0* & *Vehicle_0_Prop*), and percentage of tract workers using walking or transit to get to work (*Jtw_Walk_Prop* & *Jtw_Transit_Prop*). These measures are all positively correlated with pedestrian injuries, and some are very strongly correlated, such as zero vehicle households.

- Built environment variables including the number of jobs (*C000_WAC*) and the number of alcohol establishments (*Alc_Site_Count)* are positively correlated with pedestrian injuries. Measures of pedestrian infrastructure such as crossings and sidewalks are not available for the whole state but this research does have access to measures of sidewalk quality and completeness on ODOT's system. Miles of sidewalk on ODOT's system that are poor quality (*Sidewalk_Poor*) and miles of sidewalk on ODOT's system that have been determined to be substandard (*Sidewalk_Substandard)* are both positively correlated with pedestrian injuries though poor condition miles are very weakly associated. Total miles of sidewalk (*Sidewalk_Quality_Total)* are also positively correlated with pedestrian injuries though it is likely that this variable is a proxy for pedestrian activity, assuming sidewalk presence elicits more pedestrian activity.

- Lastly, the change in year from an older period of data representing 2008-2012 compared to a more contemporary period of data representing 2014-2018 is also positively correlated with pedestrian injuries revealing the overall growth in pedestrian injuries over time.

Figure 8.3 shows the correlation between pedestrian injuries and the sociodemographic, traffic exposure and traffic exposure variables in order to explore the relative associations between injuries and other variables, but also to show the interconnections between the covariates themselves. For instance the figure reveals that median income and zero vehicle ownership and households with disabled people are all collinear. Additionally the correlation between median income and some BIPOC populations can be seen, which helps to contextualize the relationship between these variables. For reasons documented in the literature review, BIPOC communities are more likely to be lower income and lower income tracts are correlated with many of the features that are associated with pedestrian injuries. The next section will apply statistical analysis to determine the relative risk associated with different sociodemographic, traffic exposure, and built environment and pedestrian injuries.

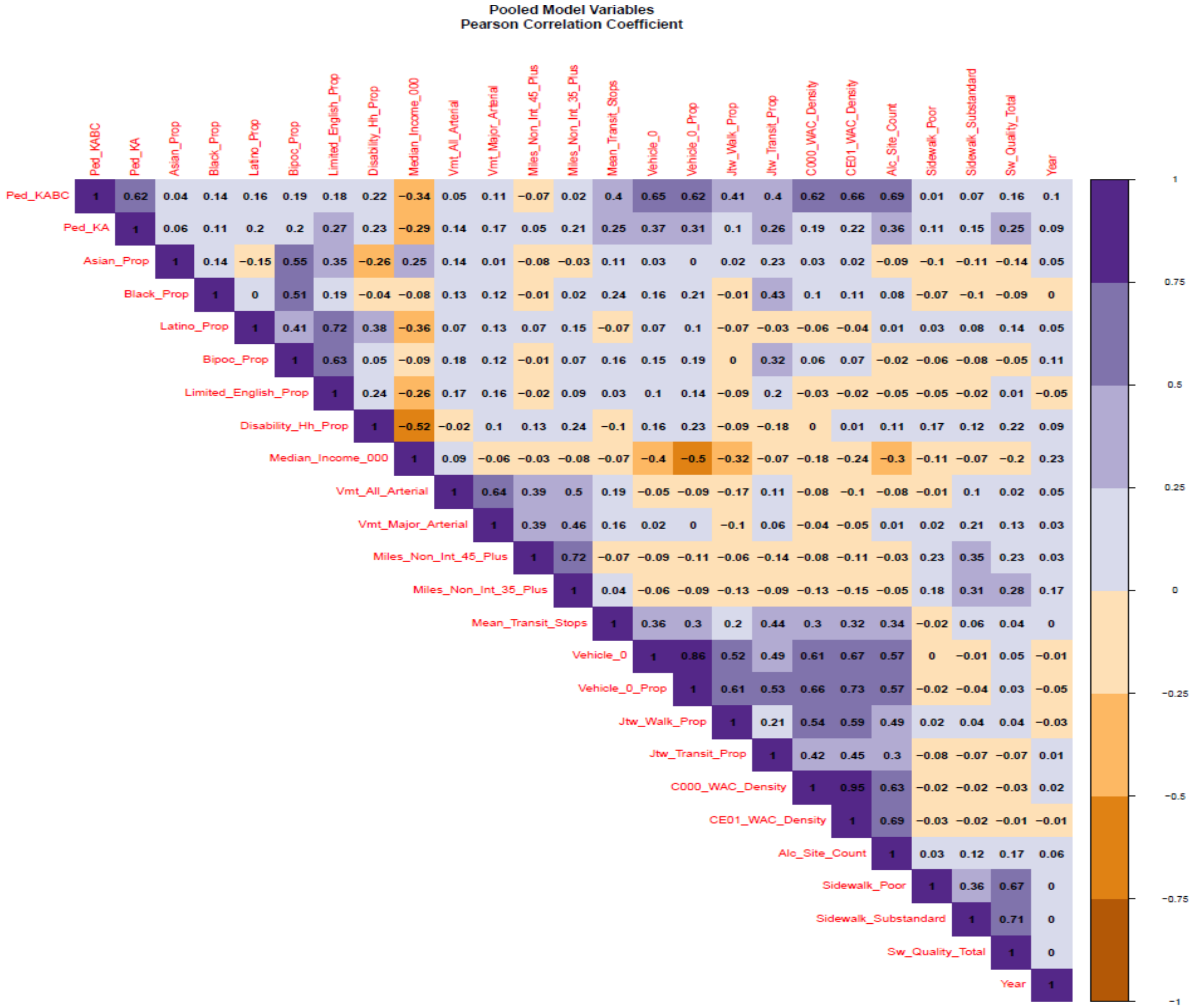

Figure 8.3: Pearson correlation coefficient for urban tracts pooled data

8.4 URBAN AREA STATISTICAL ANALSIS

This section presents statistical models using data for urban Census tracts with the aim of measuring the relative risk of pedestrian injury of tract level measures of sociodemographic, traffic exposure, and built environment factors. Three periods of data are examined including an older period (2008 to 2012), a more contemporary period (2014 to 2018), and a pooled data set that puts the older and more contemporary data together into a pooled dataset. Models were developed for two pedestrian injury categories including fatal and severe injuries as well as all (total) pedestrian injuries. Due to the structure of the pedestrian injury data, a negative binomial regression model was selected as the preferred model type. This research tried both a fixed effect model and mixed effect model with random parameter for the urban area and for the pooled data, a random parameter for the year. Performance metrics were compared across different model specifications in order to retain a model that performs well while also providing information on the relative risk associated with various sociodemographic factors. Final models developed for using the pooled data were applied to the older period and contemporary periods of data for comparison. The results of select models for all periods are presented in Appendix A-3 and A-4 for fatal and severe injury and total injury respectively.

8.4.1 Urban Area Pooled Data Fatal and Severe Injury Models

The model results in Figure 8.4 below summarize models estimating fatal and severe pedestrian injuries in urban areas using the pooled data set. Results are expressed as incident rate ratios (IRRs) which can be interpreted as the percentage increase in injury counts given a one unit change in predictor variable. Examples are given along with the description of the results below. A subset of all the models run are shown in

Figure 8.4, and includes for the mixed effect models and select fixed effects models. Other models tested are included in the appendix. Models A through K are specified using a mixed model with urban area and year as random parameter. Model L is a fixed effects model with no random parameter and estimated to understand the importance of using the random parameter specification.

8.4.1.1 Results for Sociodemographic Variables

IRR results for income, race and ethnicity are generally stable in terms of direction of effect. Based on these models:

- For income, the models show an increase of 1.6% to 2.0% in fatal and severe pedestrian injuries for every $1,000 decrease in median income of a tract, all else being equal (IRRs ranging from 0.984 ($p < 0.05$) to 0.980 ($p < 0.05$)).

- The role of race and ethnicity, the models show an increase in pedestrian injury of 91%, 95%, 120% for every percent increase in the tract's population that is BIPOC (IRRs range from of 1.91 ($p < 0.10$) to 2.2 ($p < 0.05$) in the mixed models and 2.7 ($p < 0.05$) in the fixed effects model). The relationship between the percentage of the tract that is BIPOC and the expected number of a pedestrian injuries in a tract is significant at the 0.05 level in two models and significant at the 0.10 level in two models.

- The percentage of the population that is Asian and Latinx in a tract is also correlated to an increase in the number of a pedestrian injuries in a tract. IRR for percent of the tract that is Asian ranges from 4.9 ($p < 0.05$) to 5.3 ($p < 0.05$). IRR for percent of the tract that is Latinx around 1.9 ($p < 0.10$) for both models. The variable for proportion of the tract population that is Black was not significantly correlated with pedestrian injuries in any of the models presented. Discussion of these outcomes is featured in the discussion section below.

- The percentage of households with limited English proficient speakers was included in models B and C. Pedestrian injuries increase as the percentage of the households in the tract that have limited English proficiency increases. The IRR for this variable ranges from 5.4 ($p < 0.05$) to 6.3 ($p < 0.05$). Lastly, percentage of households in the tract with a disabled person was included in models B, H and I (see appendix) with IRR values of 1.9 ($p > 0.10$) 2.3 ($p < 0.10$) and 1.9 ($p > 0.10$).

8.4.1.2 Results for Traffic Exposure Variables

Results for traffic exposure variables show that vehicle volume and speed are important contributors to pedestrian crash outcomes. Based on these models:

- An increase in VMT on major arterials is associated with an increase in the number of fatal and severe pedestrian injuries of 8.0% to 9.0% for every 1 million increase in VMT, all else being equal (IRRs of 1.08 to 1.09).

- Miles of non-interstate 45-plus mph roadways in a tract decrease the pedestrian injuries in urban tracts which is not an expected outcome with IRRs from of 0.23 ($p < 0.05$) to 0.311 ($p < 0.05$). Discussion of the possible reasons for this measured impact are featured below but might be because these facilities are in less populated parts of urban areas where less pedestrian activity is occurring.

- Miles of non-interstate roads with 35-plus roadway was shown to increase the pedestrian injuries with IRRs ranging from 3.8 ($p < 0.05$) to 4.1 ($p < 0.05$).

- An increase in the average width of arterials was shown to increase the number of pedestrian fatal and severe injuries, though this variable was only significant at the 0.10 level, indicating some uncertainty about the effect. This variable is difficult to properly operationalize at the zonal level which might be why the greater uncertainty for this variable exists.

Pedestrian traffic exposure cannot be measured directly because a systematic accounting of pedestrian traffic does not exist as it does for vehicle traffic; therefore, this research relies on measures that are available.

- The miles of sidewalk on the ODOT system was used as a proxy for pedestrian activity and was associated with 3% to 5% increase in pedestrian fatal and severe injuries for an increase of 1 mile of sidewalk in a tract (IRRs ranging 1.03 ($p < 0.05$) to 1.05 ($p < 0.05$)).

- The percentage of the tract's workers that commute by walking is significantly correlated to pedestrian injuries but the direction is unexpected revealing a decrease in pedestrian fatal and severe injury.

- The percentage of workers that take transit to work is associated with an increase in the number of expected pedestrian injuries by a factor of 9.6 to 17.8 times for every percent increase the proportion of workers that use transit to get to work (IRRs ranging from 10.6 ($p < 0.05$) to 18.8 ($p < 0.05$)).

- The relationship between pedestrian injury and transit can also be observed with the IRR for transit stop count variable, showing an increase of 10 transit stops in a tract increases the frequency of a pedestrian injuries by 0.7% to 0.8% (very stable IRRs ranging from 1.006 ($p < 0.05$) to 1.008 ($p < 0.05$)).

- The last measure of pedestrian exposure are the percentage of households with zero vehicles. It is assumed that households that do not own vehicles are more likely to walk to meet daily needs and therefore tracts with more zero vehicle households will have more people walking and more pedestrian activity. The model results presented in Figure 8.4 show that the percentage of all households with zero vehicles is not significant at the 0.05 or 0.10 levels, though was positively correlated to pedestrian injuries. The lack of statistical significance is likely due to the models accounting for likely pedestrian exposure through measures like income, transit stops and job density, making this variable a less useful proxy for pedestrian activity.

8.4.1.3 Results for Built Environment

Statewide data on pedestrian specific infrastructure such as sidewalks and crossing does not exists nor does a comprehensive database of other important features like streetlight locations. However, ODOT data on the location and quality of sidewalks on ODOT owned facilities, as well as statewide data on employment and the location of businesses that sell alcohol was utilized. These variables are considered built environment variables though some of the effects detected could be proxy measures for pedestrian traffic exposure since other research as documented the correlation of pedestrian traffic counts and employment. Two measures of sidewalk quality are used, including miles of sidewalk (on the ODOT system) that are rated as poor and miles of sidewalk that do not meet ODOT's standard.

- The number of miles of sidewalk rated poor was not significantly associated with pedestrian injury outcome but the number of miles of sidewalk rated substandard were associated with a 3.1% and 3.5% (IRR 1.03 and 1.034, $p < 0.05$) increase in pedestrian fatal and severe injuries in that tract.

- Intersection density was also included as a control variable but was not significant at the 0.05 level so the actual effect is uncertain.

- Similarly, the measure of low wage jobs was helpful for a control variable but was not statistically significant at the 0.05 level for the fatal and severe injury models.

- Total jobs per square mile was associated with fewer pedestrian injuries all else being equal with IRRs around 0.96 ($p < 0.05$).

- Lastly, the number of alcohol establishments per square mile was associated with an increase in pedestrian injuries with IRRs stable across all models. For every 10 alcohol establishments per square miles fatal and severe pedestrian injuries increase by 1% all else being equal.

Urban Tracts Pooled Data Models - Fatal & Severe (KA) Injury

Predictors	Mixed Model A *Incidence Rate Ratios*	*p*	Mixed Model B *Incidence Rate Ratios*	*p*	Mixed Model C *Incidence Rate Ratios*	*p*	Mixed Model D *Incidence Rate Ratios*	*p*	Mixed Model E *Incidence Rate Ratios*	*p*	Mixed Model F *Incidence Rate Ratios*	*p*
Intercept	1.366 (0.882 – 2.117)	0.163	0.814 (0.442 – 1.500)	0.509	1.042 (0.659 – 1.649)	0.860	1.144 (0.723 – 1.810)	0.565	1.159 (0.718 – 1.872)	0.546	1.098 (0.671 – 1.796)	0.710
% Asian	4.955 (1.311 – 18.719)	**0.018**									5.306 (1.369 – 20.558)	**0.016**
% Black	0.269 (0.045 – 1.610)	0.150										
% Latinx	1.925 (0.976 – 3.796)	0.059									1.957 (0.999 – 3.831)	0.050
% BIPOC							1.911 (0.965 – 3.784)	0.063	1.950 (0.982 – 3.873)	0.057		
% Hhs Limited English Proficiency			5.480 (1.739 – 17.270)	**0.004**	6.296 (2.019 – 19.634)	**0.002**						
% Hh Disability			1.951 (0.697 – 5.465)	0.203								
Median Income (thousand)	0.980 (0.976 – 0.985)	**<0.001**	0.984 (0.979 – 0.989)	**<0.001**	0.983 (0.978 – 0.987)	**<0.001**	0.981 (0.977 – 0.986)	**<0.001**	0.981 (0.976 – 0.986)	**<0.001**	0.981 (0.976 – 0.987)	**<0.001**
VMT on Major Arterials (million)	1.096 (1.047 – 1.147)	**<0.001**	1.087 (1.038 – 1.138)	**<0.001**	1.089 (1.040 – 1.140)	**<0.001**	1.094 (1.045 – 1.145)	**<0.001**	1.092 (1.043 – 1.143)	**<0.001**	1.093 (1.045 – 1.144)	**<0.001**
Miles of Non-Interstate Roads w/ 45 mph+	0.286 (0.129 – 0.633)	**0.002**	0.312 (0.142 – 0.684)	**0.004**	0.292 (0.132 – 0.647)	**0.002**	0.240 (0.107 – 0.538)	**0.001**	0.236 (0.105 – 0.531)	**<0.001**	0.248 (0.111 – 0.556)	**0.001**
Miles of Non-Interstate Roads w/ 35 mph+	4.107 (2.235 – 7.548)	**<0.001**	3.761 (2.033 – 6.957)	**<0.001**	3.917 (2.128 – 7.208)	**<0.001**	3.942 (2.145 – 7.246)	**<0.001**	4.012 (2.180 – 7.381)	**<0.001**	3.813 (2.075 – 7.007)	**<0.001**
Mean Width of Arterials			1.014 (0.997 – 1.031)	0.101	1.015 (0.998 – 1.032)	0.075	1.015 (0.998 – 1.032)	0.075	1.014 (0.998 – 1.031)	0.096	1.015 (0.998 – 1.032)	0.083
Sidewalk Miles (ODOT System)							1.046 (1.017 – 1.076)	**0.002**	1.030 (1.016 – 1.043)	**<0.001**	1.029 (1.016 – 1.043)	**<0.001**
% Walk Commute	0.142 (0.036 – 0.564)	**0.006**	0.247 (0.060 – 1.020)	0.053	0.203 (0.051 – 0.802)	**0.023**	0.173 (0.042 – 0.714)	**0.015**	0.172 (0.040 – 0.752)	**0.019**	0.183 (0.042 – 0.803)	**0.024**
% Transit Commute	15.148 (2.566 – 89.413)	**0.003**	12.839 (2.221 – 74.216)	**0.004**	10.600 (1.867 – 60.169)	**0.008**	11.492 (2.036 – 64.858)	**0.006**	12.474 (2.027 – 76.770)	**0.006**	12.883 (2.101 – 79.006)	**0.006**
Transit Stops	1.008 (1.004 – 1.012)	**<0.001**	1.007 (1.004 – 1.011)	**<0.001**	1.007 (1.003 – 1.011)	**<0.001**	1.006 (1.002 – 1.010)	**0.002**	1.006 (1.002 – 1.010)	**0.002**	1.007 (1.003 – 1.011)	**0.001**
% Hhs w/out Vehicle									0.911 (0.210 – 3.955)	0.901	0.937 (0.218 – 4.029)	0.930
Sidewalks Rated Substandard (Mi.) (ODOT System)	1.031 (1.009 – 1.053)	**0.005**	1.034 (1.013 – 1.055)	**0.001**	1.030 (1.008 – 1.052)	**0.007**	0.973 (0.931 – 1.016)	0.214				
Sidewalk Rated Poor (Mi.) (ODOT System)	1.026 (0.972 – 1.083)	0.349			1.032 (0.977 – 1.089)	0.257						
Intersection Density (Per Sqmi.)							0.940 (0.701 – 1.261)	0.682	0.928 (0.692 – 1.245)	0.620	0.878 (0.652 – 1.183)	0.393
Low Wage Job Density (000s per Sqmi.)	1.102 (0.929 – 1.306)	0.265	1.097 (0.925 – 1.302)	0.286	1.104 (0.931 – 1.310)	0.254	1.125 (0.950 – 1.332)	0.172	1.124 (0.944 – 1.337)	0.188	1.112 (0.935 – 1.323)	0.230
Total Jobs Density(000s per Sqmi.)	0.963 (0.941 – 0.985)	**0.001**	0.960 (0.938 – 0.983)	**0.001**	0.961 (0.939 – 0.983)	**0.001**	0.961 (0.939 – 0.983)	**0.001**	0.961 (0.939 – 0.983)	**0.001**	0.962 (0.940 – 0.985)	**0.001**
Alcohol Est. Density Count(per Sqmi.)	1.001 (1.000 – 1.002)	**<0.001**	1.001 (1.001 – 1.002)	**<0.001**	1.001 (1.001 – 1.002)	**<0.001**	1.001 (1.000 – 1.001)	**<0.001**	1.001 (1.000 – 1.002)	**<0.001**	1.001 (1.000 – 1.002)	**<0.001**
Random Effects												
σ^2	0.78		0.78		0.78		0.78		0.78		0.78	
τ_{00}	0.03 $_{Year}$ 0.08 $_{Urban\_Area}$		0.02 $_{Year}$ 0.06 $_{Urban\_Area}$		0.03 $_{Year}$ 0.06 $_{Urban\_Area}$		0.03 $_{Year}$ 0.06 $_{Urban\_Area}$		0.03 $_{Year}$ 0.06 $_{Urban\_Area}$		0.02 $_{Year}$ 0.06 $_{Urban\_Area}$	
ICC	0.12		0.10		0.10		0.10		0.10		0.10	
N	2 $_{Year}$ 39 $_{Urban\_Area}$		2 $_{Year}$ 39 $_{Urban\_Area}$		2 $_{Year}$ 39 $_{Urban\_Area}$		2 $_{Year}$ 39 $_{Urban\_Area}$		2 $_{Year}$ 39 $_{Urban\_Area}$		2 $_{Year}$ 39 $_{Urban\_Area}$	
Observations	1040		1040		1040		1040		1040		1040	
Marginal R^2 / Conditional R^2	0.345 / 0.422		0.349 / 0.411		0.349 / 0.416		0.357 / 0.419		0.359 / 0.420		0.356 / 0.419	
AIC	2864.270		2858.751		2859.100		2858.521		2860.065		2857.277	

Predictors	Mixed Model G *Incidence Rate Ratios*	*p*	Mixed Model H *Incidence Rate Ratios*	*p*	Mixed Model I *Incidence Rate Ratios*	*p*	Mixed Model J *Incidence Rate Ratios*	*p*	Fixed Model K *Incidence Rate Ratios*	*p*
Intercept	1.236 (0.780 – 1.960)	0.368	0.947 (0.519 – 1.727)	0.859	0.861 (0.463 – 1.601)	0.636	1.014 (0.659 – 1.562)	0.948	0.825 (0.572 – 1.189)	0.302
% Asian					1.849 (0.293 – 11.658)	0.513				
% Black					0.262 (0.043 – 1.591)	0.145				
% Latinx					0.819 (0.272 – 2.465)	0.723				
% BIPOC	2.291 (1.168 – 4.491)	**0.016**					2.206 (1.139 – 4.272)	**0.019**	2.706 (1.403 – 5.220)	**0.003**
% Hhs Limited English Proficiency					6.293 (0.804 – 49.248)	0.080				
% Hh Disability			2.369 (0.856 – 6.557)	0.097	1.905 (0.684 – 5.307)	0.218				
Median Income (thousand)	0.980 (0.975 – 0.984)	**<0.001**	0.982 (0.977 – 0.987)	**<0.001**	0.983 (0.978 – 0.989)	**<0.001**	0.982 (0.977 – 0.986)	**<0.001**	0.984 (0.980 – 0.988)	**<0.001**
VMT on Major Arterials (million)	1.084 (1.036 – 1.135)	**0.001**	1.093 (1.044 – 1.144)	**<0.001**	1.091 (1.042 – 1.141)	**<0.001**	1.096 (1.047 – 1.146)	**<0.001**	1.092 (1.043 – 1.143)	**<0.001**
Miles of Non-Interstate Roads w/ 45 mph+	0.233 (0.103 – 0.528)	**<0.001**	0.253 (0.114 – 0.564)	**0.001**	0.278 (0.125 – 0.619)	**0.002**	0.252 (0.113 – 0.564)	**0.001**	0.193 (0.087 – 0.426)	**<0.001**
Miles of Non-Interstate Roads w/ 35 mph+	4.100 (2.218 – 7.577)	**<0.001**	3.803 (2.057 – 7.032)	**<0.001**	3.627 (1.969 – 6.680)	**<0.001**	3.617 (1.958 – 6.680)	**<0.001**	4.980 (2.742 – 9.045)	**<0.001**
Mean Width of Arterials	1.012 (0.995 – 1.029)	0.158	1.013 (0.997 – 1.030)	0.114	1.014 (0.997 – 1.030)	0.103	1.016 (0.999 – 1.032)	0.065	1.017 (1.001 – 1.034)	**0.041**
Sidewalk Miles (ODOT System)	1.030 (1.017 – 1.044)	**<0.001**	1.029 (1.015 – 1.042)	**<0.001**	1.029 (1.015 – 1.042)	**<0.001**	1.032 (1.019 – 1.046)	**<0.001**	1.033 (1.019 – 1.046)	**<0.001**
% Walk Commute	0.143 (0.035 – 0.590)	**0.007**	0.197 (0.046 – 0.846)	**0.029**	0.238 (0.055 – 1.029)	0.055	0.159 (0.040 – 0.637)	**0.009**	0.208 (0.051 – 0.838)	**0.027**
% Transit Commute			18.802 (3.403 – 103.869)	**0.001**	14.074 (2.343 – 84.547)	**0.004**	11.272 (2.501 – 50.805)	**0.002**	10.580 (2.292 – 48.845)	**0.003**
Transit Stops	1.008 (1.004 – 1.011)	**<0.001**	1.006 (1.002 – 1.010)	**0.001**	1.007 (1.003 – 1.011)	**<0.001**	1.006 (1.002 – 1.010)	**0.003**	1.005 (1.002 – 1.009)	**0.005**
% Hhs w/out Vehicle										
Sidewalks Rated Substandard (Mi.) (ODOT System)										
Sidewalk Rated Poor (Mi.) (ODOT System)										
Intersection Density (Per Sqmi.)	0.964 (0.718 – 1.295)	0.810	0.985 (0.734 – 1.320)	0.917	0.917 (0.679 – 1.237)	0.570	0.956 (0.713 – 1.281)	0.762	0.891 (0.664 – 1.196)	0.442
Low Wage Job Density (000s per Sqmi.)	1.119 (0.943 – 1.328)	0.199	1.122 (0.948 – 1.329)	0.181	1.098 (0.927 – 1.300)	0.280	1.104 (0.929 – 1.312)	0.262	1.077 (0.903 – 1.285)	0.407
Total Jobs Density(000s per Sqmi.)	0.961 (0.939 – 0.984)	**0.001**	0.958 (0.936 – 0.981)	**<0.001**	0.961 (0.939 – 0.984)	**0.001**	0.962 (0.940 – 0.985)	**0.001**	0.966 (0.943 – 0.989)	**0.004**
Alcohol Est. Density Count(per Sqmi.)	1.001 (1.001 – 1.002)	**<0.001**	1.001 (1.000 – 1.001)	**<0.001**	1.001 (1.001 – 1.002)	**<0.001**	1.001 (1.000 – 1.002)	**<0.001**	1.001 (1.001 – 1.002)	**<0.001**
Random Effects										
σ^2	0.79		0.78		0.77		0.79			
τ_{00}	0.03 $_{Year}$ 0.05 $_{Urban\_Area}$		0.02 $_{Year}$ 0.05 $_{Urban\_Area}$		0.02 $_{Year}$ 0.05 $_{Urban\_Area}$		0.02 $_{Year}$			
ICC	0.09		0.09		0.09		0.03			
N	2 $_{Year}$ 39 $_{Urban\_Area}$		2 $_{Year}$ 39 $_{Urban\_Area}$		2 $_{Year}$ 39 $_{Urban\_Area}$		2 $_{Year}$			
Observations	1040		1040		1040		1040		1040	
Marginal R^2 / Conditional R^2	0.359 / 0.419		0.362 / 0.419		0.354 / 0.412		0.366 / 0.383		NA	
AIC	2864.141		2858.942		2854.619		2864.924		2874.005	

Figure 8.4: Urban area pooled data fatal and severe injury models results

8.4.1.4 Urban Area and Year Random Effects for Fatal and Severe Injury Models

Models A through J shown in Figure 8.4 (and A-1 appendix) use mixed model specification meaning they include a random parameter for the urban area and year to control for unobserved heterogeneity, or unmeasured differences, measured by these terms and not directly accounted for in the fixed effect terms. For the urban area random parameter the effect is likely measuring differences for specific urban areas that are not observed in the available covariates. These can be thought of as a measure of how much the urban area differs from the 'average' urban area in Oregon, considering all the fixed effects in the model (Brooks et al., 2017). The effect of specific urban areas can provide some information in addition to the fixed effect covariates described above, that could be useful for practioners above and beyond the fixed effects parameters. This section summarizes the conditional modes, or the difference between the statewide mean estimated response for a given set of fixed-effect quantities and the estimated response for each urban area.

Figure 8.5 shows the conditional modes for each urban area with negative values indicating less fatal and severe pedestrian injuries compared to the state average and controlling for all the fixed effects. Eugene, Klamath Falls-Altamount, Medford, and The Dalles have relatively large negative conditional mode values compared to the statewide average. This can be interpreted as some unmeasured direct effect in those urban areas that reduce pedestrian injuries such as less pedestrian activity, safety in numbers (so perhaps more pedestrian activity), more pedestrian safety features, or some other protective feature that the model did not include directly. It has been suggested by members of the TAC that these urban areas have extensive off-street path systems which might be playing into the effect of these conditional modes. Conversely, urban areas with relatively large conditional modes compared to the mean include Astoria, Lincoln City, Roseburg and Sandy. Similar to the interpretation of the potential protective effects in the negative conditional mode values these urban area might possess features that were not measured in the models directly that are leading to more pedestrian injuries.

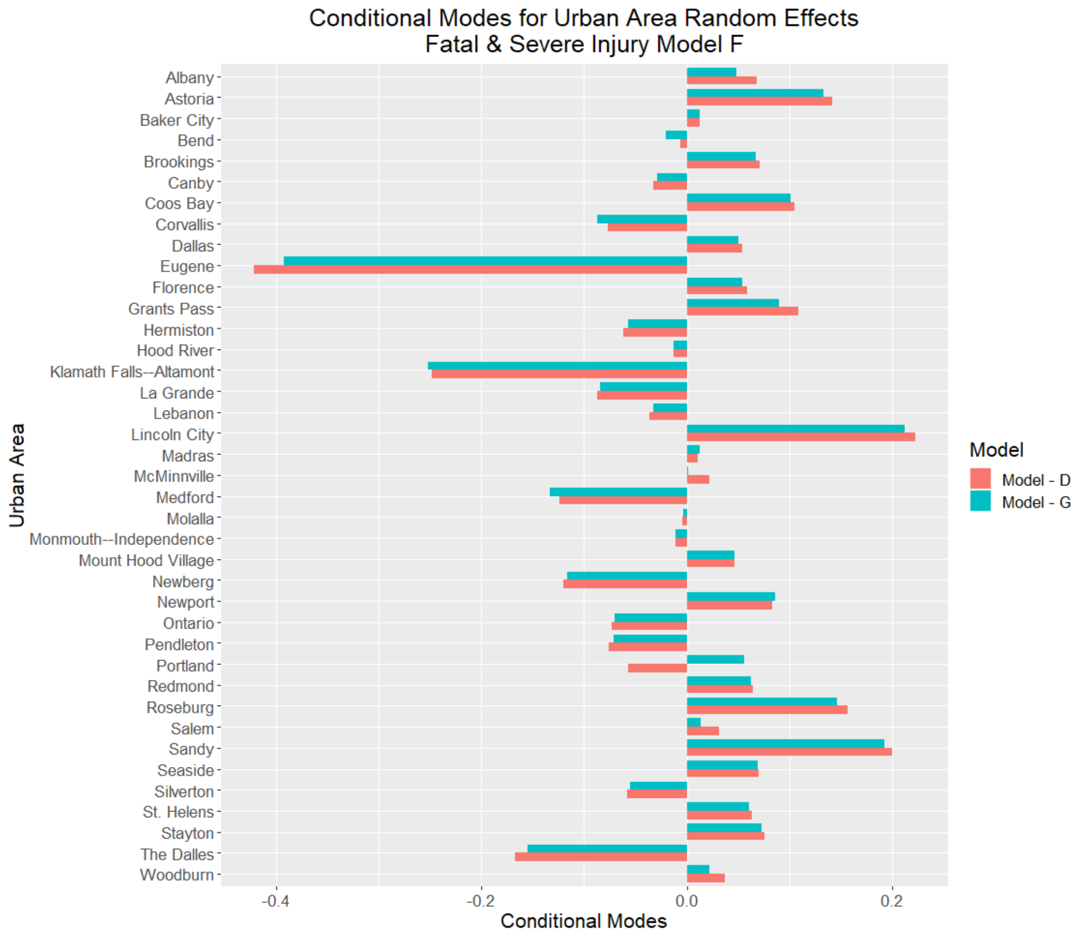

Figure 8.5: Conditional modes for urban area random effects (Model D and G)

8.4.1.5 Cross Validation Results and Model Performance Measures

In this section model results are compared based on cross-validation results and other model performance measures including AIC and marginal and conditional R^2. All models presented in

Figure 8.4 perform similarly though some differences emerge. Larger differences exist between the mixed models and the fixed effects models which is explored in this section. The models constructed and presented in

Figure 8.4 include AIC, marginal and conditional R^2 values to help understand how different specifications improve the quality of the model overall. In addition to these measures is the R^2 and RMSE based on 10-fold cross validation. These results highlight the models with the best predictive capability by partitioning the data into 10 groups and using 90% of the data to estimate a model and then to compare with the remaining 10% of data and assessing how well each model does at predicting fatal and severe pedestrian injuries at the tract level. Two types of specifications are used in the cross-validation including mixed models where random parameters for urban area and year are included but also fixed effects models where random parameters are not used. The objective of showing cross validation results for both fixed and mixed effects models is to highlight the importance of the mixed effects approach especially as it relates to predictive accuracy of the different models. Table 8.3 shows how RMSE is lower for all models when specifying a mixed effects model demonstrating the importance of this type of specification in terms of prediction.

Table 8.3: Cross Validation Results for Urban Tracts Pooled Data Models

Model	RMSE		R^2	
	Fixed	Mixed	Fixed	Mixed
Pool - A	1.43	1.36	35.6%	41.0%
Pool - B	1.41	1.35	38.7%	43.2%
Pool - C	1.40	1.34	38.6%	43.1%
Pool - D	1.44	1.38	34.8%	40.1%
Pool - E	1.42	1.37	36.8%	41.4%
Pool - F	1.43	1.37	35.7%	41.1%
Pool - G	1.42	1.34	37.4%	43.3%
Pool - H	1.40	1.35	39.1%	42.9%
Pool - I	1.43	1.37	37.3%	41.9%
Pool - J	1.41	1.38	36.7%	39.9%
Pool - K	1.41	1.40	37.5%	38.4%

Based on the performance measures in this table the best model for predictive accuracy is Model G and followed closely by models B and C. Due to the random splitting of training and testing data in the cross-validation process, it is expected these performance values have some perturbation so cross-validation results that are close are probably not meaningfully different. In tests for models with BIPOC race variable Model G appears to be preferred with the highest R2 values and one of the lowest RMSE values. In fact the model with the highest R2 is Model G of all the models tested. Along with the cross-validation results, review of the other model performance measures including AIC and marginal and conditional R^2 (0.359/0.419) reveal Model G performs relatively well and will be retained as one of the selected model. Based on model performance and the desire to make inferences for disaggregate race variables, Model A and Model F will also be used for marginal effects and adjusted relative risk summaries below to evaluate the role the disaggregated race categories. These models performed well in the cross-validation tests too with R^2 values for Model A and Model F resulting in 41% and 41.1% respectively. Model A's marginal R^2 (0.345) values was marginally lower than Model G though it's conditional R^2 (0.422) was a bit higher. Model F's marginal R^2 (0.356) values was marginally lower than Model G though it's conditional R^2 (0.419) was the same as the Model G. Based on these performance results Models F, D, and G will be retained for marginal effect and adjusted relative risk summaries below.

8.4.1.6 Marginal Effects Tests for Select Urban Tracts Pooled Data Model

Marginal effects tests are partial derivatives of statistical models estimated above and allow for simpler interpretation of model outputs by holding all variables in the model constant at the observed mean while varying the covariate(s) of interest in order to see how the response variable changes. This is done below in this section for race, ethnicity and income variables to show the relative impact of changes in these variables based on observed ranges of those variables in Oregon. Marginal effects tests are also presented in this section for other select covariates while others are presented in the Appendix.

Using the selected Model D based on cross validation results but also Model G as the BIPOC variable was significant at the 0.05 level, marginal effects and adjusted relative risk are presented in Figure 8.6. All covariates are held at the mean values based on the observed data while the median income is varied according to the range of observed values. The marginal effects (top panel) show how many fatal and severe pedestrian injuries are expected in a tract based on the median income of the tract all else being equal. Figure 8.6 shows that adjusted relative risk decreases by about 50% if the tract exhibits the state median income (~$60,000) and declines by nearly 94% in the highest income tracts. In fact, in the seven urban tracts (~37,000 people) in Oregon where the median income is greater than $150,000 there was only one severe injury in 10 years while in tracts with less than $25,000 (~124,000 people) there were 50 fatal and severe injuries during the same time period. There does not seem to be a significant difference between the two models based on these tests. These figures highlight the clear relationship between pedestrian fatal and severe injuries and a tract's median income even considering the confidence intervals.

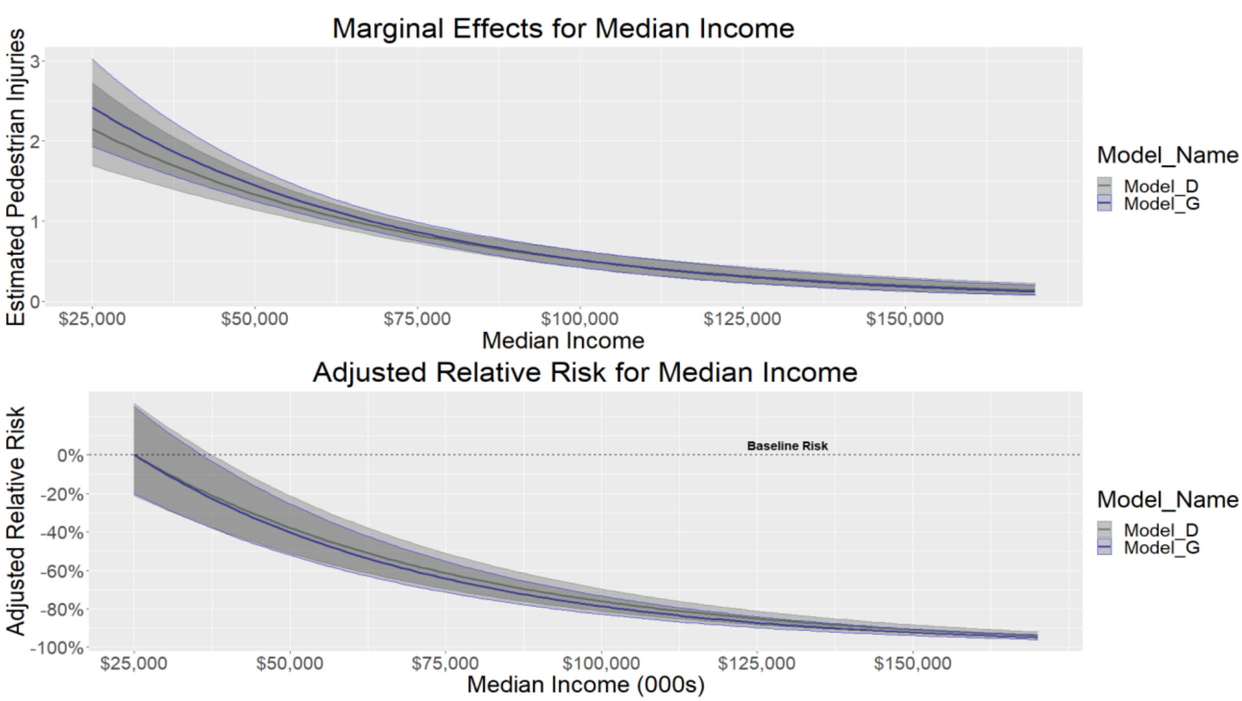

Figure 8.6: Marginal effects and adjusted relative risk for median income (Urban tracts using Model D & G)

The next set of marginal effects and adjusted relative risk results are presented in Figure 8.7. This figure shows how the percentage of the tract's population that is BIPOC effects pedestrian injury outcomes. The IRR in models D and G were 1.91 and 1.95 respectively though the variables were not significant at the 0.05 level meaning the level of precision for the effect is much larger. This lack of precision can be seen in Figure 8.7 the lower and upper limits of the marginal effects and adjusted relative risk are much wider than compared to the results presented in the median income. Though the precision of the estimate is lower, the effect of BIPOC variable can be observed where adjusted relative risk increases by about 15% in tracts with the state average percent of tract population that is BIPOC (22%) with tracts in the upper range of BIPOC % exhibiting up to 45% to 55% more risk than tracts with no BIPOC communities, all else being equal.

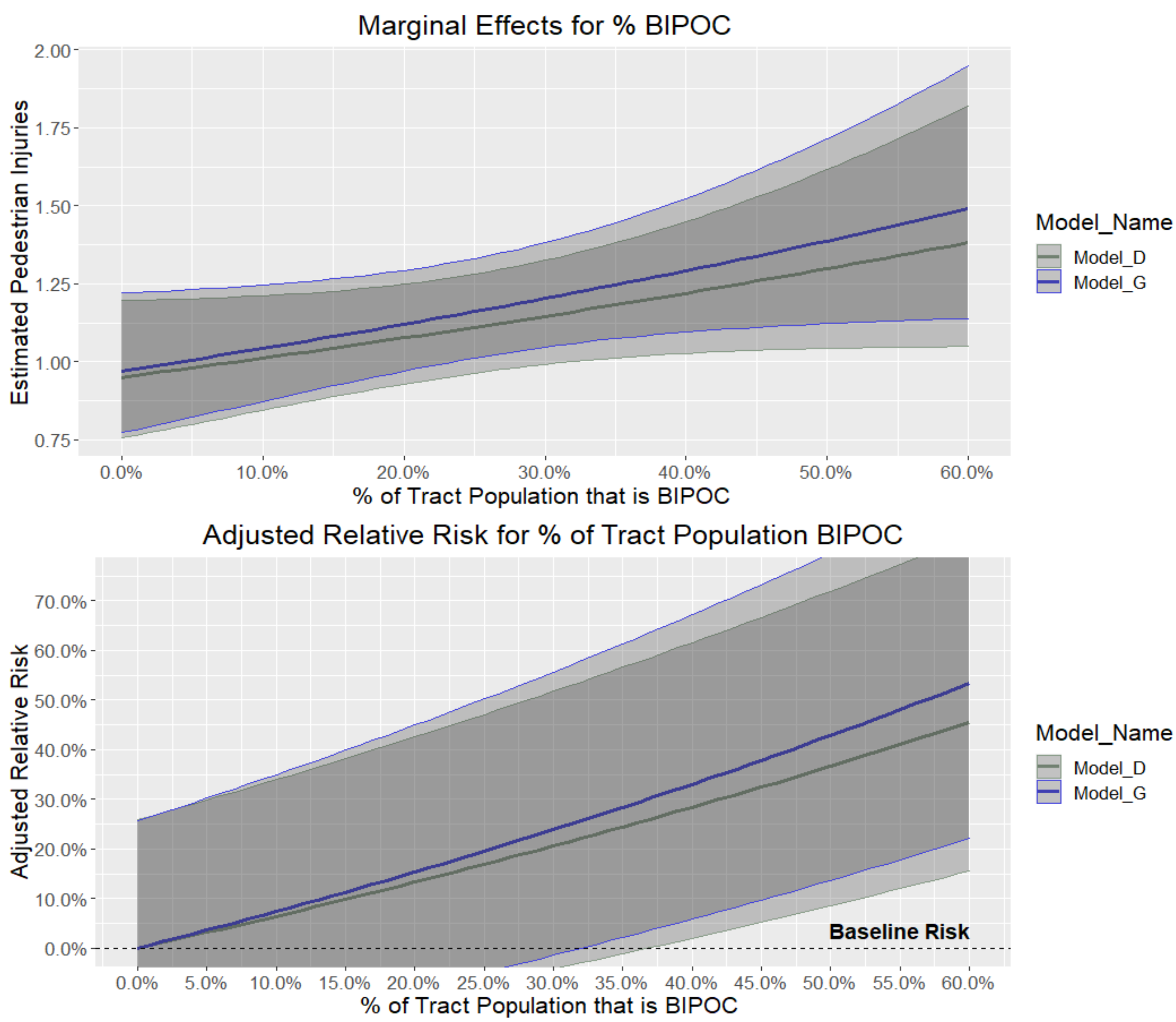

Figure 8.7: Marginal effects and adjusted relative risk for percentage of tract's population that is BIPOC (Urban tracts using Model D & G)

The next set of marginal effects and adjusted relative risk measures are presented in Figure 8.8 include the estimated effect of the percentage of the population that is Asian and Latinx based on Model F results. The estimated IRRs for percentage Asian and percentage Latinx from Model F are 5.3 ($p < 0.05$) and 1.9 ($p < 0.10$) respectively. Because the variables for percentage Black was not significant at the 0.05 level, this parameter is not included. The parameter estimates for percentage Latino are less certain because the estimate is just over the 0.05 p-value threshold which can be observed in the confidence intervals which have considerable spread. That said, the increase in the percentage of the tract's population that is Asian or Latinx appears to increase relative risk even considering the uncertainty.

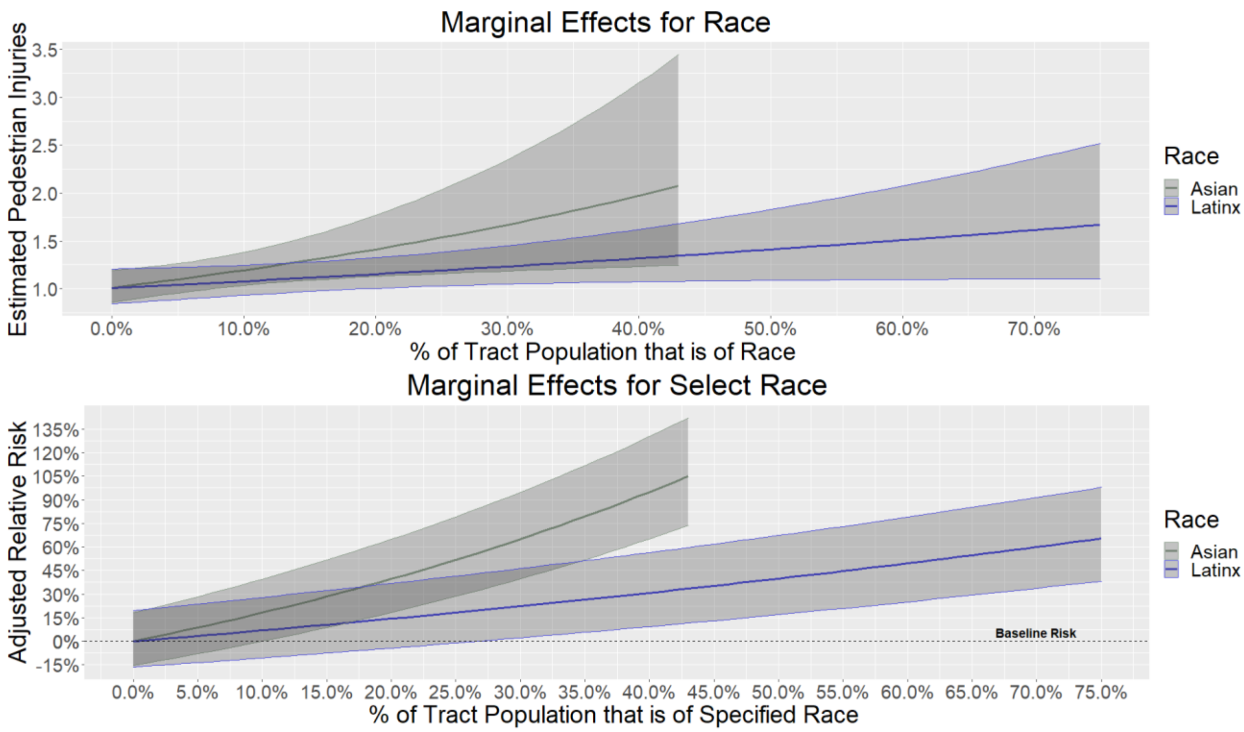

Figure 8.8: Marginal effects and adjusted relative risk for percentage of tract's population that is Asian and Latinx (Urban tracts using Model F)

8.4.1.7 Fatal and Severe Pedestrian Injury Models Discussion

The section above details the results of various statistical models attempting to understand the effects of sociodemographic, traffic exposure, and built environmental factors on fatal and severe pedestrian injury outcomes at the tract level using an ecological analysis approach. Even after controlling for traffic exposure and built environmental factors from available data, income and race measures are positively correlated with pedestrian injuries. Income is a very stable measure varying minimally in the size of the effect from model to model with relatively precise confidence intervals. The impact of the percent BIPOC variable is less certain but models above show a significant effect and correlation with pedestrian fatal and sever injuries. Similarly, for disaggregate race variables percent Asian and percent Latinx are associated with more fatal and severe pedestrian injuries. Percent of the tracts population that is Black is not significantly associated with pedestrian injuries as mentioned above, potentially because of small numbers issues since the total number of Black people in Oregon is very small, just around 70,000 people (ACS 2014 – 2018 sample) which is just 2.6% of the urban population in Oregon. Based on cross validation results the mixed models appear to outperform the fixed effects models.

8.4.2 Urban Area Pooled Data All Injury Models

While Section 7.4.2 focuses on severe and fatal injuries, this section provides a comparable analysis but for all pedestrian injuries (which includes fatal and severe injuries). The model results featured in

Figure 8.10 summarize models estimating total pedestrian injuries (all severities) in urban areas using the pooled data set. Results in the figure are expressed as incident rate ratios (IRRs) which can be interpreted as the percentage increase in injury counts given a one unit change in predictor variable. Examples will be given along with the description of the results below.

Figure 8.10 shows a subset of models with the appendix featuring other models that were tested. The below figure includes results for the mixed and select fixed effects models. Models A through I are specified using a mixed model with urban area and year as random parameter. Model K are fixed effects models with no random parameter and estimated to understand the importance of using the random parameter specification.

8.4.2.1 Results for Socioeconomic Variables

IRR results for income, race and ethnicity are generally stable in terms of direction of effect.

- For income, the models show an increase of 1.5% to 1.2% in total pedestrian injury for every $1,000 decrease in median income of a tract all else being equal (IRRs ranging from 0.985 ($p < 0.05$) to 0.988 ($p < 0.05$)).

- The role of race and ethnicity variables varies by model with an increase in pedestrian injury of 70%, 100%, 100%, respectively, for every percent increase in the tracts population that is BIPOC the percentage of the tract that is BIPOC (significant at the 0.05 level all the models tested, with IRRs of 1.7 ($p < 0.05$) to 2.0 ($p < 0.05$) in the mixed models and 2.0 ($p < 0.05$) in the fixed effects).

- The percentage of the population that is Asian and Latinx in a tract is also correlated to an increase in the number of a pedestrian injuries in a tract. IRR for percent of the tract that is Asian ranges from 2.9 ($p < 0.05$) to 3.5 ($p < 0.05$). IRR for percent of the tract that is Latinx ranges from 2.0 ($p < 0.05$) to 2.1 ($p < 0.05$). The variable for proportion of the tract population that is Black was not significantly correlated with pedestrian injuries in any of the models presented. Discussion of this outcomes is featured in the discussion section below.

- The percentage of households with limited English proficient speakers correlates to an increase in pedestrian injuries as the percentage of the households in the tract that have limited English proficiency increases. The IRR for this variable ranges from 3.2 ($p < 0.05$) to 3.7 ($p < 0.05$).

- Lastly, percentage of households in the tract with a person with a disability was included in models B and I with IRR values of 2.1 ($p > 0.05$).

8.4.2.2 Results for Traffic Exposure Variables

Results for traffic exposure variables show that vehicle volume and speed are important contributors to pedestrian crash outcomes.

- VMT on major arterials increase the number of pedestrian injuries. For every million VMT on major arterials pedestrian injuries increases by 9.0% to 9.7%, all else being equal.

- Miles of non-interstate 45-plus mph roadways in a tract decrease the pedestrian injuries in urban tracts with IRR range of 0.21 ($p < 0.05$) to 0.25 ($p < 0.05$).

- Miles of non-interstate roads with 35-plus roadway was shown to increase the pedestrian injuries with a stable IRR of 1.5 ($p < 0.05$).

- An increase in the average width of arterials was shown to increase the number of pedestrian fatal and severe injuries, though this variable was only significant at the 0.10 level in one of the mixed effects model and was also significant in the fixed effect model.

As mentioned previously, pedestrian traffic exposure cannot be measured directly because a systematic accounting of pedestrian traffic does not exist and instead some proxies for pedestrian activity are used.

- The miles of sidewalk on the ODOT system was used as a proxy for pedestrian activity and was shown to increase pedestrian injuries by roughly 2% increase for an increase of 1 mile of sidewalk in a tract (IRRs ranging 1.017 ($p < 0.05$) to 1.025 ($p < 0.05$)).

- The percentage of workers that walk to work is significantly correlated to pedestrian injuries. The direction of effect shows that this variable is associated with more pedestrian injuries as would be expected but is the opposite of the effect found in the fatal and sever injury models above. Some discussion of the potential reasons for this is result is offered below.

- The variable for the percentage of workers that take transit to work is a significant predictor of pedestrian injury with IRRs ranging from 3.4 ($p < 0.05$) to 7.0 ($p < 0.05$).

- The relationship between pedestrian injury and transit is also measured by using the transit stop count variable with IRRs ranging from 1.008 ($p < 0.05$) to 1.010

(p < 0.05). These IRRs reveal that an increase of 10 transit stops in a tract increases the frequency of a pedestrian injuries by 0.8% to 1.0%.

- The model results show that the percentage of all households with zero vehicles increases the expected number of pedestrian injuries with IRRs ranging from 2.4 (p < 0.10) to 2.5 (p < 0.10).

8.4.2.3 Results for Built Environment

As mentioned above this research lacks data on some important build environmental variables such as sidewalks, pedestrian crossings, and street lighting for the entire transportation system in Oregon. However this research has access to measures of sidewalk miles and quality on the ODOT system as well as measures of jobs and alcohol establishment location. Miles of sidewalk on the ODOT system is associated with an increase in pedestrian crash injury, likely because sidewalks are where pedestrians are using the system so more sidewalks is likely to equal more pedestrian activity, all else being equal. However, because this particular measure of sidewalks is only for the ODOT system this variable might be picking up an effect of some other feature of the ODOT system that we do not have a direct measure for. Miles of sidewalk rated as substandard and the percentage of all sidewalks (on ODOT's system) rated as poor were tested with the former showing a statistically significant increase in the frequency of pedestrian injuries while the latter was not statistically significant. The sidewalks rated substandard variable was dropped in favor of total sidewalk miles (on ODOT system) starting in Models D since the limited coverage of these data means the former variable may be providing biased inferences.

Many variables for jobs were tested in models with the theory that job locations would be proxies for built environments where pedestrians used the system.

- Total job density was associated with a decrease in pedestrian injury with IRRs ranging from 0.950 (p < 0.05) to 0.953 (p < 0.05).

- The number of low wage workers ($1,250 a month of less) was correlated to an increase in pedestrian injuries with IRRs ranging from 1.29 (p < 0.05) to 1.34 (p < 0.05). This finding indicates that in addition to home location of low income people, work location should also be considered as a place where pedestrian and vehicle conflicts occur.

Lastly, alcohol establishment density is associated with an increase in pedestrian injuries with a stable IRR of 1.001.

8.4.2.4 Urban Area and Year Random Effects for All Injury Models

As in the fatal and severe injury models, the total pedestrian injury Models A through J shown in Figure 8.8 (and appendix) use mixed model specification, meaning they include a random parameter for the urban area and year to control for unobserved heterogeneity, or unmeasured differences, measured by these terms. For the urban area random parameter, the effect is likely measuring differences for specific urban areas that are not observed in the available covariates. These can be thought of as a measure of how much the urban area differs from the ‘average’ urban area in Oregon, considering all the fixed effects in the model (Brooks et al. (2017). The effect of specific urban areas can provide some information in addition to the fixed effect covariates described above, that could be useful for practioners. This section summarizes the conditional modes, or the difference between the statewide mean estimated response for a given set of fixed-effect quantities and the estimated response for each urban area.

Figure 8.8 shows the conditional modes for each urban area with negative values indicating fewer total injuries compared to the state average and controlling for all the fixed effects. Eugene, Corvallis, La Grande, Klamath Falls-Altamont, and Newberg have relatively large negative conditional mode values compared to the statewide average. This can be interpreted as some unmeasured direct effect of those urban areas that is reducing pedestrian injuries, such as less pedestrian activity, safety in numbers (so perhaps more pedestrian activity), more pedestrian safety features, or some other protective feature that the model did not include directly. All of these urban areas have universities or colleges, and there may be something about the student population that is affecting the fixed effects portion of the models. Urban areas with relatively large conditional modes compared to the mean include Astoria, Grants Pass, Ontario, and Sandy. Similar to the interpretation of the potential protective effects in the negative conditional mode values, these urban area might possess features that are not measured in the models that are leading to more pedestrian injuries.

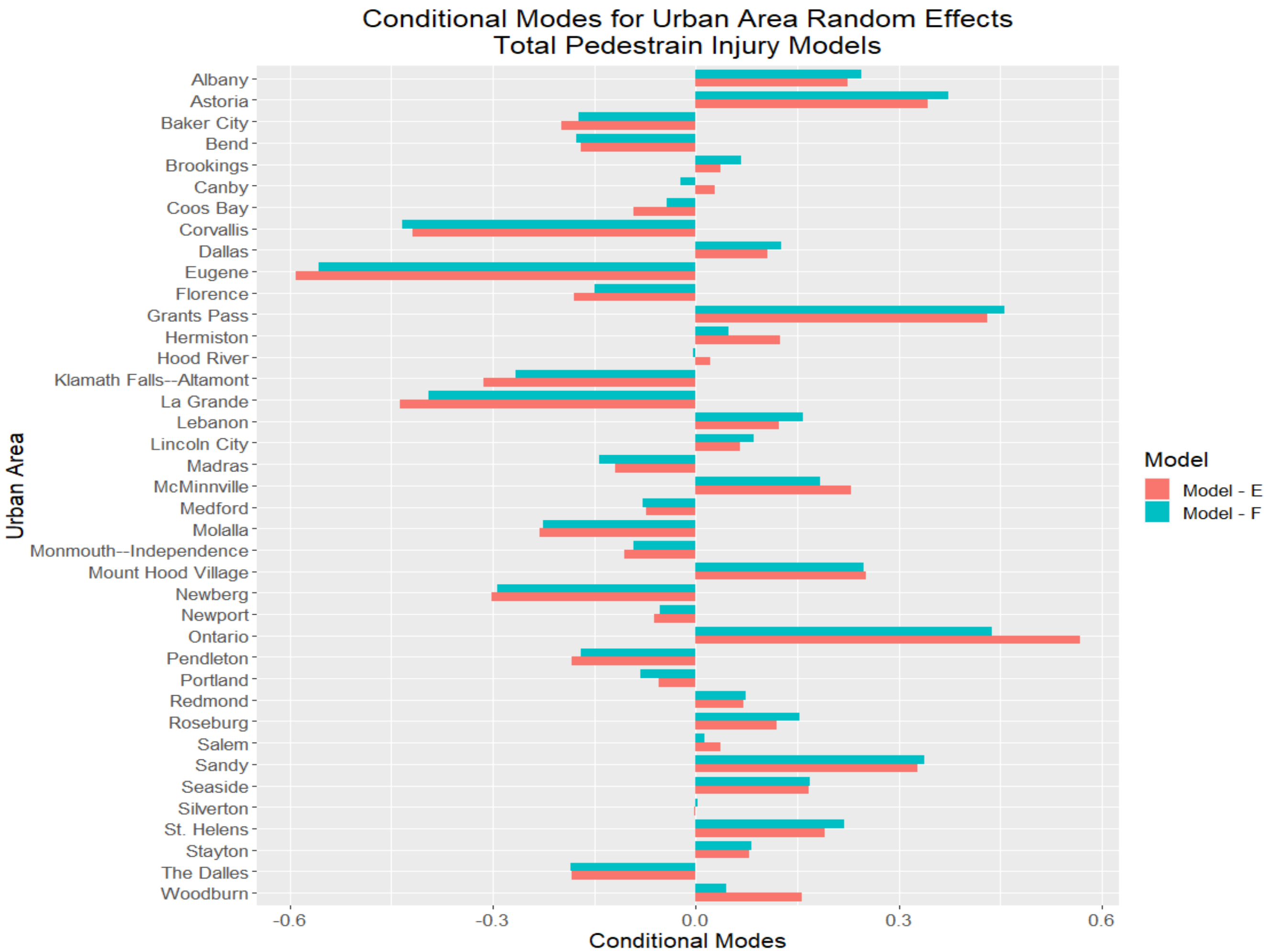

Figure 8.9: Urban tracts pooled tract all pedestrian injury models

Urban Tracts Pooled Data Models - All (KABCO) Injury

	Mixed Model A			Mixed Model B			Mixed Model C			Mixed Model D		
Predictors	*Incidence Rate Ratios*	*CI*	*p*	*Incidence Rate Ratios*	*CI*	*p*	*Incidence Rate Ratios*	*CI*	*p*	*Incidence Rate Ratios*	*CI*	*p*
Intercept	5.591	3.898 – 8.020	**<0.001**	3.877	2.494 – 6.026	**<0.001**	5.275	3.620 – 7.688	**<0.001**	5.450	3.759 – 7.902	**<0.001**
% Asian	2.990	1.300 – 6.877	**0.010**									
% Black	0.560	0.186 – 1.685	0.302									
% Latinx	2.120	1.366 – 3.292	**0.001**									
% BIPOC										1.810	1.163 – 2.817	**0.009**
% Hhs Limited English Proficiency				3.284	1.536 – 7.022	**0.002**	3.797	1.787 – 8.066	**0.001**			
% Hh Disability				2.168	1.136 – 4.139	**0.019**						
Median Income (thousand)	0.985	0.983 – 0.988	**<0.001**	0.988	0.985 – 0.991	**<0.001**	0.986	0.983 – 0.989	**<0.001**	0.985	0.983 – 0.988	**<0.001**
VMT on Major Arterials (million)	1.094	1.061 – 1.128	**<0.001**	1.092	1.059 – 1.126	**<0.001**	1.090	1.057 – 1.124	**<0.001**	1.096	1.063 – 1.130	**<0.001**
Miles of Non-Interstate Roads w/ 45 mph+	0.231	0.129 – 0.415	**<0.001**	0.248	0.139 – 0.443	**<0.001**	0.246	0.137 – 0.442	**<0.001**	0.205	0.114 – 0.371	**<0.001**
Miles of Non-Interstate Roads w/ 35 mph+	1.589	1.059 – 2.386	**0.025**	1.439	0.952 – 2.175	0.084	1.539	1.020 – 2.320	**0.040**	1.538	1.018 – 2.322	**0.041**
Mean Width of Arterials				1.007	0.998 – 1.017	0.137	1.007	0.998 – 1.017	0.137	1.007	0.998 – 1.017	0.143
Sidewalk Miles (ODOT System)										1.018	1.008 – 1.028	**<0.001**
% Walk Commute	1.672	0.711 – 3.929	0.239	2.509	1.040 – 6.056	**0.041**	1.913	0.815 – 4.487	0.136	1.823	0.747 – 4.448	0.187
% Transit Commute	6.094	1.981 – 18.745	**0.002**	6.028	1.989 – 18.267	**0.001**	4.964	1.656 – 14.879	**0.004**	4.717	1.558 – 14.284	**0.006**
Transit Stops	1.010	1.007 – 1.012	**<0.001**	1.009	1.007 – 1.012	**<0.001**	1.009	1.007 – 1.012	**<0.001**	1.009	1.006 – 1.011	**<0.001**
% Hhs w/out Vehicle												
Sidewalks Rated Substandard (Mi.) (ODOT System)	1.023	1.008 – 1.038	**0.002**	1.021	1.007 – 1.035	**0.003**	1.022	1.008 – 1.037	**0.003**			
Sidewalk Rated Poor (Mi.) (ODOT System)	0.988	0.946 – 1.032	0.582				0.989	0.947 – 1.033	0.616			
Intersection Density (Per Sqmi.)										0.920	0.767 – 1.104	0.369
Total Jobs Density(000s per Sqmi.)	0.952	0.936 – 0.968	**<0.001**	0.950	0.934 – 0.967	**<0.001**	0.951	0.935 – 0.967	**<0.001**	0.951	0.935 – 0.968	**<0.001**
Low Wage Jobs Density (000s per Sqmi.)	1.312	1.170 – 1.472	**<0.001**	1.309	1.166 – 1.469	**<0.001**	1.317	1.173 – 1.478	**<0.001**	1.334	1.189 – 1.497	**<0.001**
Alcohol Est. Density Count(per Sqmi.)	1.001	1.000 – 1.001	**<0.001**	1.001	1.000 – 1.001	**<0.001**	1.001	1.000 – 1.001	**<0.001**	1.001	1.000 – 1.001	**<0.001**

	Mixed Model E			Mixed Model F			Mixed Model G			Mixed Model I			Fixed Model K		
Predictors	*Incidence Rate Ratios*	*CI*	*p*	*Incidence Rate Ratios*	*CI*	*p*	*Incidence Rate Ratios*	*CI*	*p*	*Incidence Rate Ratios*	*CI*	*p*	*Incidence Rate Ratios*	*CI*	*p*
Intercept	4.988	3.408 – 7.300	**<0.001**	4.536	3.101 – 6.636	**<0.001**	5.723	3.938 – 8.316	**<0.001**	3.724	2.401 – 5.777	**<0.001**	4.911	3.500 – 6.891	**<0.001**
% Asian				3.376	1.420 – 8.031	**0.006**				3.526	1.142 – 10.884	**0.028**			
% Black										0.614	0.202 – 1.864	0.390			
% Latinx				2.140	1.384 – 3.311	**0.001**				2.033	1.012 – 4.083	**0.046**			
% BIPOC	1.747	1.122 – 2.720	**0.013**				1.965	1.264 – 3.055	**0.003**				2.023	1.309 – 3.127	**0.002**
% Hhs Limited English Proficiency										0.959	0.256 – 3.585	0.950			
% Hh Disability										2.176	1.134 – 4.176	**0.019**			
Median Income (thousand)	0.986	0.983 – 0.989	**<0.001**	0.987	0.984 – 0.990	**<0.001**	0.984	0.982 – 0.987	**<0.001**	0.987	0.984 – 0.991	**<0.001**	0.985	0.983 – 0.988	**<0.001**
VMT on Major Arterials (million)	1.095	1.062 – 1.129	**<0.001**	1.095	1.062 – 1.129	**<0.001**	1.092	1.059 – 1.126	**<0.001**	1.097	1.064 – 1.131	**<0.001**	1.106	1.071 – 1.142	**<0.001**
Miles of Non-Interstate Roads w/ 45 mph+	0.213	0.118 – 0.385	**<0.001**	0.217	0.120 – 0.390	**<0.001**	0.207	0.114 – 0.376	**<0.001**	0.220	0.122 – 0.398	**<0.001**	0.228	0.124 – 0.417	**<0.001**
Miles of Non-Interstate Roads w/ 35 mph+	1.519	1.007 – 2.292	**0.046**	1.457	0.967 – 2.193	0.072	1.545	1.021 – 2.339	**0.040**	1.386	0.917 – 2.093	0.121	1.268	0.825 – 1.947	0.279
Mean Width of Arterials	1.006	0.997 – 1.016	0.191	1.007	0.997 – 1.016	0.171	1.006	0.996 – 1.016	0.222	1.007	0.997 – 1.017	0.151	1.009	0.999 – 1.019	0.084
Sidewalk Miles (ODOT System)	1.019	1.009 – 1.029	**<0.001**	1.019	1.009 – 1.029	**<0.001**	1.019	1.009 – 1.029	**<0.001**	1.017	1.007 – 1.027	**0.001**	1.025	1.015 – 1.035	**<0.001**
% Walk Commute	1.421	0.563 – 3.586	0.457	1.554	0.618 – 3.907	0.349	1.627	0.663 – 3.995	0.288	2.417	0.971 – 6.015	0.058	0.954	0.394 – 2.309	0.917
% Transit Commute	3.374	1.057 – 10.772	**0.040**	3.929	1.240 – 12.445	**0.020**				7.378	2.356 – 23.102	**0.001**	3.936	1.450 – 10.684	**0.007**
Transit Stops	1.009	1.006 – 1.011	**<0.001**	1.009	1.007 – 1.012	**<0.001**	1.010	1.007 – 1.012	**<0.001**	1.009	1.007 – 1.012	**<0.001**	1.008	1.005 – 1.010	**<0.001**
% Hhs w/out Vehicle	2.449	0.967 – 6.201	0.059	2.391	0.950 – 6.016	0.064									
Sidewalks Rated Substandard (Mi.) (ODOT System)															
Sidewalk Rated Poor (Mi.) (ODOT System)															
Intersection Density (Per Sqmi.)	0.926	0.772 – 1.110	0.406	0.892	0.741 – 1.074	0.229	0.932	0.776 – 1.119	0.451	0.911	0.755 – 1.100	0.334	0.977	0.809 – 1.179	0.807
Total Jobs Density(000s per Sqmi.)	0.952	0.936 – 0.968	**<0.001**	0.953	0.937 – 0.970	**<0.001**	0.951	0.935 – 0.968	**<0.001**	0.952	0.935 – 0.968	**<0.001**	0.950	0.933 – 0.968	**<0.001**
Low Wage Jobs Density (000s per Sqmi.)	1.301	1.157 – 1.464	**<0.001**	1.289	1.146 – 1.449	**<0.001**	1.333	1.186 – 1.498	**<0.001**	1.309	1.167 – 1.469	**<0.001**	1.344	1.187 – 1.522	**<0.001**
Alcohol Est. Density Count(per Sqmi.)	1.001	1.000 – 1.001	**<0.001**	1.001	1.000 – 1.001	**<0.001**	1.001	1.000 – 1.001	**<0.001**	1.001	1.000 – 1.001	**<0.001**	1.001	1.000 – 1.001	**<0.001**

Random Effects	Mixed Model A	Mixed Model B	Mixed Model C	Mixed Model D	Mixed Model E	Mixed Model F	Mixed Model G	Mixed Model I	Fixed Model K
σ^2	0.35	0.35	0.35	0.35	0.35	0.35	0.36	0.35	0.38
τ_{00}	0.04 $_{Year}$	0.03 $_{Year}$	0.04 $_{Year}$	0.04 $_{Year}$	0.04 $_{Year}$	0.03 $_{Year}$	0.04 $_{Year}$	0.03 $_{Year}$	0.03 $_{Year}$
	0.11 $_{Urban\_Area}$	0.10 $_{Urban\_Area}$	0.11 $_{Urban\_Area}$	0.11 $_{Urban\_Area}$	0.11 $_{Urban\_Area}$	0.10 $_{Urban\_Area}$	0.11 $_{Urban\_Area}$	0.10 $_{Urban\_Area}$	
ICC	0.29	0.28	0.30	0.29	0.29	0.28	0.29	0.26	0.08
N	2 $_{Year}$	2 $_{Year}$	2 $_{Year}$	2 $_{Year}$	2 $_{Year}$	2 $_{Year}$	2 $_{Year}$	2 $_{Year}$	2 $_{Year}$
	39 $_{Urban\_Area}$	39 $_{Urban\_Area}$	39 $_{Urban\_Area}$	39 $_{Urban\_Area}$	39 $_{Urban\_Area}$	39 $_{Urban\_Area}$	39 $_{Urban\_Area}$	39 $_{Urban\_Area}$	
Observations	1040	1040	1040	1040	1040	1040	1040	1040	1040
Marginal R^2 / Conditional R^2	0.452 / 0.614	0.454 / 0.606	0.449 / 0.613	0.452 / 0.613	0.451 / 0.611	0.458 / 0.609	0.453 / 0.611	0.464 / 0.606	0.495 / 0.534
AIC	5445.930	5442.649	5447.870	5449.581	5448.013	5438.608	5454.996	5439.767	5511.831

Figure 8.10: Urban tracts pooled tract all pedestrian injury models

8.4.2.5 Cross Validation Results and Model Selection

The models constructed and presented in Figure 8.10 include AIC, marginal and conditional R^2 values to help understand how different specifications improve the quality of the model overall. In addition to these measures is the RMSE based on 10-fold cross-validation. R^2 values are also presented for additional model evaluation measures. These results highlight the models with the best predictive capability by partitioning the data into 10 groups and using 90% of the data to estimate a model and then to compare with the remaining 10% of data and assessing how well each model does at predicting total pedestrian injuries at the tract level. Two types of specifications are used in the cross-validation including mixed models where random parameters for urban area and year are included but also fixed effects models where random parameters are not used. The objective of showing cross validation results for both fixed and mixed effects models is to highlight the importance of the mixed effects approach. The differences between the mixed and fixed effects model are particularly noticeable where the best fixed effect model results in an RMSE of 20.1 in Model E while the best mixed effect model attains an RMSE of 9.6 with both Model E and model F. Table 8.4 shows how RMSE is lower for all models when specifying a mixed effects model demonstrating the importance of this type of specification in terms of prediction.

Table 8.4: Cross Validation Results for Urban Tracts Pooled Data Models

Model	RMSE		R^2	
	Fixed	Mixed	Fixed	Mixed
Pool - Base	183.6	83.2	15%	16%
Pool - A	22.1	10.0	29%	43%
Pool - B	41.3	13.0	25%	39%
Pool - C	24.0	10.0	28%	44%
Pool - D	91.8	31.2	21%	28%
Pool - E	20.1	9.6	30%	44%
Pool - F	22.2	9.6	29%	43%
Pool - G	24.3	10.1	29%	43%
Pool - H	33.2	12.3	27%	40%
Pool - I	28.1	12.2	29%	42%
Pool - J	22.3	10.0	26%	41%
Pool - K	17.9	13.5	31%	35%

Based on the performance measures in this table Models E and F appear to perform best and these two models also very good performance based on Nagelkerke marginal and conditional R^2 of 0.451/0.611 and 0.0458/0.609 respectively. Model E operationalizes race using an aggregate variable grouping all BIPOC people while Model F uses disaggregate measures including just the proportion of people in a tract that are Asian or Latinx. Based on model performance and the desire to make inferences for disaggregate race variables, Model A and Model F will also be used for marginal effects and adjusted relative risk summaries below to evaluate the role the disaggregated race categories.

Model B performed reasonably well with RMSE of 13 and a pseudo marginal/conditional R^2 of 0.454/0.606 and will also be explored in more detail in the marginal effect and relative risk section below.

8.4.2.6 Marginal Effects Tests for Select Urban Tracts Pooled Data Model

As explained above, marginal effects tests are partial derivatives of statistical models estimated above and allow for simpler interpretation of model outputs by holding all variables in the model constant at the observed mean while varying the covariate(s) of interest in order to see how the response variable changes. This is done below for income, race, ethnicity, disability, and English proficiency to show the relative impact of changes in these variables based on observed ranges of those variables in Oregon. Marginal effects tests are also presented in this section for other select covariates while others are presented in the Appendix.

Using the selected Model E and Model F marginal effects and adjusted relative risk are presented in Figure 8.11. All covariates are held at the mean values based on the observed data while the median income is varied according to the range of observed values. The marginal effects (top panel) show how total pedestrian injuries are expected in a tract based on the median income of the tract all else being equal. Figure 8.11 shows that adjusted relative risk decreases by about 40% if the tract exhibits the state median income (~$60,000) and declines by nearly 94% in the highest income tracts. In fact, in the seven urban tracts in Oregon where the median income is greater than $150,000 (~37,000 people) there was only nine pedestrian injuries in 10 years while in tracts with less than $25,000 (~124,000 people) there were 551 fatal and severe injuries during the same time period. There does not seem to be a significant difference between the two models based on these tests. These figures highlight the clear relationship between pedestrian injuries and a tract's median income even considering the confidence intervals.

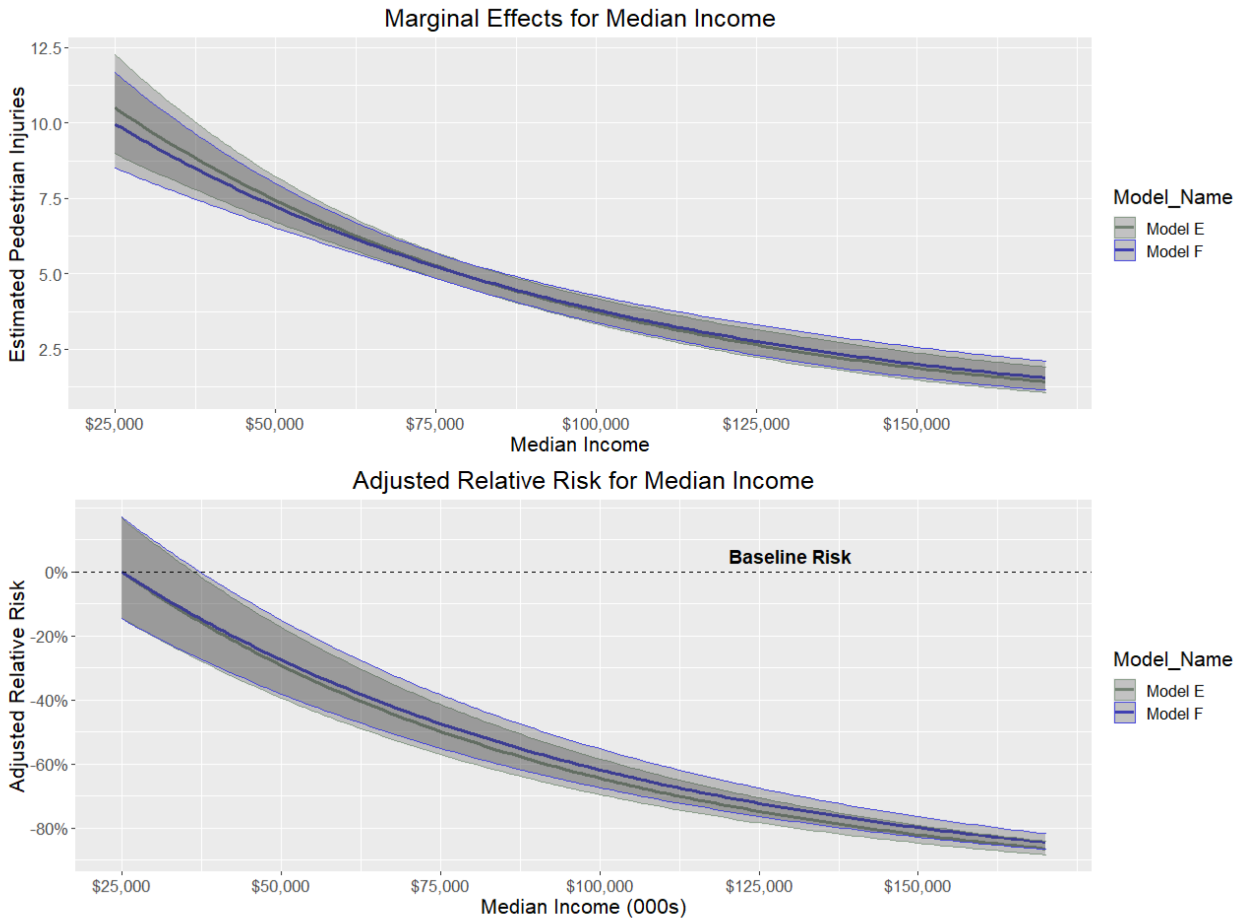

Figure 8.11: Marginal effects and adjusted relative risk for median income (Urban tracts using Model E & F)

The next set of marginal effects and adjusted relative risk results are presented in Figure 8.12. This figure shows how the percentage of the tract's population that is BIPOC effects pedestrian injury outcomes. The precision of the percent BIPOC variable is better for the total injury models compared to the fatal and severe model summarized above. The impact of this variable can be observed in the figure below where adjusted relative risk increases by about 13% in tracts with the state average (22%) percent of tract population that is BIPOC with tracts in the upper range of BIPOC % exhibiting up to 40% more risk than tracts with no BIPOC communities, all else being equal.

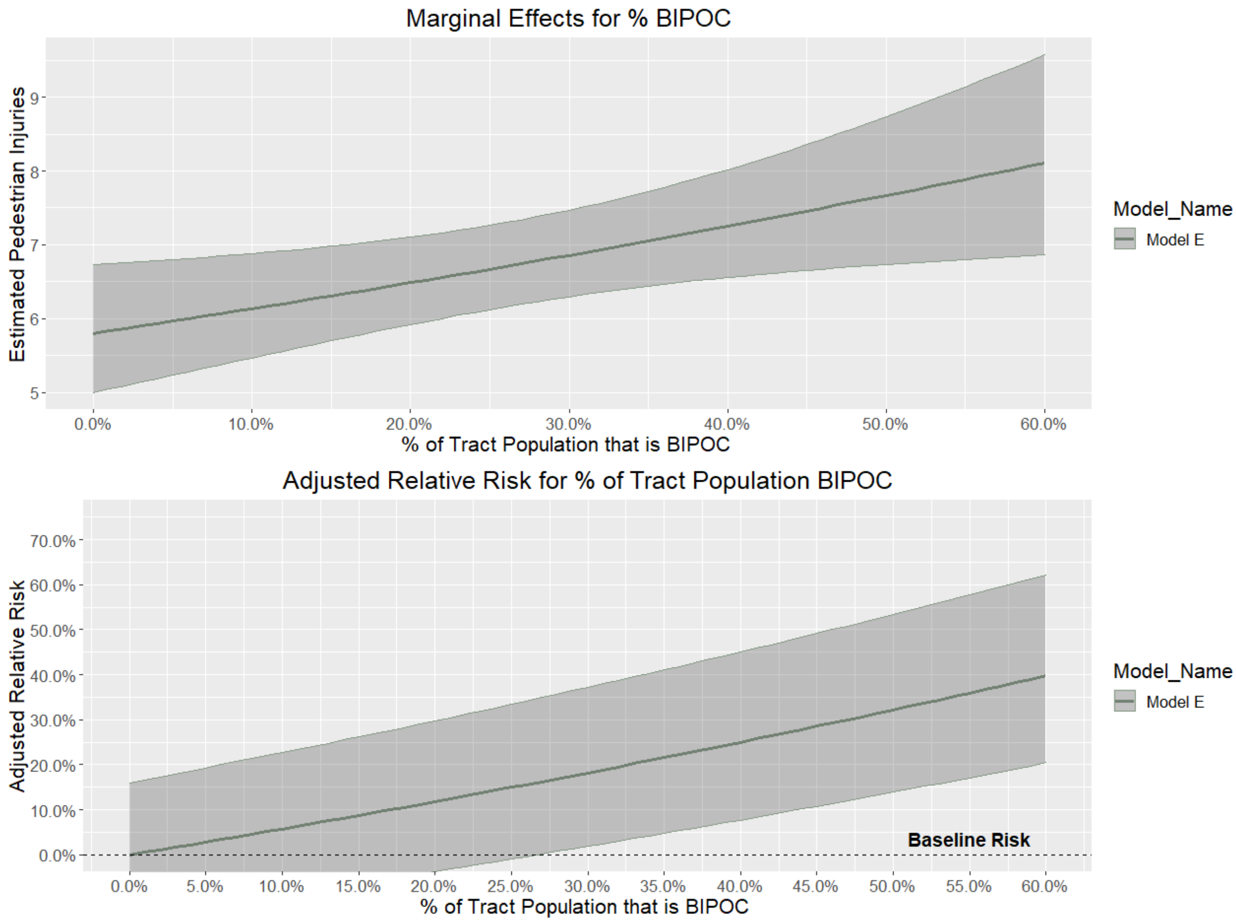

Figure 8.12: Marginal effects and adjusted relative risk for percent of tract population BIPOC (Urban tracts using Model E)

In Figure 8.13 presents marginal effects and adjusted relative risk is presented using the percent Asian and percent Latinx variables from Model F. Other races were not modeled because variables representing other measures of race, as quantified by the Census, were not significantly correlated to pedestrian injuries at the Census tract level. The figure below shows the positive correlation between percent Asian and Latinx by applying the model and calculating the margin effects. As the proportion increase so does the expected number of pedestrian injuries in the tract. Tracts with larger percentages of the population being Asian or Latinx peoples experience significantly more risk compared to tracts with lower percentages of the Asian and Latinx people.

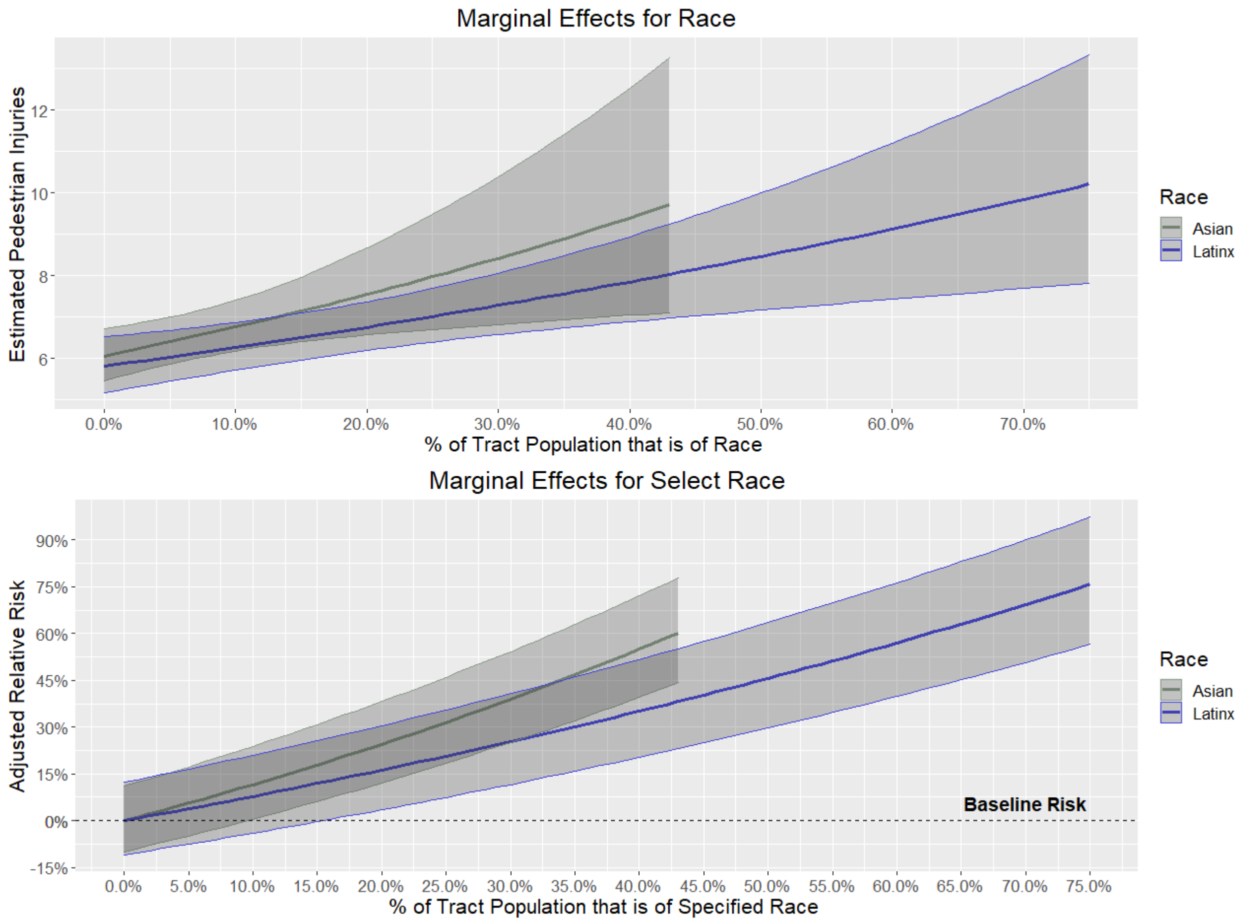

Figure 8.13: Marginal effects and adjusted relative risk for Asian and Latinx variables (Urban tracts using Model F)

The marginal effects and adjusted relative risk for the variable that accounts for the percent of the tracts households that have an individual with a disability are presented in Figure 8.14. This figure shows how the increase in the proportion of households in a tract that have a disabled person increases the frequency of pedestrian injuries and associated relative risk.

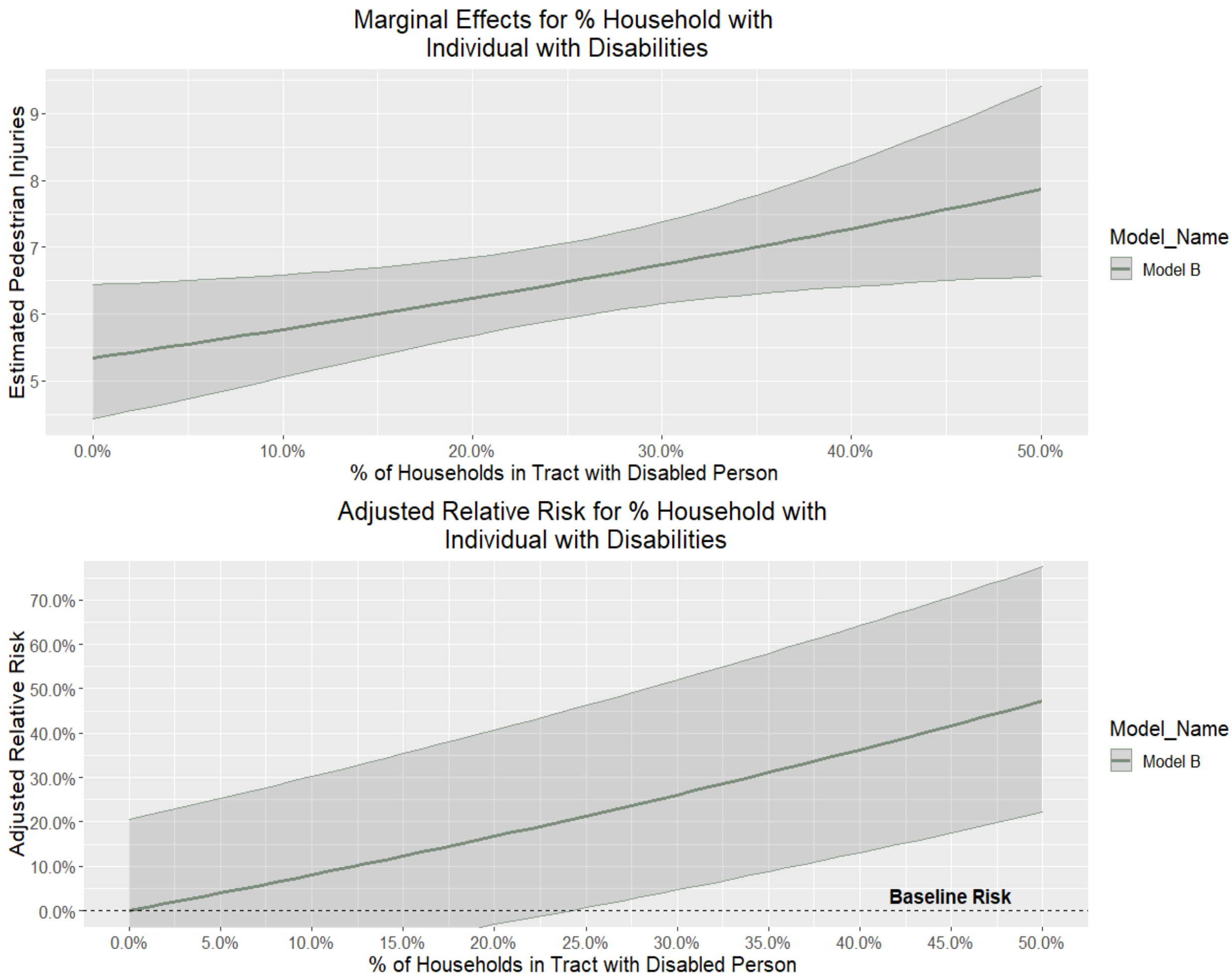

Figure 8.14: Marginal effects and adjusted relative risk for percentage of tract's households that have individual with disability (Urban tracts using Model B)

8.4.2.7 All Pedestrian Injury Models Discussion

The section above details the results of various statistical models attempting to understand the effects of sociodemographic, traffic exposure, and built environmental factors on total pedestrian injury outcomes at the tract level using an ecological analysis approach. Even after controlling for traffic exposure and built environmental factors from available data, income and race measures are positively correlated with pedestrian injuries. Total injury models appear more stable and precise than the fatal and severe injury models, likely due to the larger number of incidents recorded. Income is a very stable measure varying minimally in the size of the effect from model to model with relatively precise confidence intervals. The impact of the percent BIPOC variable is less certain but models above show a significant effect and correlation with pedestrian fatal and sever injuries. Similarly, for disaggregate race variables percent Asian and percent Latinx are associated with more fatal and severe pedestrian injuries. Percent of the tracts population that is Black is not significantly associated with pedestrian injuries as mentioned above, potentially because of small numbers issues mentioned in the fatal and severe injury discussion above.

Exposure to VMT on major arterials is an important factor in predicting where pedestrian injuries occur, as is the miles of non-interstate roadway with posted speed limits of 35 mph or higher. Though direct measures of pedestrian activity were not available transit measures including the percentage of workers using transit and the number of transit stops were positively associated with more total pedestrian injuries. Additionally, the number of sidewalk miles (on ODOT's system) were also positively associated with pedestrian injuries. Available measures of the built environment such as the number of miles of sidewalk (on ODOT's system) rated as substandard were positively correlated with pedestrian injuries though it's not clear from this analysis if models are picking up on pedestrian activity with this variable or if its measuring the built environment. Built environment measures such as job density, low wage job density, and alcohol establishment density are also positively associated with pedestrian injuries.

8.5 CENSUS TRACT ANALYSIS DISCUSSION

This chapter tests several model specifications aiming to find models that aid in the understanding of the association between income, ethnicity, and race at the tract level and pedestrian injury outcomes. This chapter develops statistical models using pooled data to determine high performing models which are evaluating in detailed cross-validation, marginal effects and adjusted relative risk measures. This analysis highlights the importance of considering the effects of income at the tract level in understanding where pedestrian injuries occur. The income parameter is a consistent and stable predictor of pedestrian injury across study periods and injury severities. Race is a significant variable in the pooled data and latter period (2014-2018) but is less stable across periods for the fatal and severe injury models (See Appendix A-3). For the fatal and severe injury models, the early period (2008 to 2012) of data shows that some race variables are not significant at the 0.05 level such as in the percent Asian and percent BIPOC, though percent BIPOC is significant at the 0.10 level for this early period and is significant at the 0.05 level in the latter period (2014-2018) and pooled data. For the total pedestrian injury models (see Appendix A-4) the percent BIPOC variable is significant in the latter period (2014-2018) and pooled data sets but not in the earlier study (2008-2014) period. The disaggregate racial variables including percent Latinx and percent Asian are stable for the latter period and the pooled data but percent Latinx effect is smaller and just outside the 0.05 level of significance ($p = 0.052$) while percent Asian effect is smaller and not significant at the 0.05 level.

The differences in tract level analysis across time periods shows that, over time, disparities based on race may be growing. This is corroborated by the FARS analysis detailed in Chapter 4 where pedestrian fatal injury rate disparities have grown between similar time periods as those analyzed in the tract level analysis. In Table 8.5 pedestrian injury rates are summarized and show the difference between fatal pedestrian injury BIPOC rates and the Oregon average rates. BIPOC fatal injury rates were 1.62 deaths per 100,000 people in 2009-2013 compared to the Oregon average of 1.46, a difference of 10 percent. In the 2014-2018 time period this difference grew to 15% with BIPOC injury rate of 2.85 and the Oregon average of 2.08.

Table 8.5: Pedestrian Fatal Injury Rates per 100,000 people

FARS Period	Fatal Injury Rate per 100,000 People		
	White	**BIPOC**	**Oregon**
2009-2013	1.27 (1.26-1.28)	1.62 (1.54-1.7)	1.46 (1.45 - 1.47)
2014-2018	1.56 (1.55-1.57)	2.85 (2.78-2.92)	2.08 (2.07 - 2.09)

95% Confidence Interval shown in parentheses

8.6 LIMITATIONS

The analysis in this chapter uses an ecological approach where variables measured at the zonal level are used to understand disaggregate outcomes of pedestrian injury. Many of the zonal measures represent residential information but this doesn't necessarily mean that the pedestrian crash participants are the people who live in these Census tracts. However, as demonstrated in Chapter 6 where home and incident location are analyzed to better understand the likelihood of crash participants being struck in their home tract, we know that a substantial proportion of people are struck in their home tract or a tract bordering their home tract. Nevertheless the results of the statistical analysis tell us Census tract measures associated with pedestrian injuries and associating any sociodemographic measures to individual pedestrian injuries becomes an ecological fallacy and is not a proper way to interpret these results. As mentioned in the future research section, agencies should adopt reporting protocols that include some measure of income and race in their crash database of record to more directly measure these sociodemographic data elements so as to monitor disparities more directly.

Another limitation of this work is the imperfect assignment of crash injury locations to polygons, especially in cases where the crash is on a street that also represents a border of two Census geographies. Based on the analysis of spatial autocorrelation featured in section 2.3.1, the bias introduced is likely negligible. The zonal analysis featured here is meant as a starting point for a more disaggregate analysis of the network where roadway segments and intersections take the place of the Census tracts as the unit of analysis. Many of these spatial data issues can be more easily resolved using this approach though it's unclear if the overall findings would change. A network -based analysis is being proposed for the next phase of this work and findings from this Technical Report should be compared to the next phase of work to see how spatial resolution impacts the overall story presented in this document.

9.0 FUTURE RESEARCH

Even though this research utilized data from a variety of sources to document existing pedestrian injury disparities based on race and income, only the racial disparities are directly observable using the FARS data. It would be ideal to have the income of crash participants to better control for income effects that are likely having a bigger effect in pedestrian injury outcomes compared to race. This data element would be difficult to collect but proxy measures for income could more easily be derived and appended to crash databases of record such as those maintained by ODOT. Potential proxy measures could be based on health system information such as if the crash participant is a recipient of Medicaid (Oregon Health Plan). Since Medicaid recipients qualify for coverage based on income this would provide a rough measure of income. Another potential proxy could be the income or poverty status of the Census geography, either block group or tract. This would not be a direct measure of the crash participant's income but could still be very useful to monitoring these disparities.

FARS data does gather race of the crash participant it would be ideal to have this data element for other injury severities too. By linking with health system data this attribute could be successfully added to agencies' crash database of record for at least severe injuries. This would likely require staff collecting those data to understand nuances with racial categorization and adopt a data domain that allows for racial categories that fit people's self-identified racial identities but are still collapsible to a level useful for measuring social disparities.

A key objective of this research was to determine if disparities have changed but it is outside the purview of this research to answer *why* disparities have changed. Based on the analysis in this chapter, future research should explore the causes of the growing disparity. Potential lines of inquiry could include the changing spatial distribution of poverty and whether low income people are increasingly moving to more automobile centric environments where pedestrian injury rates are likely higher. Another line of inquiry would be to investigate the link between travel behavior and economic recovery following the 2008 Financial Crisis and related recession. The theory is that because low wage jobs disappeared in greater numbers during the 2008 recession, perhaps people in low income households reduced their pedestrian exposure by working less and making fewer trips overall. This shows up in the crash injury data as fewer pedestrian injuries and lower rates, especially for people of color who are more likely to be low income. Examining how pedestrian exposure is changing as more economic opportunities have been created for low income people since the end of 2008 economic recession would be a useful line of new research.

Future research should also explore the role that vehicle design is having on pedestrian injury outcomes. Between 1988 and 2018 the average weight of personal vehicles has increased by 26% (EPA 2020). Severity of pedestrian injury is likely higher due to increased weight of vehicles but it's not clear if this increase is severity is experienced by everyone equally. Future research could determine if changing vehicle design is exacerbating racial and income disparities.

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APPENDIX A

Urban Tracts Pooled Data Models - Fatal & Severe (KA) Injury

	Mixed Model A		Mixed Model B		Mixed Model C		Mixed Model D		Mixed Model E		Mixed Model F		Mixed Model G		Mixed Model H		Mixed Model I		Mixed Model J		Fixed Model K	
Predictors	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*
Intercept	1.342 (0.866 – 2.080)	0.188	0.786 (0.422 – 1.463)	0.447	1.025 (0.644 – 1.631)	0.916	1.104 (0.695 – 1.753)	0.675	1.089 (0.671 – 1.767)	0.729	1.020 (0.620 – 1.678)	0.937	1.111 (0.701 – 1.761)	0.655	0.865 (0.469 – 1.596)	0.644	0.806 (0.430 – 1.509)	0.500	0.967 (0.624 – 1.499)	0.882	0.771 (0.533 – 1.117)	0.169
% Asian	4.917 (1.297 – 18.637)	**0.019**									5.232 (1.348 – 20.308)	**0.017**					1.888 (0.298 – 11.965)	0.500				
% Black	0.244 (0.040 – 1.480)	0.125															0.228 (0.037 – 1.398)	0.110				
% Latinx	1.925 (0.971 – 3.814)	0.061									1.941 (0.989 – 3.813)	0.054					0.821 (0.272 – 2.478)	0.727				
% BIPOC							1.867 (0.933 – 3.738)	0.078	1.856 (0.923 – 3.730)	0.083			2.041 (1.023 – 4.071)	**0.043**					2.087 (1.063 – 4.097)	**0.033**	2.239 (1.136 – 4.413)	**0.020**
% Hhs Limited English Proficiency			5.419 (1.698 – 17.296)	**0.004**	6.315 (2.002 – 19.921)	**0.002**											6.011 (0.762 – 47.433)	0.089				
% Hh Disability			2.004 (0.713 – 5.627)	0.187											2.448 (0.882 – 6.791)	0.086	1.963 (0.703 – 5.484)	0.198				
Median Income (thousand)	0.980 (0.975 – 0.985)	**<0.001**	0.984 (0.979 – 0.989)	**<0.001**	0.982 (0.978 – 0.987)	**<0.001**	0.981 (0.976 – 0.985)	**<0.001**	0.981 (0.976 – 0.986)	**<0.001**	0.982 (0.976 – 0.987)	**<0.001**	0.980 (0.975 – 0.984)	**<0.001**	0.982 (0.977 – 0.987)	**<0.001**	0.983 (0.978 – 0.989)	**<0.001**	0.981 (0.977 – 0.986)	**<0.001**	0.983 (0.979 – 0.987)	**<0.001**
VMT on Major Arterials (million)	1.096 (1.047 – 1.147)	**<0.001**	1.086 (1.037 – 1.137)	**<0.001**	1.088 (1.039 – 1.139)	**<0.001**	1.092 (1.043 – 1.143)	**<0.001**	1.092 (1.043 – 1.143)	**<0.001**	1.093 (1.045 – 1.144)	**<0.001**	1.087 (1.038 – 1.138)	**<0.001**	1.094 (1.045 – 1.145)	**<0.001**	1.091 (1.043 – 1.142)	**<0.001**	1.096 (1.047 – 1.146)	**<0.001**	1.095 (1.046 – 1.146)	**<0.001**
Miles of Non-Interstate Roads w/ 45 mph+	0.286 (0.129 – 0.637)	**0.002**	0.311 (0.141 – 0.686)	**0.004**	0.291 (0.131 – 0.647)	**0.002**	0.238 (0.106 – 0.535)	**0.001**	0.239 (0.106 – 0.539)	**0.001**	0.251 (0.112 – 0.565)	**0.001**	0.242 (0.107 – 0.548)	**0.001**	0.257 (0.115 – 0.573)	**0.001**	0.283 (0.127 – 0.630)	**0.002**	0.255 (0.114 – 0.572)	**0.001**	0.221 (0.100 – 0.492)	**<0.001**
Miles of Non-Interstate Roads w/ 35 mph+	4.147 (2.256 – 7.622)	**<0.001**	3.783 (2.044 – 7.001)	**<0.001**	3.952 (2.147 – 7.275)	**<0.001**	4.042 (2.195 – 7.443)	**<0.001**	4.036 (2.191 – 7.434)	**<0.001**	3.829 (2.082 – 7.044)	**<0.001**	4.099 (2.217 – 7.582)	**<0.001**	3.816 (2.061 – 7.063)	**<0.001**	3.640 (1.975 – 6.709)	**<0.001**	3.654 (1.977 – 6.755)	**<0.001**	4.548 (2.495 – 8.291)	**<0.001**
Mean Width of Arterials			1.014 (0.998 – 1.031)	0.095	1.015 (0.999 – 1.032)	0.073	1.015 (0.998 – 1.032)	0.080	1.015 (0.998 – 1.032)	0.085	1.015 (0.999 – 1.033)	0.071	1.014 (0.998 – 1.031)	0.095	1.015 (0.998 – 1.032)	0.086	1.015 (0.998 – 1.032)	0.083	1.017 (1.000 – 1.034)	0.051	1.019 (1.003 – 1.036)	**0.023**
Sidewalk Miles (ODOT System)							1.031 (1.017 – 1.044)	**<0.001**	1.031 (1.017 – 1.044)	**<0.001**	1.031 (1.017 – 1.044)	**<0.001**	1.032 (1.018 – 1.046)	**<0.001**	1.030 (1.017 – 1.044)	**<0.001**	1.030 (1.016 – 1.043)	**<0.001**	1.033 (1.020 – 1.047)	**<0.001**	1.035 (1.021 – 1.049)	**<0.001**
% Walk Commute	0.168 (0.043 – 0.656)	**0.010**	0.295 (0.073 – 1.198)	0.088	0.241 (0.062 – 0.934)	**0.039**	0.216 (0.053 – 0.885)	**0.033**	0.207 (0.047 – 0.906)	**0.037**	0.221 (0.050 – 0.972)	**0.046**	0.203 (0.050 – 0.834)	**0.027**	0.269 (0.063 – 1.147)	0.076	0.301 (0.071 – 1.286)	0.105	0.204 (0.051 – 0.813)	**0.024**	0.269 (0.068 – 1.067)	0.062
% Transit Commute	12.635 (1.978 – 80.715)	**0.007**	10.504 (1.680 – 65.681)	**0.012**	8.889 (1.442 – 54.783)	**0.019**	9.063 (1.481 – 55.464)	**0.017**	8.617 (1.310 – 56.677)	**0.025**	8.774 (1.327 – 58.011)	**0.024**			12.671 (2.086 – 76.957)	**0.006**	10.507 (1.635 – 67.516)	**0.013**	8.102 (1.626 – 40.380)	**0.011**	5.526 (1.116 – 27.359)	**0.036**
Transit Stops	1.008 (1.004 – 1.012)	**<0.001**	1.008 (1.004 – 1.012)	**<0.001**	1.008 (1.004 – 1.012)	**<0.001**	1.007 (1.003 – 1.011)	**<0.001**	1.007 (1.003 – 1.011)	**<0.001**	1.007 (1.003 – 1.011)	**<0.001**	1.008 (1.004 – 1.012)	**<0.001**	1.007 (1.003 – 1.011)	**<0.001**	1.008 (1.004 – 1.012)	**<0.001**	1.006 (1.003 – 1.010)	**0.001**	1.006 (1.003 – 1.010)	**0.001**
% Hhs w/out Vehicle									1.144 (0.273 – 4.786)	0.854	1.137 (0.274 – 4.717)	0.860										
Sidewalks Rated Substandard (Mi.) (ODOT System)	1.033 (1.011 – 1.055)	**0.003**	1.035 (1.014 – 1.056)	**0.001**	1.031 (1.009 – 1.053)	**0.005**																
Sidewalk Rated Poor (Mi.) (ODOT System)	1.024 (0.970 – 1.081)	0.392			1.030 (0.975 – 1.087)	0.290																
Intersection Density (Per Sqmi.)							0.905 (0.672 – 1.221)	0.515	0.906 (0.672 – 1.221)	0.515	0.854 (0.631 – 1.156)	0.308	0.912 (0.675 – 1.232)	0.550	0.949 (0.703 – 1.280)	0.730	0.888 (0.655 – 1.206)	0.448	0.926 (0.687 – 1.249)	0.615	0.851 (0.633 – 1.144)	0.284
Less than College Job Density(000s per Sqmi.)	1.091 (0.823 – 1.446)	0.544	1.092 (0.824 – 1.448)	0.541	1.077 (0.813 – 1.427)	0.606	1.143 (0.858 – 1.523)	0.360	1.142 (0.857 – 1.521)	0.364	1.147 (0.864 – 1.524)	0.342	1.277 (0.970 – 1.682)	0.081	1.199 (0.904 – 1.591)	0.208	1.161 (0.872 – 1.547)	0.306	1.162 (0.870 – 1.552)	0.310	1.370 (1.048 – 1.792)	**0.021**
Total Jobs Density(000s per Sqmi.)	0.975 (0.963 – 0.988)	**<0.001**	0.972 (0.960 – 0.985)	**<0.001**	0.974 (0.961 – 0.986)	**<0.001**	0.977 (0.964 – 0.990)	**0.001**	0.977 (0.964 – 0.990)	**0.001**	0.977 (0.964 – 0.991)	**0.001**	0.979 (0.966 – 0.992)	**0.002**	0.975 (0.962 – 0.989)	**<0.001**	0.975 (0.962 – 0.989)	**<0.001**	0.977 (0.964 – 0.991)	**0.001**	0.981 (0.968 – 0.994)	**0.006**
Alcohol Est. Density Count(per Sqmi.)	1.001 (1.000 – 1.002)	**0.001**	1.001 (1.000 – 1.002)	**<0.001**	1.001 (1.000 – 1.002)	**<0.001**	1.001 (1.000 – 1.002)	**0.001**	1.001 (1.000 – 1.002)	**0.002**	1.001 (1.000 – 1.002)	**0.001**	1.001 (1.000 – 1.002)	**0.001**	1.001 (1.000 – 1.001)	**0.002**	1.001 (1.000 – 1.002)	**<0.001**	1.001 (1.000 – 1.002)	**0.001**	1.001 (1.000 – 1.001)	**0.004**
Random Effects																						
σ^2	0.78		0.78		0.78		0.78		0.78		0.78		0.79		0.78		0.78		0.79			
τ_{00}	0.02 Year		0.02 Year		0.02 Year		0.02 Year		0.02 Year		0.02 Year		0.02 Year		0.02 Year		0.02 Year		0.02 Year			
	0.08 Urban_Area		0.06 Urban_Area		0.06 Urban_Area		0.06 Urban_Area		0.06 Urban_Area		0.06 Urban_Area		0.05 Urban_Area		0.05 Urban_Area		0.05 Urban_Area					
ICC	0.11		0.09		0.10		0.09		0.09		0.09		0.08		0.08		0.08		0.02			
N	2 Year		2 Year		2 Year		2 Year		2 Year		2 Year		2 Year		2 Year		2 Year		2 Year			
	39 Urban_Area		39 Urban_Area		39 Urban_Area		39 Urban_Area		39 Urban_Area		39 Urban_Area		39 Urban_Area		39 Urban_Area		39 Urban_Area					
Observations	1040		1040		1040		1040		1040		1040		1040		1040		1040		1040		1040	
Marginal R^2 / Conditional R^2	0.348 / 0.421		0.352 / 0.410		0.351 / 0.415		0.362 / 0.418		0.361 / 0.417		0.358 / 0.417		0.365 / 0.417		0.366 / 0.416		0.358 / 0.411		0.370 / 0.383		NA / 0.302	
AIC	2865.186		2859.551		2860.182		2859.032		2860.998		2857.837		2862.713		2859.189		2854.765		2865.184		2869.263	

Figure A-1: Pooled data urban tracts fatal and severe injury models

Urban Tracts Pooled Data Models - ALl (KABCO) Injury

Predictors	Mixed Model A *Incidence Rate Ratios*	*p*	Mixed Model B *Incidence Rate Ratios*	*p*	Mixed Model C *Incidence Rate Ratios*	*p*	Mixed Model D *Incidence Rate Ratios*	*p*	Mixed Model E *Incidence Rate Ratios*	*p*	Mixed Model F *Incidence Rate Ratios*	*p*
Intercept	5.591 (3.898 – 8.020)	**<0.001**	3.877 (2.494 – 6.026)	**<0.001**	5.275 (3.620 – 7.688)	**<0.001**	5.450 (3.759 – 7.902)	**<0.001**	4.988 (3.408 – 7.300)	**<0.001**	4.536 (3.101 – 6.636)	**<0.001**
% Asian	2.990 (1.300 – 6.877)	**0.010**									3.376 (1.420 – 8.031)	**0.006**
% Black	0.560 (0.186 – 1.685)	0.302										
% Latinx	2.120 (1.366 – 3.292)	**0.001**									2.140 (1.384 – 3.311)	**0.001**
% BIPOC							1.810 (1.163 – 2.817)	**0.009**	1.747 (1.122 – 2.720)	**0.013**		
% Hhs Limited English Proficiency			3.284 (1.536 – 7.022)	**0.002**	3.797 (1.787 – 8.066)	**0.001**						
% Hh Disability			2.168 (1.136 – 4.139)	**0.019**								
Median Income (thousand)	0.985 (0.983 – 0.988)	**<0.001**	0.988 (0.985 – 0.991)	**<0.001**	0.986 (0.983 – 0.989)	**<0.001**	0.985 (0.983 – 0.988)	**<0.001**	0.986 (0.983 – 0.989)	**<0.001**	0.987 (0.984 – 0.990)	**<0.001**
VMT on Major Arterials (million)	1.094 (1.061 – 1.128)	**<0.001**	1.092 (1.059 – 1.126)	**<0.001**	1.090 (1.057 – 1.124)	**<0.001**	1.096 (1.063 – 1.130)	**<0.001**	1.095 (1.062 – 1.129)	**<0.001**	1.095 (1.062 – 1.129)	**<0.001**
Miles of Non-Interstate Roads w/ 45 mph+	0.231 (0.129 – 0.415)	**<0.001**	0.248 (0.139 – 0.443)	**<0.001**	0.246 (0.137 – 0.442)	**<0.001**	0.205 (0.114 – 0.371)	**<0.001**	0.213 (0.118 – 0.385)	**<0.001**	0.217 (0.120 – 0.390)	**<0.001**
Miles of Non-Interstate Roads w/ 35 mph+	1.589 (1.059 – 2.386)	**0.025**	1.439 (0.952 – 2.175)	0.084	1.539 (1.020 – 2.320)	**0.040**	1.538 (1.018 – 2.322)	**0.041**	1.519 (1.007 – 2.292)	**0.046**	1.457 (0.967 – 2.193)	0.072
Mean Width of Arterials			1.007 (0.998 – 1.017)	0.137	1.007 (0.998 – 1.017)	0.137	1.007 (0.998 – 1.017)	0.143	1.006 (0.997 – 1.016)	0.191	1.007 (0.997 – 1.016)	0.171
Sidewalk Miles (ODOT System)							1.018 (1.008 – 1.028)	**<0.001**	1.019 (1.009 – 1.029)	**<0.001**	1.019 (1.009 – 1.029)	**<0.001**
% Walk Commute	1.672 (0.711 – 3.929)	0.239	2.509 (1.040 – 6.056)	**0.041**	1.913 (0.815 – 4.487)	0.136	1.823 (0.747 – 4.448)	0.187	1.421 (0.563 – 3.586)	0.457	1.554 (0.618 – 3.907)	0.349
% Transit Commute	6.094 (1.981 – 18.745)	**0.002**	6.028 (1.989 – 18.267)	**0.001**	4.964 (1.656 – 14.879)	**0.004**	4.717 (1.558 – 14.284)	**0.006**	3.374 (1.057 – 10.772)	**0.040**	3.929 (1.240 – 12.445)	**0.020**
Transit Stops	1.010 (1.007 – 1.012)	**<0.001**	1.009 (1.007 – 1.012)	**<0.001**	1.009 (1.007 – 1.012)	**<0.001**	1.009 (1.006 – 1.011)	**<0.001**	1.009 (1.006 – 1.011)	**<0.001**	1.009 (1.007 – 1.012)	**<0.001**
% Hhs w/out Vehicle									2.449 (0.967 – 6.201)	0.059	2.391 (0.950 – 6.016)	0.064
Sidewalks Rated Substandard (Mi.) (ODOT System)	1.023 (1.008 – 1.038)	**0.002**	1.021 (1.007 – 1.035)	**0.003**	1.022 (1.008 – 1.037)	**0.003**						
Sidewalk Rated Poor (Mi.) (ODOT System)	0.988 (0.946 – 1.032)	0.582			0.989 (0.947 – 1.033)	0.616						
Intersection Density (Per Sqmi.)							0.920 (0.767 – 1.104)	0.369	0.926 (0.772 – 1.110)	0.406	0.892 (0.741 – 1.074)	0.229
Total Jobs Density(000s per Sqmi.)	0.952 (0.936 – 0.968)	**<0.001**	0.950 (0.934 – 0.967)	**<0.001**	0.951 (0.935 – 0.967)	**<0.001**	0.951 (0.935 – 0.968)	**<0.001**	0.952 (0.936 – 0.968)	**<0.001**	0.953 (0.937 – 0.970)	**<0.001**
Low Wage Jobs Density (000s per Sqmi.)	1.312 (1.170 – 1.472)	**<0.001**	1.309 (1.166 – 1.469)	**<0.001**	1.317 (1.173 – 1.478)	**<0.001**	1.334 (1.189 – 1.497)	**<0.001**	1.301 (1.157 – 1.464)	**<0.001**	1.289 (1.146 – 1.449)	**<0.001**
Alcohol Est. Density Count(per Sqmi.)	1.001 (1.000 – 1.001)	**<0.001**	1.001 (1.000 – 1.001)	**<0.001**	1.001 (1.000 – 1.001)	**<0.001**	1.001 (1.000 – 1.001)	**<0.001**	1.001 (1.000 – 1.001)	**<0.001**	1.001 (1.000 – 1.001)	**<0.001**
Random Effects												
σ^2	0.35		0.35		0.35		0.35		0.35		0.35	
τ_{00}	0.04 Year		0.03 Year		0.04 Year		0.04 Year		0.04 Year		0.03 Year	
	0.11 Urban_Area		0.10 Urban_Area		0.11 Urban_Area		0.11 Urban_Area		0.11 Urban_Area		0.10 Urban_Area	
ICC	0.29		0.28		0.30		0.29		0.29		0.28	
N	2 Year		2 Year		2 Year		2 Year		2 Year		2 Year	
	39 Urban_Area		39 Urban_Area		39 Urban_Area		39 Urban_Area		39 Urban_Area		39 Urban_Area	
Observations	1040		1040		1040		1040		1040		1040	
Marginal R^2 / Conditional R^2	0.452 / 0.614		0.454 / 0.606		0.449 / 0.613		0.452 / 0.613		0.451 / 0.611		0.458 / 0.609	
AIC	5445.930		5442.649		5447.870		5449.581		5448.013		5438.608	

Predictors	Mixed Model G *Incidence Rate Ratios*	*p*	Mixed Model H *Incidence Rate Ratios*	*p*	Mixed Model I *Incidence Rate Ratios*	*p*	Mixed Model J *Incidence Rate Ratios*	*p*	Fixed Model K *Incidence Rate Ratios*	*p*
Intercept	5.723 (3.938 – 8.316)	**<0.001**	4.275 (2.751 – 6.643)	**<0.001**	3.724 (2.401 – 5.777)	**<0.001**	4.911 (3.500 – 6.891)	**<0.001**	3.816 (3.045 – 4.781)	**<0.001**
% Asian					3.526 (1.142 – 10.884)	**0.028**				
% Black					0.614 (0.202 – 1.864)	0.390				
% Latinx					2.033 (1.012 – 4.083)	**0.046**				
% BIPOC	1.965 (1.264 – 3.055)	**0.003**					2.023 (1.309 – 3.127)	**0.002**	2.671 (1.716 – 4.158)	**<0.001**
% Hhs Limited English Proficiency					0.959 (0.256 – 3.585)	0.950				
% Hh Disability			2.526 (1.326 – 4.811)	**0.005**	2.176 (1.134 – 4.176)	**0.019**				
Median Income (thousand)	0.984 (0.982 – 0.987)	**<0.001**	0.986 (0.983 – 0.989)	**<0.001**	0.987 (0.984 – 0.991)	**<0.001**	0.985 (0.983 – 0.988)	**<0.001**	0.988 (0.986 – 0.991)	**<0.001**
VMT on Major Arterials (million)	1.092 (1.059 – 1.126)	**<0.001**	1.096 (1.063 – 1.130)	**<0.001**	1.097 (1.064 – 1.131)	**<0.001**	1.106 (1.071 – 1.142)	**<0.001**	1.101 (1.065 – 1.138)	**<0.001**
Miles of Non-Interstate Roads w/ 45 mph+	0.207 (0.114 – 0.376)	**<0.001**	0.224 (0.124 – 0.403)	**<0.001**	0.220 (0.122 – 0.398)	**<0.001**	0.228 (0.124 – 0.417)	**<0.001**	0.170 (0.092 – 0.312)	**<0.001**
Miles of Non-Interstate Roads w/ 35 mph+	1.545 (1.021 – 2.339)	**0.040**	1.459 (0.964 – 2.210)	0.074	1.386 (0.917 – 2.093)	0.121	1.268 (0.825 – 1.947)	0.279	1.919 (1.249 – 2.948)	**0.003**
Mean Width of Arterials	1.006 (0.996 – 1.016)	0.222	1.007 (0.997 – 1.016)	0.173	1.007 (0.997 – 1.017)	0.151	1.009 (0.999 – 1.019)	0.084	1.012 (1.002 – 1.022)	**0.024**
Sidewalk Miles (ODOT System)	1.019 (1.009 – 1.029)	**<0.001**	1.017 (1.007 – 1.027)	**0.001**	1.017 (1.007 – 1.027)	**0.001**	1.025 (1.015 – 1.035)	**<0.001**	1.025 (1.015 – 1.036)	**<0.001**
% Walk Commute	1.627 (0.663 – 3.995)	0.288	2.287 (0.917 – 5.703)	0.076	2.417 (0.971 – 6.015)	0.058	0.954 (0.394 – 2.309)	0.917	1.203 (0.484 – 2.993)	0.690
% Transit Commute			7.081 (2.336 – 21.464)	**0.001**	7.378 (2.356 – 23.102)	**0.001**	3.936 (1.450 – 10.684)	**0.007**	3.376 (1.213 – 9.397)	**0.020**
Transit Stops	1.010 (1.007 – 1.012)	**<0.001**	1.009 (1.006 – 1.011)	**<0.001**	1.009 (1.007 – 1.012)	**<0.001**	1.008 (1.005 – 1.010)	**<0.001**	1.007 (1.005 – 1.010)	**<0.001**
% Hhs w/out Vehicle										
Sidewalks Rated Substandard (Mi.) (ODOT System)										
Sidewalk Rated Poor (Mi.) (ODOT System)										
Intersection Density (Per Sqmi.)	0.932 (0.776 – 1.119)	0.451	0.988 (0.824 – 1.185)	0.898	0.911 (0.755 – 1.100)	0.334	0.977 (0.809 – 1.179)	0.807	0.896 (0.739 – 1.087)	0.266
Total Jobs Density(000s per Sqmi.)	0.951 (0.935 – 0.968)	**<0.001**	0.949 (0.933 – 0.966)	**<0.001**	0.952 (0.935 – 0.968)	**<0.001**	0.950 (0.933 – 0.968)	**<0.001**	0.956 (0.937 – 0.975)	**<0.001**
Low Wage Jobs Density (000s per Sqmi.)	1.333 (1.186 – 1.498)	**<0.001**	1.326 (1.181 – 1.489)	**<0.001**	1.309 (1.167 – 1.469)	**<0.001**	1.344 (1.187 – 1.522)	**<0.001**	1.301 (1.144 – 1.480)	**<0.001**
Alcohol Est. Density Count(per Sqmi.)	1.001 (1.000 – 1.001)	**<0.001**	1.001 (1.000 – 1.001)	**<0.001**	1.001 (1.000 – 1.001)	**<0.001**	1.001 (1.000 – 1.001)	**<0.001**	1.001 (1.001 – 1.001)	**<0.001**
Random Effects										
σ^2	0.36		0.35		0.35		0.38			
τ_{00}	0.04 Year		0.03 Year		0.03 Year		0.03 Year			
	0.11 Urban_Area		0.10 Urban_Area		0.10 Urban_Area					
ICC	0.29		0.27		0.26		0.08			
N	2 Year		2 Year		2 Year		2 Year			
	39 Urban_Area		39 Urban_Area		39 Urban_Area					
Observations	1040		1040		1040		1040		1040	
Marginal R^2 / Conditional R^2	0.453 / 0.611		0.457 / 0.605		0.464 / 0.606		0.495 / 0.534		NA / 0.328	
AIC	5454.996		5448.606		5439.767		5511.831		5557.362	

Figure A-2: Pooled data urban tracts total injury models

Urban Tracts - All Periods Select Models - Fatal & Severe (KA) Injury

	KA Model F - 2008-2012		KA Model G - 2008-2012		KA Model F - 2014-2018		KA Model G - 2014-2018		KA Model F - Pooled		KA Model G - 2014-2018	
Predictors	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*
Intercept	0.976 (0.524 – 1.818)	0.938	1.100 (0.628 – 1.925)	0.739	1.382 (0.755 – 2.529)	0.294	1.398 (0.808 – 2.420)	0.231	1.098 (0.671 – 1.796)	0.710	1.236 (0.780 – 1.960)	0.368
% Asian	2.291 (0.256 – 20.468)	0.458			6.992 (1.283 – 38.102)	**0.025**			5.306 (1.369 – 20.558)	**0.016**		
% Latinx	3.026 (1.268 – 7.222)	**0.013**			1.243 (0.481 – 3.212)	0.653			1.957 (0.999 – 3.831)	0.050		
% BIPOC			2.136 (0.871 – 5.242)	0.097			2.597 (1.003 – 6.729)	**0.049**			2.291 (1.168 – 4.491)	**0.016**
Median Income (thousand)	0.979 (0.971 – 0.987)	**<0.001**	0.979 (0.972 – 0.986)	**<0.001**	0.980 (0.974 – 0.987)	**<0.001**	0.979 (0.973 – 0.985)	**<0.001**	0.981 (0.976 – 0.987)	**<0.001**	0.980 (0.975 – 0.984)	**<0.001**
VMT on Major Arterials (million)	1.058 (0.992 – 1.128)	0.085	1.064 (0.997 – 1.134)	0.061	1.124 (1.055 – 1.197)	**<0.001**	1.116 (1.048 – 1.189)	**0.001**	1.093 (1.045 – 1.144)	**<0.001**	1.084 (1.036 – 1.135)	**0.001**
Mean Width of Arterials	1.023 (0.999 – 1.048)	0.062	1.015 (0.992 – 1.039)	0.197	1.008 (0.985 – 1.031)	0.513	1.007 (0.985 – 1.030)	0.540	1.015 (0.998 – 1.032)	0.083	1.012 (0.995 – 1.029)	0.158
Miles of Non-Interstate Roads w/ 45 mph+	0.269 (0.085 – 0.849)	**0.025**	0.249 (0.078 – 0.789)	**0.018**	0.217 (0.068 – 0.691)	**0.010**	0.196 (0.060 – 0.639)	**0.007**	0.248 (0.111 – 0.556)	**0.001**	0.233 (0.103 – 0.528)	**<0.001**
Miles of Non-Interstate Roads w/ 35 mph+	4.849 (1.803 – 13.042)	**0.002**	4.933 (1.815 – 13.412)	**0.002**	2.892 (1.335 – 6.267)	**0.007**	2.979 (1.361 – 6.519)	**0.006**	3.813 (2.075 – 7.007)	**<0.001**	4.100 (2.218 – 7.577)	**<0.001**
Sidewalk Miles (ODOT System)	1.025 (1.008 – 1.042)	**0.004**	1.028 (1.011 – 1.046)	**0.001**	1.034 (1.015 – 1.053)	**<0.001**	1.034 (1.014 – 1.054)	**0.001**	1.029 (1.016 – 1.043)	**<0.001**	1.030 (1.017 – 1.044)	**<0.001**
% Walk Commute	0.269 (0.039 – 1.872)	0.185	0.129 (0.019 – 0.876)	**0.036**	0.156 (0.019 – 1.301)	0.086	0.163 (0.022 – 1.228)	0.078	0.183 (0.042 – 0.803)	**0.024**	0.143 (0.035 – 0.590)	**0.007**
% Transit Commute	13.964 (1.406 – 138.724)	**0.024**			5.950 (0.503 – 70.452)	0.157			12.883 (2.101 – 79.006)	**0.006**		
Transit Stops	1.006 (1.001 – 1.012)	**0.016**	1.007 (1.002 – 1.012)	**0.008**	1.007 (1.002 – 1.013)	**0.011**	1.008 (1.003 – 1.014)	**0.002**	1.007 (1.003 – 1.011)	**0.001**	1.008 (1.004 – 1.011)	**<0.001**
% Hhs w/out Vehicle	0.265 (0.035 – 2.012)	0.199			2.125 (0.251 – 17.993)	0.489			0.937 (0.218 – 4.029)	0.930		
Intersection Density (Per Sqmi.)	0.825 (0.530 – 1.285)	0.395	0.922 (0.597 – 1.423)	0.713	0.961 (0.647 – 1.428)	0.844	1.070 (0.724 – 1.581)	0.735	0.878 (0.652 – 1.183)	0.393	0.964 (0.718 – 1.295)	0.810
Total Jobs Density(000s per Sqmi.)	0.952 (0.916 – 0.989)	**0.012**	0.949 (0.912 – 0.987)	**0.009**	0.980 (0.949 – 1.012)	0.213	0.978 (0.947 – 1.010)	0.170	0.962 (0.940 – 0.985)	**0.001**	0.961 (0.939 – 0.984)	**0.001**
Low Wage Job Density(000s per Sqmi.)	1.204 (0.931 – 1.559)	0.157	1.201 (0.925 – 1.558)	0.169	0.935 (0.701 – 1.248)	0.648	0.961 (0.721 – 1.280)	0.785	1.112 (0.935 – 1.323)	0.230	1.119 (0.943 – 1.328)	0.199
Alcohol Est. Density Count(per Sqmi.)	1.001 (1.000 – 1.002)	**0.005**	1.001 (1.001 – 1.002)	**0.001**	1.001 (1.000 – 1.002)	**0.020**	1.001 (1.000 – 1.002)	**0.004**	1.001 (1.000 – 1.002)	**<0.001**	1.001 (1.001 – 1.002)	**<0.001**
Random Effects												
σ^2	0.75		0.76		0.78		0.79		0.78		0.79	
τ_{00}	0.00 $_{Urban\_Area}$		0.00 $_{Urban\_Area}$		0.12 $_{Urban\_Area}$		0.11 $_{Urban\_Area}$		0.02 $_{Year}$ 0.06 $_{Urban\_Area}$		0.03 $_{Year}$ 0.05 $_{Urban\_Area}$	
ICC					0.13		0.12		0.10		0.09	
N	39 $_{Urban\_Area}$		39 $_{Urban\_Area}$		39 $_{Urban\_Area}$		39 $_{Urban\_Area}$		2 $_{Year}$ 39 $_{Urban\_Area}$		2 $_{Year}$ 39 $_{Urban\_Area}$	
Observations	520		520		520		520		1040		1040	
Marginal R^2 / Conditional R^2	0.392 / NA		0.372 / NA		0.365 / 0.446		0.373 / 0.449		0.356 / 0.419		0.359 / 0.419	
AIC	1346.422		1349.777		1520.047		1520.717		2857.277		2864.141	

Figure A-3: All period's data urban tracts fatal & severe injury select models

Predictors	KABC Model D - 2008-2012 *Incidence Rate Ratios*	*p*	KABC Model F - 2008-2012 *Incidence Rate Ratios*	*p*	KABC Model D - 2014-2018 *Incidence Rate Ratios*	*p*	KABC Model F - 2014-2018 *Incidence Rate Ratios*	*p*	KABC Model D - Pooled *Incidence Rate Ratios*	*p*	KABC Model F - 2014-2018 *Incidence Rate Ratios*	*p*
Intercept	6.507 (4.493 – 9.424)	**<0.001**	4.791 (3.172 – 7.237)	**<0.001**	5.642 (4.060 – 7.840)	**<0.001**	4.774 (3.309 – 6.889)	**<0.001**	5.443 (3.754 – 7.892)	**<0.001**	4.536 (3.101 – 6.636)	**<0.001**
% Asian			2.555 (0.636 – 10.257)	0.186			3.348 (1.103 – 10.163)	**0.033**			3.376 (1.420 – 8.030)	**0.006**
% Latinx			1.854 (0.996 – 3.450)	0.052			2.214 (1.235 – 3.969)	**0.008**			2.140 (1.384 – 3.311)	**0.001**
% BIPOC	1.024 (0.544 – 1.926)	0.942			2.095 (1.143 – 3.840)	**0.017**			1.806 (1.161 – 2.812)	**0.009**		
Median Income (thousand)	0.980 (0.976 – 0.985)	**<0.001**	0.984 (0.979 – 0.989)	**<0.001**	0.985 (0.982 – 0.988)	**<0.001**	0.988 (0.985 – 0.992)	**<0.001**	0.985 (0.983 – 0.988)	**<0.001**	0.987 (0.984 – 0.990)	**<0.001**
VMT on Major Arterials (million)	1.112 (1.064 – 1.162)	**<0.001**	1.113 (1.065 – 1.162)	**<0.001**	1.070 (1.026 – 1.117)	**0.002**	1.078 (1.032 – 1.126)	**0.001**	1.097 (1.063 – 1.131)	**<0.001**	1.095 (1.062 – 1.129)	**<0.001**
Miles of Non-Interstate Roads w/ 45 mph+	0.240 (0.094 – 0.613)	**0.003**	0.257 (0.100 – 0.664)	**0.005**	0.181 (0.085 – 0.385)	**<0.001**	0.199 (0.094 – 0.423)	**<0.001**	0.206 (0.114 – 0.372)	**<0.001**	0.217 (0.120 – 0.390)	**<0.001**
Miles of Non-Interstate Roads w/ 35 mph+	1.390 (0.659 – 2.931)	0.387	1.203 (0.575 – 2.520)	0.623	1.688 (1.023 – 2.788)	**0.041**	1.575 (0.954 – 2.598)	0.076	1.531 (1.013 – 2.313)	**0.043**	1.457 (0.967 – 2.193)	0.072
Mean Width of Arterials	1.003 (0.989 – 1.017)	0.709	1.004 (0.990 – 1.018)	0.560	1.007 (0.994 – 1.021)	0.287	1.009 (0.996 – 1.023)	0.171	1.007 (0.998 – 1.017)	0.137	1.007 (0.997 – 1.016)	0.171
Sidewalk Miles (ODOT System)	1.042 (1.007 – 1.078)	**0.018**	1.017 (1.003 – 1.032)	**0.021**	1.015 (0.982 – 1.049)	0.366	1.024 (1.010 – 1.038)	**0.001**	1.023 (0.999 – 1.047)	0.058	1.019 (1.009 – 1.029)	**<0.001**
Sidewalks Rated Substandard (Mi.) (ODOT System)	0.957 (0.911 – 1.005)	0.075			1.009 (0.964 – 1.056)	0.695			0.993 (0.960 – 1.026)	0.669		
% Walk Commute	0.876 (0.260 – 2.959)	0.832	0.922 (0.243 – 3.498)	0.905	1.369 (0.412 – 4.554)	0.609	1.870 (0.515 – 6.789)	0.342	1.821 (0.746 – 4.443)	0.188	1.554 (0.618 – 3.907)	0.349
% Transit Commute	4.302 (0.786 – 23.537)	0.092	2.771 (0.484 – 15.866)	0.252	4.560 (1.055 – 19.710)	**0.042**	3.976 (0.849 – 18.633)	0.080	4.660 (1.537 – 14.129)	**0.007**	3.929 (1.240 – 12.446)	**0.020**
Transit Stops	1.009 (1.005 – 1.012)	**<0.001**	1.010 (1.006 – 1.013)	**<0.001**	1.007 (1.004 – 1.011)	**<0.001**	1.008 (1.005 – 1.012)	**<0.001**	1.009 (1.006 – 1.011)	**<0.001**	1.009 (1.007 – 1.012)	**<0.001**
% Hhs w/out Vehicle			2.401 (0.635 – 9.081)	0.197			2.003 (0.526 – 7.619)	0.308			2.391 (0.950 – 6.016)	0.064
Intersection Count	1.192 (0.962 – 1.478)	0.108			1.279 (1.044 – 1.568)	**0.018**						
Intersection Density (Per Sqmi.)			0.935 (0.706 – 1.239)	0.641			0.883 (0.689 – 1.132)	0.327	0.921 (0.768 – 1.105)	0.378	0.892 (0.741 – 1.074)	0.229
Total Jobs Density(000s per Sqmi.)	0.945 (0.919 – 0.972)	**<0.001**	0.952 (0.926 – 0.980)	**0.001**	0.948 (0.927 – 0.969)	**<0.001**	0.953 (0.932 – 0.975)	**<0.001**	0.951 (0.935 – 0.967)	**<0.001**	0.953 (0.937 – 0.970)	**<0.001**
Low Wage Job Density(000s per Sqmi.)	1.363 (1.136 – 1.636)	**0.001**	1.288 (1.075 – 1.543)	**0.006**	1.343 (1.130 – 1.595)	**0.001**	1.317 (1.104 – 1.571)	**0.002**	1.336 (1.190 – 1.500)	**<0.001**	1.289 (1.146 – 1.449)	**<0.001**
Alcohol Est. Density Count(per Sqmi.)	1.001 (1.000 – 1.001)	**0.009**	1.001 (1.000 – 1.001)	**0.009**	1.001 (1.000 – 1.001)	**0.002**	1.001 (1.000 – 1.001)	**0.007**	1.001 (1.000 – 1.001)	**<0.001**	1.001 (1.000 – 1.001)	**<0.001**
Random Effects												
σ^2	0.36		0.36		0.34		0.34		0.35		0.35	
τ_{00}	0.09 $_{\text{Urban\_Area}}$		0.08 $_{\text{Urban\_Area}}$		0.07 $_{\text{Urban\_Area}}$		0.07 $_{\text{Urban\_Area}}$		0.04 $_{\text{Year}}$ 0.11 $_{\text{Urban\_Area}}$		0.03 $_{\text{Year}}$ 0.10 $_{\text{Urban\_Area}}$	
ICC	0.20		0.19		0.17		0.18		0.29		0.28	
N	39 $_{\text{Urban\_Area}}$		39 $_{\text{Urban\_Area}}$		39 $_{\text{Urban\_Area}}$		39 $_{\text{Urban\_Area}}$		2 $_{\text{Year}}$ 39 $_{\text{Urban\_Area}}$		2 $_{\text{Year}}$ 39 $_{\text{Urban\_Area}}$	
Observations	520		520		520		520		1040		1040	
Marginal R^2 / Conditional R^2	0.495 / 0.597		0.493 / 0.590		0.495 / 0.581		0.487 / 0.577		0.453 / 0.613		0.458 / 0.609	
AIC	2643.331		2643.562		2831.147		2834.904		5451.397		5438.608	

Figure A-4: All period's data urban tracts total injury select models