Safe from Crime at Location-Specific Transit Facilities: Final Project Report

WA-RD 882.1

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SAFE FROM CRIME AT LOCATION-SPECIFIC TRANSIT FACILITIES

FINAL PROJECT REPORT

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16. Abstract

Transit agencies identify two types of exposure to crime: the safety of riders and security. Transit operators have long monitored crime and are cognizant of high incident locations. However, they lack data-driven tools to readily match crime events spatially with the locations of individual transit facilities, and temporally with transit service periods. This pilot project explored the use of data-driven tools to (1) identify concentrations of criminal activity near transit facilities, and (2) assist decision-making regarding the selection of countermeasures and the allocation of future safety investments, using the results of models estimating environmental and socioeconomic predictors of crime near transit facilities. The project used two novel data sets: location-specific, police-reported crime incidents by type; and individual ORCA card (electronic transit fare payment system) transaction records, yielding transit ridership data.

Two sets of models were developed to examine exposure to crime while waiting for transit (within 100 m from transit stops) and while walking to transit (within 400 m from transit stops). The hypotheses were that within 100 m of a stop, amenities at stops act as deterrents of crime; and within 400 m different characteristics of the built, social, and transportation environment are associated with crime. Analyses were restricted to the City of Seattle, and models were run using all stops and only stops located in the City's urban villages (hosting 90 percent of the City's ridership and the stops with the most crime). We found that amenities at stops have mixed associations with crime, suggesting that amenities serve to provide riders with added comfort but not necessarily more safety. Higher ridership provides safety while waiting for transit (100-m models) but exposes riders to more crime as they walk to and from transit (400-m models). In urban villages, sidewalks are associated with a lower likelihood of crime. However, a more connected street network, which characterizes the oldest, most urban areas of Seattle, is associated with more crime.

The project illustrated how novel sets of disaggregated data on both crime and transit ridership can serve to develop models assessing the safety of transit riders at specific locations. Future research should continue to examine how transit riders can be protected from crime while they wait for transit as well as while they walk to and from it.

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CHAPTER 1: Introduction

Population growth in metropolitan areas has brought increases in demand for mobility. Given limited facilities for individual car-based travel in cities, much of the new mobility demand has been assigned to transit systems. In Washington state, the Puget Sound region has experienced a growth in transit ridership of more than 2 percent per year over the past three years. This growth is also fueled by demographic changes such as younger generations purchasing cars later in life than their parents, and by attitudinal changes about the impacts of single occupant vehicle (SOV) travel on the environment and on quality of life.

Regional increases in transit ridership have come hand in hand with major increases in transit investments, which include the expansion of both the light rail and the bus rapid transit (Rapid Ride) systems. The public sector, including local agencies and policy makers, has been heavily engaged in further promoting transit use through not only service improvements but also advances in the quality of the transit experience. The transit vehicle fleet is being continuously upgraded, as are stop and station facilities. This project adds to these efforts by focusing on safety issues near and around transit stop facilities.

This project examined individual crime incidents that may affect transit users over an entire metropolitan area in combination with detailed transit ridership information in both space and time. It took advantage of two novel data sets: one of location-specific police-reported crime incidents by type and the other of individual ORCA card (electronic transit fare payment system) transaction records. Crime and trip data were contextualized in order to disentangle the effects of transit on crime from those of the socioeconomic conditions surrounding the transit facilities. The data were analyzed in geographic information systems (GIS) by using parcel-based land-use and other built environment data, as well as socioeconomic data from the US Census.

The project's overall goal was to provide transit agency planners with new data and tools for crime surveillance and prevention and to help agencies better protect transit riders on their way to and from the transit systems and while waiting for transit. The project responded to Puget Sound transit agencies' priority goal to ensure the safety and security of transit riders (http://metro.kingcounty.gov/safety/transit-police.html; http://m.soundtransit.org/node/1438). Fitting into the theme of "developing data driven solutions and decision-making for safe transport," the project analyzed criminal incidents that occurred at or near individual transit stops or stations and park-and-rides. Methods were devised that will help monitor criminal incidents for surveillance purposes, predict hot spots for prevention purposes, and explore the effects of possible countermeasures to improve the safety of transit users.

CHAPTER 2: Literature Review

Transit agencies address exposure to crime and related victimization by identifying two types of issues: the safety of riders, which involves reducing exposure to crime on the way to, while waiting for, and while traveling in transit vehicles; and security, which involves cooperation with law enforcement to protect transit riders. Transit operators have long monitored crime and are cognizant of high incident locations. However, they lack data-driven tools to readily match crime events spatially with the locations of individual transit facilities, and temporally with transit service periods and their associated transit ridership characteristics (e.g., commuters, night riders, etc.). [1]

Past studies of transit related crime had to rely on selected case studies of high crime locations because they lacked access to data on the entire extent of the transit systems. [2, 3] Nonetheless, the studies found that factors contributing to crime differed for each stop, suggesting that site-specific analyses were required to correct security problems. [4] Recommendations were to examine each location separately in order to determine the root cause of the problem and then to apply countermeasures to correct the situation.

Importantly, successfully ensuring transit riders' safety in and around transit facilities will do more than protect them (and the general public) from harm: it also promises to promote transit as (1) an efficient, sustainable, and safe mode of transportation, and (2) a means of travel superior to private cars in most urban and some suburban areas. [5-7] Not surprisingly, past research has shown that transit-related crime affects people's decisions to use public transportation. Researchers have noted that "both acts and perceptions of violence have been shown to cause loss of ridership and revenue." [8] Given the sensitivity of transit clientele to

transit-related crime, the Federal Transit Administration has persuasively argued for diligent monitoring and effective interventions. [2, 3]

Although comparatively rare, attacks on bus drivers and passengers can fuel perceptions that transit is dangerous, despite decreasing trends in on-bus assaults. [9] Additionally, transit serves places where people tend to congregate. Such places typically experience more crimes simply because they contain more people. This situation creates the false impression that traveling by transit increases one's risk of being victimized, when in fact the per-person risk of victimization may be no different than any other place. [10] The Seattle metropolitan area transit system has not been immune to negative perceptions of safety. [11] Transit operators must combat misperceptions by using sound data and analysis available to the public. [12]

CHAPTER 3: Data and Approach

In its 2014 *Data-Driven Approaches to Crime and Traffic Safety* (DDACTS), [1] the National Highway Safety Administration showed that the data revolution presents a unique opportunity to provide transit operators with the tools to track, prevent, and clearly communicate the risk of all types of transit crimes.

Four unique data sets were used in this project. First, several of the region's cities are now making location-specific crime data available to the public. These data enable crime events to be matched with specific transit facilities locations, some of which are known as crime attractors (e.g., bus stops, stations, park and rides). Second, ORCA card transaction records (the pass for regional transit in the Puget Sound region) are being analyzed, providing for the first time detailed locations and times when transit riders access transit facilities and vehicles, along with the locations and durations of transit transfers. Both crime and ridership data are geolocated and time-stamped, which allow for precise spatial and temporal matching. Thus crime events in close proximity to transit facilities can be analyzed in relation to ridership along with factors such as peak-period commute times, weather conditions, natural lighting, etc. Third, land-use data can provide complementary information on development patterns (e.g., residential and employment densities, socioeconomic characteristics of the areas) [13, 14] and activities surrounding transit facilities (e.g., serving to co-locate crime attractors such as bars, and liquor stores, as well as vulnerable populations—elderly housing, schools, etc.). [15] Proximal land uses offer a rich set of explanatory variables of crime incidents. Fourth, data on transit stop or station characteristics (shelters, benches, lighting, etc.) complement land use with micro-environment data that also allow consideration of the entire range of environmental exposures that may be associated with criminal events. Integrating these four data sets would provide a

state-of-the-art system for monitoring crime in both space and time, and developing and testing countermeasures for crime prevention.

The project piloted a set of analyses that sought to explore possible relationships between crime and transit use. While transit operators monitor crime within transit vehicles, the focus of the present study was on the risk of being exposed to crime in two different sets of circumstances related to transit stops: (1) while *waiting for transit*, and (2) while *walking to transit*.

The present research was applied to the City of Seattle, for which data were readily available. Furthermore, because there is a direct relationship between population density and crime, the analyses extended to not only the city as a whole but also to its "designated urban villages," which are official areas of concentrated residential and commercial activity.

CHAPTER 4: Method

4.1 Overview

In this project, transit stops were the unit of analysis, and crime was the main outcome of the analyses. Crime events were initially tallied within four buffer areas around each transit stop: 100-m and 200-m street network buffers around stops were considered to be areas where people wait for the bus; and 400-m and half-mile (800-m) street network buffers were considered to be locations where people walk to the bus. However, it is commonly understood that people walk approximately one quarter mile (400 m) to get to transit. Given that almost all land area and crimes are captured by a half-mile buffer around a stop, the 400-m buffer was chosen to represent people's experience walking to the bus, and the half-mile buffer was removed from the analysis. The 200-m buffer was also eliminated to focus the analysis of "waiting for transit" on the immediate area (100-m buffer) surrounding transit stops.

Different models were estimated, with transit stops being stratified as being within or outside of a designated urban village because preliminary analyses showed both ridership and crime concentrated in urban villages.

Transit ridership at each stop was used as a confounder, as the number of people boarding or alighting a transit vehicle can positively or negatively affect the risk of being criminalized: whereas more people taking transit may increase the number of potential offenders, larger numbers of people taking transit can also better protect each other from being criminalized (i.e., safety in numbers). The explanatory variables for the waiting for transit analyses were the characteristics of transit stops, because the main question was whether the amenities provided at the stop protected riders from being criminalized. For the walking to transit analyses, the explanatory variables were the characteristics of the built, social, and transportation environment

near transit stops, because the question was whether attributes of the environment traversed by the rider to and from the transit stop were associated with a risk of being criminalized.

4.2 Variables and Measures

4.2.1 Urban Villages

We considered all transit stops in the City of Seattle, as well as those located in designated urban villages. Seattle categorizes its urban villages into three sub-categories: 1) Urban center villages within urban centers, 2) Hub urban villages, and 3) Residential urban villages. We considered all three types of urban villages (see Seattle's data portal at: https://data.seattle.gov/dataset/Urban-Villages/ugw3-tp9e), but we did not include manufacturing and industrial centers. The village boundaries were obtained from the map on page 8 of the urban village section of the Seattle Comprehensive Plan, https://www.seattle.gov/Documents/Departments/OPCD/OngoingInitiatives/SeattlesComprehensivePlan/UrbanVillageElement.pdf. Table 4-1 summarizes the characteristics of urban villages.

Table 4-1: Characteristics of urban villages

	Seattle	Urban Villages	Percent in urban villages
Jobs	567,393	467,144	82%
Housing units	336,188	148,066	44%
Land area (acres)	53,435	9,623	18%

There were 1,229 transit stops within and 1,744 outside of urban villages designated as centers of activity by the City of Seattle's comprehensive plan.

4.2.2 Transit Stops and Their Characteristics

A database of bus stops was retrieved from King County Metro Transit (King County GIS Center. May 19, 2017. Metro Bus Stops in King County / bus stop point. Retrieved from:

https://gis-kingcounty.opendata.arcgis.com/datasets/metro-bus-stops-in-king-county--busstop-point). The county-level data included the locations of 7,996 stops and detailed information on stop-level amenities, including awnings (165), bike racks (2), news boxes (16), and shelters (1,753). To obtain information on lighting, which is not an attribute in the King County Metro database, a separate file was received from King County that included lighting at the stops (961). The two bus stop databases were combined and augmented with information on the locations of Sound Transit Link light rail and Sounder stations.

The King County Metro bus stop data were clipped at the boundary of the Seattle city limits to capture only stops within the city. A small buffer of 50 ft from the centerline was applied along the city limits so that stops that lay outside the city limit but represented one direction of a route that was otherwise within the limits would also be captured. As shown in figure 4-2, of the 2,973 stops within the city limits, 121 had awnings, one had bike racks, 16 had newspaper boxes, 938 had one or more shelters, and 521 had lights. Four locations had both an awning and a shelter. Because of the low number of observations, and the presumed minimal effect on crime at transit stops, bicycle racks and newspaper boxes were not carried further into the analysis.

Furthermore, given the skewed distribution of the remaining single amenities, analyses grouped amenities at the unique stop level to include (i) stops with shelters only (527); (ii) with shelters and lights (407); (iii) "other" stops (210), which grouped those with awnings only (92), lights only (89), awnings and lights (25), and shelters and awnings (4). These were then compared them with (iv) stops with no amenities (1829). Tables 4-2 and 4-3 and figure 4-1 show the distribution of stops by types of amenities in the city and in the urban villages.

Table 4-2: Distribution of stops by type of amenities

	all stops	all stops %	**not in urban village**	not in urban village %	**in urban villages**	in urban village %
Awnings	121	4.07%	11	0.63%	110	8.95%
Shelters	938	31.55%	387	22.19%	551	44.83%
Lights	521	17.52%	181	10.38%	340	27.66%
No amenity	1829	61.52%	1294	74.20%	535	43.53%
Total (NOT UNIQUE STOPS)	*3409*	*114.67%*	*1873*	*107%*	*1536*	*125%*
Combination						
Awning & Lights	25		1		24	
Awning & Shelter	4		1		3	
Shelter & Lights	407		127		280	

Table 4-3: Distribution of unique stops and corresponding combination of amenities

Type of amenity	all stops	%	stops in urban villages	%
No amenity	1829	61.52	535	43.53
Shelter only	527	17.73	268	21.81
Shelter and light	407	13.69	280	22.78
Awning only	92	3.09	83	6.75
Light only	89	2.99	36	2.93
Awning and light	25	0.84	24	1.95
Shelter & awning	4	0.13	3	0.24
Total	2973	100	1229	100

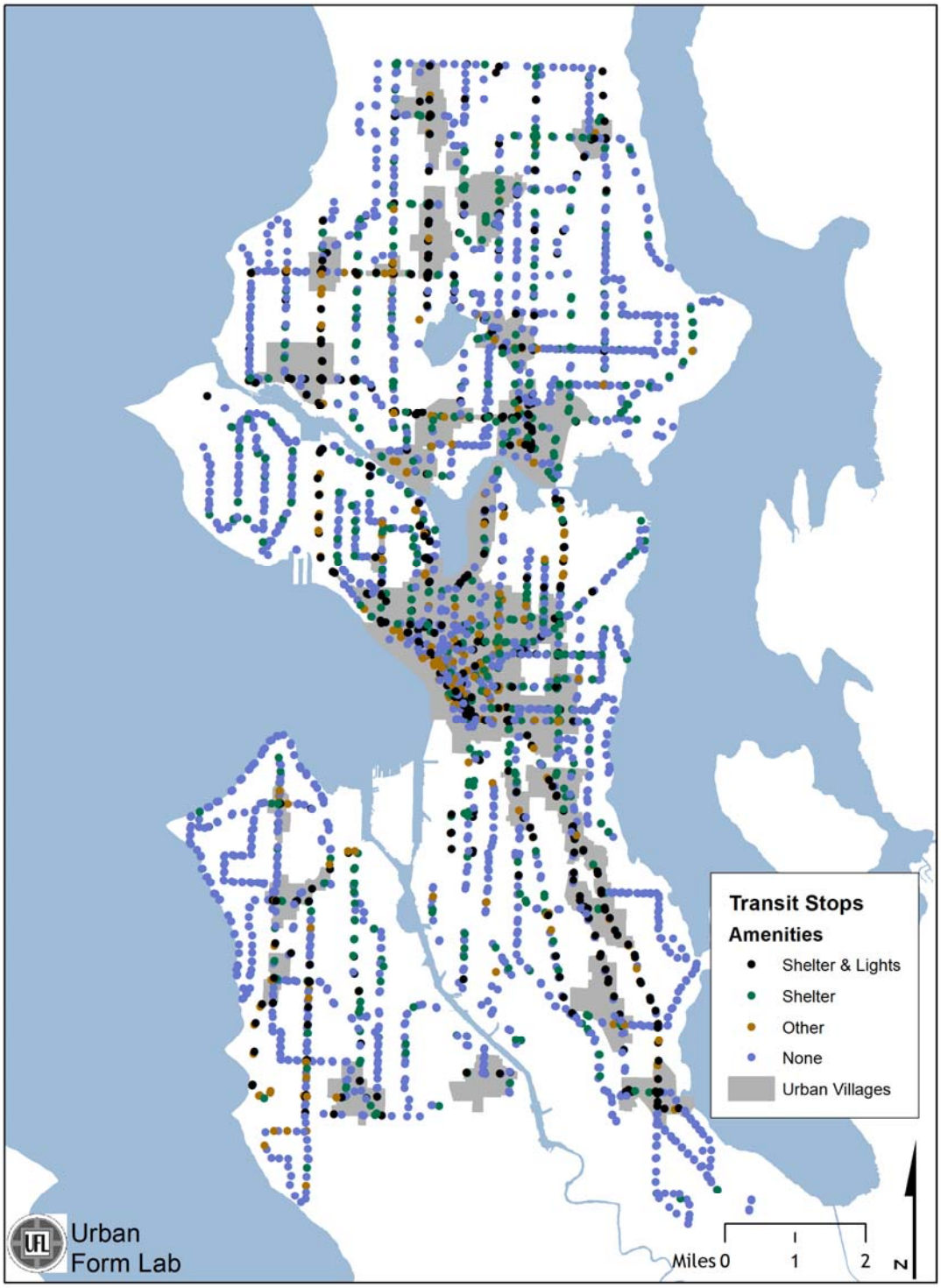

Figure 4-1: Transit stop amenities

4.2.3 Crime

Reliable and complete crime data that are geographically referenced to the actual location where a crime occurred are difficult to obtain. For this project, the possibility of using crime data for the cities of Federal Way and Seattle, two cities for which detailed crime incident data were thought to be readily available to the project team, was explored. The cities could serve as exemplary cases for the region in that Seattle has the highest transit ridership in the state, and Federal Way could represent the many suburban cities with relatively high transit ridership. Also, the socioeconomic profile of transit users in the two cities would include those with high to medium income (Seattle) as well as lower income (Seattle and Federal Way).

Federal Way. During initial investigation, the research team determined that crime data for the City of Federal Way were neither accessible through the web nor regularly updated. Our team requested a data set of crimes and received a database with 54,510 reported incidents from between January 1, 2013, and October 31, 2015.

The data set did not contain the latitudes and longitudes of the crime locations, making it necessary to use the provided addresses to geolocate the crimes. However, the addresses were inconsistent at best. For example, under the field for "City," there were 20 unique (and often incorrect) variations of spelling for Federal Way, including for example, "FEDERLA WAY," "FFEDERAL WAY," and "Federal Wa". These types of issues were simple to account for in early data cleaning, in this case reducing the data set of likely locations within Federal Way (as opposed to the City of Auburn, for example) to 53,098. However, doing so for individual street addresses was prohibitive in terms of time and local knowledge. An initial attempt to match the addresses led to 29,943 exact matches, a match rate of 56 percent, which was unacceptable if for no other reason than it was unclear what bias would exist as a result of the data being left out.

These types of issues were not present in the City of Seattle data set, so only data from the City of Seattle were considered.

Seattle. Crime data for the City of Seattle are accessible through the city's open data portal (City of Seattle. May 19, 2017. Seattle Police Department Police Report Incident. Retrieved from: https://data.seattle.gov/Public-Safety/Seattle-Police-Department-Police-Report-Incident/7ais-f98f). The data set is updated daily, with data beginning on January 1, 2014. The data set included 155,420 crimes through May 19, 2017 (for a total of 504 days), which was when the data were last retrieved for this project.

We established four broad categories of crimes by using the Federal Uniform Crime Reporting Program along with information from previous efforts related to transit and crime. [7] The categories were 1) property, 2) violent, 3) vice and vagrancy, and 4) other crimes that do not affect waiting for or walking to transit.

1. Property (n = 103,217): bike theft, burglary, burglary-secure parking-res, car prowl, mail theft, other property, pickpocket, property damage, purse snatch, shoplifting, stolen property, vehicle theft
2. Vice and Vagrancy (n = 14,275): disorderly conduct, disturbance, firework, liquor violation, loitering, narcotics, prostitution, public nuisance, threats
3. Violent (n = 18,543): assault, homicide, injury, obstruct, robbery, weapon
4. Not related to taking transit or walking: animal complaint, bias incident, counterfeit, dispute, DUI, eluding, embezzle, escape, extortion, false report, forgery, fraud, fraud and financial, gamble, harbor calls, illegal dumping, lost property, pornography, reckless burning, recovered property, stay out of area of drugs, theft of services, traffic, trespass, violation of court order, warrant arrest.

The three categories of crime in the data set encompassed 136,035 crimes, which varied by time of day (table 4-4). Time periods were defined as AM (6:00 am-9:00 am), Midday (9:00 am-3:00 pm), PM (3:00 pm-6:00 pm), Evening (6:00 pm-10:00 pm), and Night (10:00 pm-6:00 am).

Table 4-4: Number of crimes by type and time of day (Jan 1, 2014, through May 19, 2017)

Time	Hours	Property	Vice and Vagrancy	Violent	TOTAL	% Total Crime
AM	6AM-9AM	9,483	951	1,197	11,631	8.6
Midday	9AM-3PM	26,818	4,736	4,610	36,164	26.6
PM	3PM-6PM	16,516	2,572	2,640	21,728	16.0
Evening	6PM-10PM	23,951	2,776	4,313	31,040	22.8
Night	10PM-6AM	26,449	3,240	5,783	35,472	26.1
TOTAL		103,217	14,275	18,543	136,035	100

Table 4-5 provides the distribution of crime by type and by proximity to transit stop.

Table 4-5: Number of crimes near transit stops, total crimes for the data period (504 days)

Buffer	All		Property		Vice and vagrancy		Violent	
	count	percent	count	percent	count	percent	count	percent
100 meter	66,455	48.9	45,912	44.5	8,507	59.6	12,036	64.9
400 meter	129,023	94.8	97,081	94.1	13,877	97.2	18,065	97.4
All Crimes	136,035	100	103,217	100	14,275	100	18,543	100

Tables 4-6 and 4-7 provide the tertile distribution of total crimes per stop in the City for the 6:00 am to 6:00 pm period and for the 6:00 am to 10:00 pm period, respectively, for both the 100-meter and 400-meter buffers around stops. Almost 74 percent of the stops that were in the

highest crime tertile were in urban villages. Also, although 20 percent of all stops had zero crime between 6:00 am and 6:00 pm, less than 8 percent of stops in the villages had no crime.

Figure 4-2 is a heat map of all crimes recorded in our data set at the 100-m buffer.

Table 4-6: Tertiles of crime per transit stops between 6:00 AM and 10:00 PM

	ALL STOPS	Stops in Villages	% of Stops in Villages	**Tertiles of Crimes per Stop** (100 meter)	**Tertiles of Crimes per Stop** (400 meter)
T1	991	178	18.0%	**0 -- 5**	**0 -- 76**
T2	991	319	32.2%	**5 -- 20**	**76 -- 197**
T3	991	732	73.9%	**20 -- 1802**	**197 --6934**
TOTAL	2973	1229	41.3%		

Table 4-7: Tertiles of crime per transit stops between 6:00 AM and 6:00 PM

	ALL STOPS	Stops in Villages	% of stops in Villages	**Tertiles of crimes per stop** (100 meter)	**Tertiles of crimes per stop** (400 meter)
T1	991	178	18.0%	**0–3**	**0–50**
T2	991	319	32.2%	**3–14**	**51–135**
T3	991	732	73.9%	**14–1,234**	**135–4,752**
TOTAL	2973	1229	41.3%		
WITH ZERO CRIME	597	94			

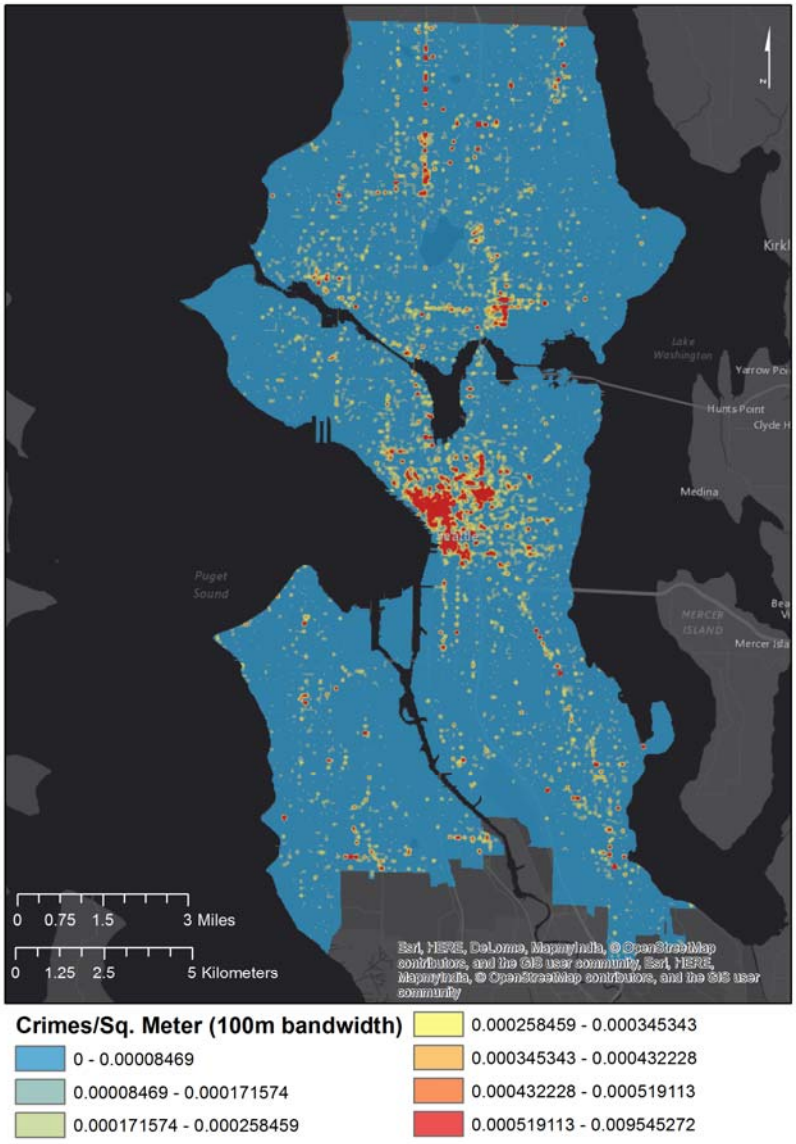

Figure 4-2: Heat map of crimes showing concentration in the urban villages

4.2.4 Transit Ridership: ORCA Transactions

ORCA transaction records were used for estimates of ridership per transit stop. Data available for this project came from the Washington State Transportation Center, University of Washington, and included all transit on-boards, or "taps," from February 17, 2015, to April 14, 2015, and again from March 26, 2016, to May 27, 2016. There were nearly 44 million records for the Puget Sound region, which comprises the Regional Transit Authority (RTA), King,

Pierce, and Snohomish counties. For each record, an individual identifier was retained for the ORCA card, the date, time, and stop location identified by stop number (and locations). Stop numbers are crucial for connecting the ORCA transactions to the physical locations of stops from the King County Metro bus stop data (Hallenbeck et al. 2017, http://depts.washington.edu/trac/bulkdisk/pdf/863.1.pdf). In some instances, it is desirable to use the stop locations identified by the ORCA data because some of the King County bus stop locations are unverified. However, because the ORCA locations are imputed, they are not necessarily on the street network or directly at the locations of the stops, so for this project, which relied on distances from those stops, we tried to be as precise about stop locations as possible.

Summary statistics were calculated for the number of ORCA card taps at each transit stop by weekday and specific weekday time period. As expected, ORCA taps, representing ridership, were higher within the City of Seattle than within the Puget Sound region (table 4-8).

Table 4-8: Weekday daily ORCA transactions per transit stop (February 17, 2015, to April 14, 2015, and from March 26, 2016, to May 27, 2016)

Time of Day	Location	Mean	SD	Min	Max
AM (6AM-9AM)	All Records	13.14	49.31	1	1335
	Seattle	23.44	64.38	1	1335
Midday (9AM-3PM)	All Records	12.9	50.05	1	2100
	Seattle	26.19	83.36	1	2100
PM (3PM-6PM)	All Records	14.83	90.63	1	5486
	Seattle	31.6	156.33	1	5486
Evening (6PM-10PM)	All Records	7.69	34.91	1	1354
	Seattle	15.29	57.98	1	1354
Night (10PM-6AM)	All Records	4.73	16.52	1	467
	Seattle	5.49	15.3	1	285
Daily Total	All Records	42.64	192.62	1	7,335
	Seattle	89.74	321.62	1	7,335

Table 4-9 shows the distribution of ridership per stop by tertile of ridership in the City as a whole and in the urban villages. As shown, 41.3 percent of all transit stops within Seattle were located within urban villages, which received 87.9 percent of the City's transit ridership. Altogether 67.6 percent of the stops in the highest tertile of ridership were located within urban villages, and 91.2 percent of ridership in the highest tertile of ridership was also located within villages.

Table 4-9: Tertiles of ridership per transit stops and share of ridership within urban villages

TERTILES Daily Ridership PER STOP	All stops	Stops in Villages	% of Stops in Villages	% Village Stops of All Stops	Total Ridership All Stops	Total Ridership Villages Stops	% Ridership in Villages
T1: 1–6.867	991	206	16.8	20.8	2,848	1,039	36.5%
T2: 6.884–36.432	991	353	28.7	35.6	1,7766	8,914	50.2%
T3: 36.56–7,335.36	991	670	54.5	67.6	246,170	224,446	91.2%
Total	2,973	1,229	100	41.3	266,784	234,399	87.9%

Figure 4-3 shows daily average ORCA transactions, or taps, by tertile in the City as a whole and in the urban villages.

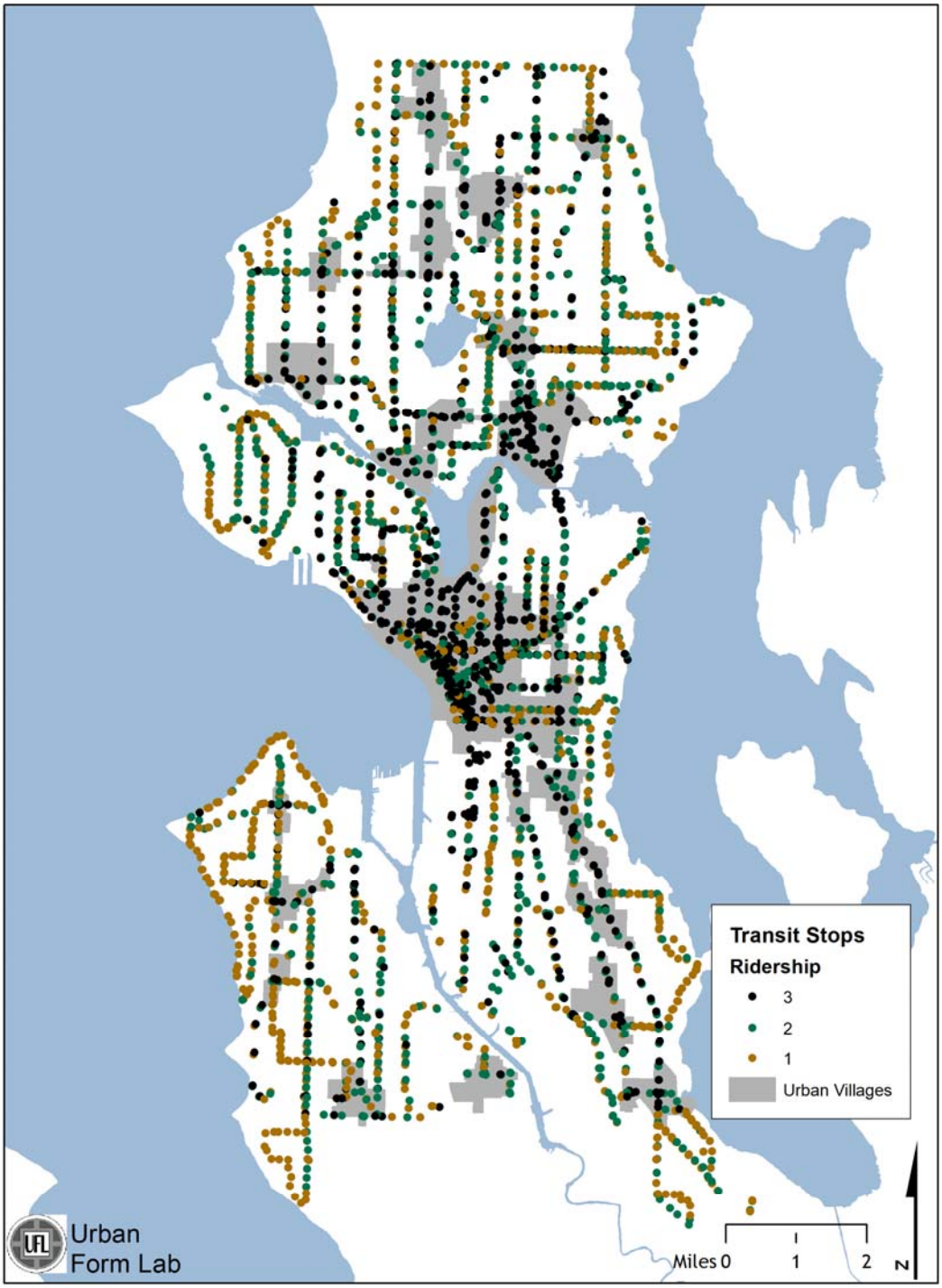

Figure 4-3: Daily average ORCA transactions by tertile

4.2.5 Built, Social, and Transportation Environment Factors

The characteristics of the social and physical environment near stops can affect the propensity to use transit and potential exposure to crime. The development intensity of the neighborhood environment was captured by residential and employment densities (housing units and employees per acre, respectively). Data came from the King County Assessor and the Puget Sound Regional Council (PSRC. July 27, 2017. Tractemp2015.xls; https://www.psrc.org/covered-employment-estimates). Property values were used as a proxy for socio-economic neighborhood factors. They were retrieved from the King County assessor (King County GIS Center. July 2, 2017. King County Real Property. Retrieved from: https://gis-kingcounty.opendata.arcgis.com/datasets/king-county-real-property--realprop-area). Also identified were the land uses that were expected to have a positive relationship with crime, including alcohol and marijuana retailers. The addresses of all alcohol and marijuana retailers were retrieved from the Washington State Alcohol and Cannabis Board (Washington State Alcohol and Cannabis Board. July 27, 2017. Frequently requested lists. Retrieved from: https://lcb.wa.gov/records/frequently-requested-lists).

Additionally, the characteristics of the transportation environment affect how people travel on their way to the bus or train. They include street connectivity (which affects route directness), sidewalks (which affect route safety) [16] traffic volumes (reported as average annual weekday traffic, AAWDT) (SDOT_2014_Traffic_Flow_Counts; https://data.seattle.gov/), and street designation as an arterial (the latter are safety measures pertaining to exposure to vehicular traffic). Street connectivity was measured as a ratio between a route network and the Euclidean distances away from a transit stop. The presence of sidewalks was measured as a percentage of the network buffer area within 400 m of transit stops that had

sidewalks on at least one side of the street. Where available, AAWDT volumes were reported for the street segment to which a transit stop was adjacent. Finally, whether a street on which a transit stop was located was classified as an arterial was included as a binary variable (2,912 yes; 61 no). Summary statistics for these variables are included in table 4-10.

Table 4-10: Summary statistics for built environment factors

Buffer	BE variable	Measurement unit	Mean	SD	Min.	Max.
100 meter	Residential Density	Res units/acre	47	72.5	0	1,475.50
	Employment Density	Jobs/acre	490	3,418.10	0	48,044.20
	Alcohol and Marijuana Retailers	Count	0.3	0.6	0	4
	Property Values	Mean value of res unit in buffer	$381,930	$185,439	$29,706	$2,066,800
	Street Connectivity	Ratio of network buffer to Euclidean buffer	0.1	0	0	0.4
	Sidewalk	Ratio of streets with sidewalks to all streets, excluding freeways	0.7	0.3	0	3
	AAWDT	Reported average annual weekday traffic for the street that a bus stop is on.	19,116.40	11,778.10	0	94,800.00
400 meter	Residential Density	Res units/acre	34.5	21.1	0	234.7
	Employment Density	Jobs/acre	73.5	334.9	0	3,805.90
	Alcohol and Marijuana Retailers	Count	2	2.7	0	18
	Property Values	Mean value of res unit in buffer	$395,843	$179,928	$55,165	$3,459,000
	Street Connectivity	Ratio of network buffer area to Euclidean buffer area	0.6	0.1	0	0.8
	Sidewalk	Ratio of streets with sidewalks to all streets, excluding freeways	0.7	0.2	0	1.2
	AAWDT	Reported average annual weekday traffic for the street that a bus stop is on.	23,880.40	14,718.20	3,200.00	107,300.00

4.3 Analyses

Two sets of models capturing *waiting for transit* (100-m buffer) and *walking to transit* (400-m buffer) were developed. Two models were estimated within each set, one including all stops and the other including only stops in the urban villages. For all four models in both sets, the transit stop was the unit of analysis, with the total number of crimes (for the given data period of

504 days) within either buffer over the study period as the outcome. Daytime crimes occurring between 6:00 am and 10:00 pm were used to capture the times when most people utilize transit. Total crime was measured continuously or as a binary outcome in some of the models.

For both 100-m and 400-m models, daily ridership from ORCA transactions was included as a confounder, under the assumption that more people at a transit stop could mean either higher (i.e., one or more persons as potential offenders) or lower (i.e., more persons being protective of crime, "safety in numbers") risk of being exposed to crime. For the same reasons, the state of being in an urban village or not was treated as a confounder in the all stop models—higher numbers of riders in urban villages could either increase the likelihood of a crime or be protective of being criminalized. The presence of alcohol or marijuana outlets was included as a covariate.

Predictor variables differed for the *waiting for transit* and *walking to transit* models. In *waiting for transit*, the question was whether the amenities provided at the stop protected riders from being exposed to a crime. Whether the transit stop had a shelter only, a shelter and light, other amenities, or no amenities was used to predict the occurrence of a crime or the number of crimes.

In *walking to transit*, the question was whether attributes of the social, built, and transportation environments traversed by the transit rider to and from the transit stop were associated with being exposed to crime. Property values and various attributes capturing development densities and traffic conditions served as predictors.

The distribution of counts of crime within the 100-meter network buffer had both over-dispersion and an over-abundance of null values. The multiple zero values suggested the use of a zero-inflated Poisson model, while overdispersion suggested the use of a zero-inflated negative

binomial (ZINB) model. Rootograms were used to assess the goodness of fit of either model. There was no zero inflation in the 400-m models, and a negative binomial model was used.

CHAPTER 5: Results

5.1 Waiting for Transit (100-m Models)

5.1.1 Correlations

Figures 5-1 and 5-2 show correlations between outcomes, confounders, and covariates for the 100-m models for all stops and for stops in the urban villages, respectively. While alcohol and marijuana outlets were significantly but weakly correlated to ridership, the correlation of the two variables with crime was significant, but also stronger. Correlation coefficients were similar for all stops and for stops in urban villages.

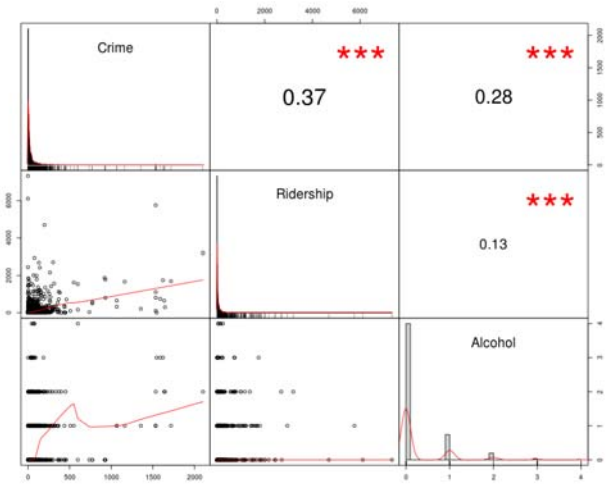

Figure 5-1: Correlations for all stops in the 100-m buffer

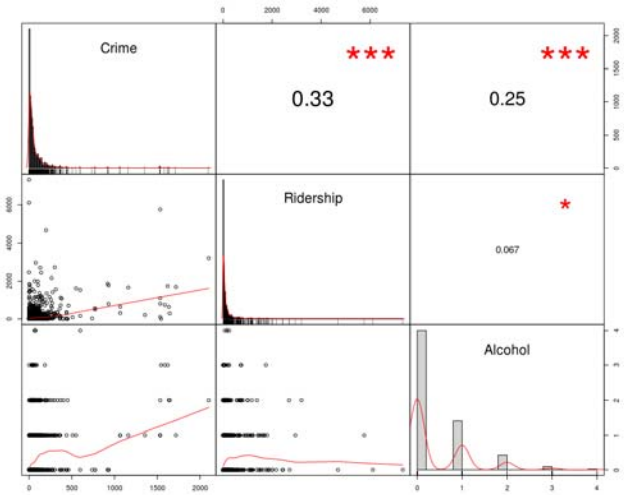

Figure 5-2: Correlations for stops in the urban villages in the 100-m buffer

5.1.2 Models

Agreement between predicted and observed counts was higher for the zero-inflated negative binomial (ZINB) model than for the zero-inflated Poisson model in models for all stops and models including only stops in the urban villages (figures 5-3 and 5-4).

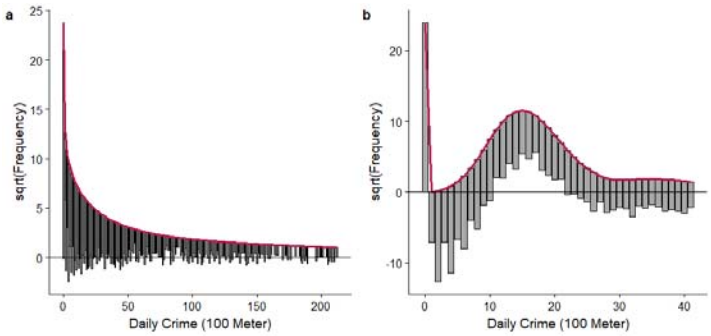

Figure 5-3: Rootogram of all stops comparing ZINB and zero-inflated Poisson model

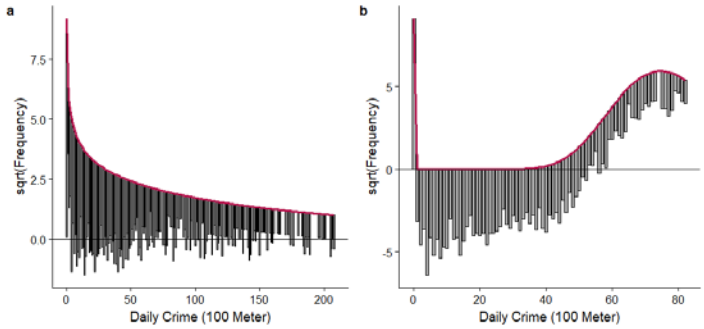

Figure 5-4: Rootogram of all stops comparing ZINB and zero-inflated Poisson model

Table 5-1 summarizes the results of the ZINB model for all stops as well as for only the stops located in urban villages. The top part of the table shows the count model coefficients (negbin with log link) predicting the likelihood of an additional crime occurring (in the 504 days represented by the data). The bottom part shows the zero-inflation model coefficients (binomial with logit link) predicting the likelihood of a crime occurring versus not, for only continuous variables.

The all-stop models indicated that a stop being in an urban village was significantly and strongly associated with the likelihood of more crime occurring at the stop. All types of amenities were significantly associated with more crime. However, ridership was significantly and negatively related to crime, suggesting protection from a crime occurring. In the urban village models, a stop having a shelter was no longer significantly associated with crime, and the relationship was negative. Having a shelter and lights or a combination of amenities was positively and significantly associated with crime. The presence of an alcohol or marijuana outlet was not significantly associated with the likelihood of a crime.

Table 5-1: Waiting for transit model results

	Dependent variable:						
	Crime (total)						
	(All)	(All)	(Village)	(All)	(Village)	(All)	(Village)
Shelter	0.285***	0.212***	−0.138	0.253***	−0.131	0.242***	−0.131
	(0.079)	(0.069)	(0.104)	(0.068)	(0.102)	(0.067)	(0.102)
Shelter & Lights	0.438***	0.126	0.278**	0.127	0.281**	0.132	0.281**
	(0.102)	(0.089)	(0.118)	(0.089)	(0.116)	(0.088)	(0.116)
Other	1.420***	0.898***	0.883***	0.918***	0.893***	0.907***	0.893***
	(0.115)	(0.102)	(0.128)	(0.102)	(0.128)	(0.100)	(0.128)
Village		1.633***		1.689***		1.670***	
		(0.054)		(0.054)		(0.053)	
Constant	3.405***	2.509***	4.253***	2.453***	4.243***	2.479***	4.243***
	(0.041)	(0.042)	(0.061)	(0.042)	(0.059)	(0.041)	(0.059)
Ridership				−0.050***	−2.989	−0.038***	−2.559***
				(0.013)		(0.009)	(0.367)
Alcohol						−12.175	−2.591
						(158.368)	(106.637)
Constant	−2.128***	−1.423***	−4.617***	−1.613***	−5.719	−1.407***	−5.063
	(0.160)	(0.114)	(1.548)	(0.151)	(31.694)	(0.130)	(35.972)
Observations	2,973	2,973	1,229	2,973	1,229	2,973	1,229
Log Likelihood	−12,597.290	−12,134.740	−6,416.844	−12,155.580	−6,417.081	−12,136.910	−6,417.080
Note:							*p<0.1; **p<0.05; ***p<0.01

5.2 Walking to Transit (400-m Models)

5.2.1 Correlations

In the 400-m buffer, BE variables were significantly but relatively weakly correlated (fig. 5-5). Property values were not significantly related to residential densities, employment densities, or ridership. Ridership was significantly and more strongly correlated to alcohol and marijuana outlets, employment density, and crime. Focusing on stops located in urban villages, correlation patterns were similar, but their strength was attenuated (fig. 5-6). Surprisingly, however, property values were positively correlated with crime. Additionally, AAWDT was no longer associated with alcohol and marijuana outlets, ridership, or crime.

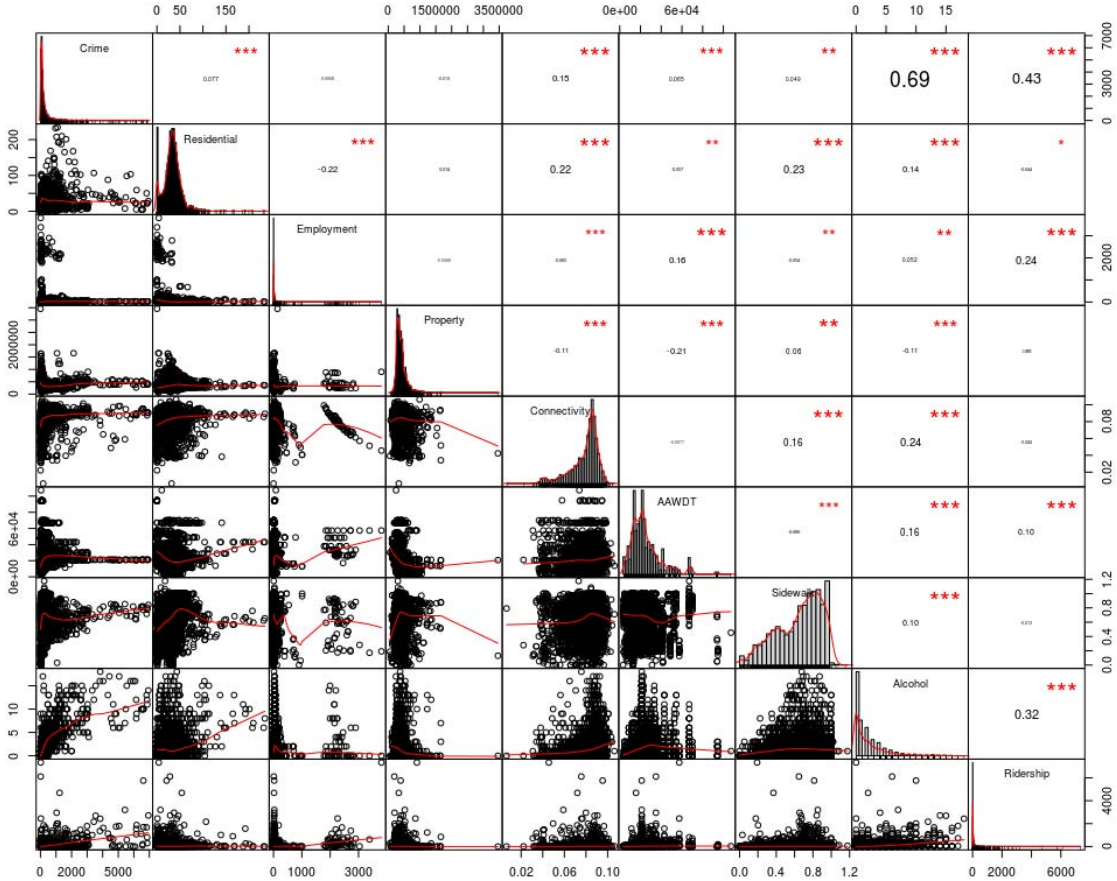

Figure 5-5: Correlations for all stops in the 400-m buffer

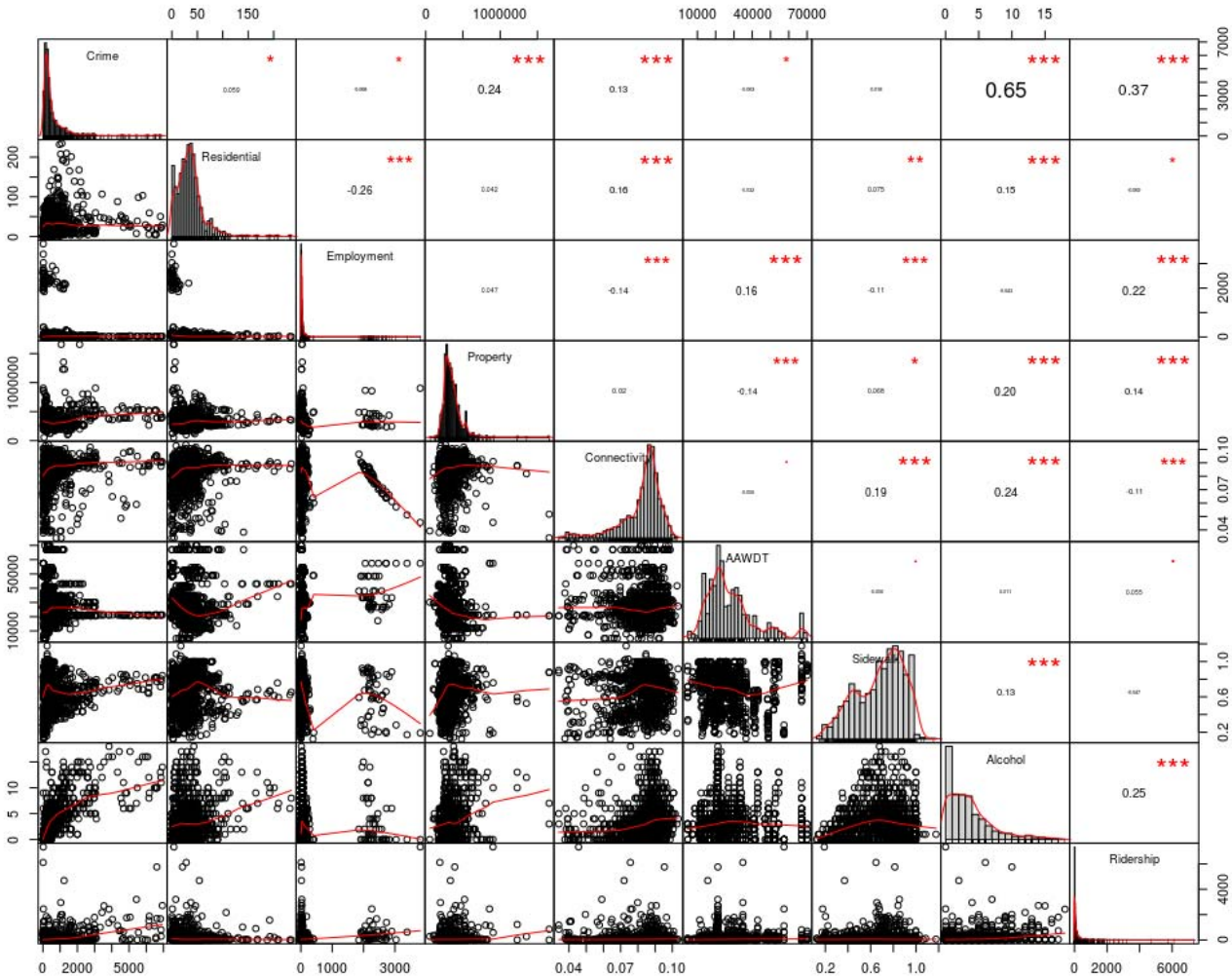

Figure 5-6: Correlations for stops in the urban villages in the 400-m buffer

5.2.2 Models

The results of the negative binomial models are shown in table 5-2. In both models, those including all stops and those including only the stops in the urban villages, employment density was significantly protective of crime occurring. On the other hand, residential density was positively related to crime except in urban villages, where it was not significant. Coefficients were low for both measures of density. Ridership also had a low coefficient, but it was significantly and positively associated with crime. Alcohol and marijuana outlets were

significantly, positively, and more strongly related to crime. Streets lined with sidewalks were significantly related to crime in all models, but they were protective of crime in the urban village models and not in the all-stop models. Finally, the connectivity of the street network, an indicator of the older, more dense parts of Seattle, was the BE variable most strongly associated with crime in both all-stop and urban village models.

Table 5-2: Walking to transit model results

	Dependent variable:					
	Crime (total)					
	(All)	(Village)	(All)	(Village)	(All)	(Village)
Residential	0.004***	0.002**	0.003***	0.0004	0.002***	0.0004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Employment	−0.0001*	−0.00003	−0.0002***	−0.0002***	−0.0002***	−0.0002***
	(0.0001)	(0.0001)	(0.00005)	(0.0001)	(0.00005)	(0.0001)
Property	−0.00000**	0.00000***	−0.00000***	0.00000*	−0.00000***	0.00000***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Village	1.820***		1.007***		0.966***	
	(0.033)		(0.031)		(0.031)	
Ridership	0.001***	0.001***	0.0004***	0.0004***	0.0005***	0.0004***
	(0.00005)	(0.0001)	(0.00004)	(0.00005)	(0.00004)	(0.00005)
Alcohol			0.227***	0.215***	0.205***	0.209***
			(0.005)	(0.006)	(0.006)	(0.007)
Arterial					0.107	0.263
					(0.141)	(0.235)
AAWDT					0.00001***	−0.00000
					(0.00000)	(0.00000)
Sidewalk					0.144***	−0.669***
					(0.055)	(0.098)
Connectivity					8.308***	4.328**
					(1.089)	(1.908)
Constant	4.350***	5.421***	4.333***	5.203***	3.428***	5.022***
	(0.050)	(0.083)	(0.040)	(0.065)	(0.168)	(0.291)
Observations	2,833	1,180	2,833	1,180	2,445	1,148
Log Likelihood	−17,592.260	−8,712.073	−16,924.160	−8,344.994	−14,953.280	−8,129.735
θ	1.581*** (0.039)	1.202*** (0.044)	2.404*** (0.062)	2.025*** (0.078)	2.546*** (0.070)	2.101*** (0.082)
Akaike Inf. Crit.	35,196.510	17,434.150	33,862.320	16,701.990	29,928.560	16,279.470
Note:						*p<0.1; **p<0.05; ***p<0.01

CHAPTER 6: Discussion

Efforts to reduce transit riders' exposure to crime should focus on the locations where more people may be affected and where a higher number of crimes occurs. The results of the 100-meter *waiting for transit* and 400-meter *walking to transit* models suggest that efforts should be focused in urban villages. Areas outside of urban villages have a uniformly lower incidence of crime. In addition, high employment densities, which are found in urban villages, are associated with lower incidence of crime.

Differences in the results of the 100-m and 400- models revealed important differences in environmental influences at different levels. While waiting for transit, more riders at transit stops are protective of crime, but while walking to transit, a higher number of riders is associated with a higher likelihood of a crime occurring. The associations indicated that densities of people at the neighborhood versus the stop level may have different effects on criminal activity. Larger numbers of people in a neighborhood corresponds to larger numbers of potential offenders, and in addition, provide some level of anonymity for offenders. But larger numbers of people in a small area provide more "eyes on the street" that can expose criminals, thereby protecting the potential victims. Similar mechanisms may be at work regarding alcohol and marijuana outlets, which were significantly related to crime in the 400-m models but not in the 100-m models

Results of the 100-m models were mixed regarding the effects of stop-level amenities on crime. In the urban village models, locations with shelters are not associated with crimes, while locations with lights and shelters, or with other combinations of amenities, are associated with higher crime rates. Further work will be needed to better understand whether the strategies aimed at increasing the comfort of transit patrons at transit stops also have a benefit with respect to crime.

The provision of sidewalks, which support walking, has an association with a lower incidence of crime in urban villages. Further investments in sidewalks, especially near transit stops because people who choose to use transit tend to walk more, would have the double benefit of promoting transit use and improving the safety of transit users.

Urban form and infrastructure alone cannot resolve all of the issues of exposure to crime near transit stops. The association between the number of alcohol and marijuana retailers in neighborhoods around transit stops and the number of crimes suggests that increased police presence may be warranted. However, future research on this topic should explore the potentially different effects between marijuana and alcohol retailers. In the Seattle area, because all food stores sell alcohol, there are thousands of alcohol retailers but there are many fewer recreational marijuana outlets. It may be the case that crime is more associated with one than the other.

This research can be expanded in several ways. First, we focused on all crimes in aggregate, and further work, assuming sufficient data, could group the crimes into sub-categories. This would be particularly important, as, for example, property-related crime may less directly affect transit users than violent crime. In the present analyses, property crime represented almost 75 percent of the crime events, thus perhaps not corresponding to the type of crime that might most affect transit users. Some countermeasures might be more effective for one type of crime than another. Similarly, while we only considered an aggregate daytime timeframe, with sufficient data, it might be possible to discern some variability if multiple time periods were used (e.g., morning, midday, evening, and night) and different days of the week were considered.

Second, the research was limited to "waking hours," including commute times (6:00 am to 10:00 pm), which are times when transit service is highest. Further research should consider

temporal variation in both transit service and crime, focusing on commute time alone, night time, week days, and weekends, as well as seasons.

Third, the limitations of acquiring usable crime data from cities other than Seattle made considering additional cities impractical for this project. As police gain better access to tools that help store crime data, and especially geospatial data, and as data storage and portals improve, it will likely be possible to consider applying this type of analysis to other jurisdictions and to examine possible differences in different settings (e.g., urban versus suburban). Despite these limitations, transit agencies and jurisdictions should continue to make walking to transit and waiting for transit comfortable and convenient for transit users with the knowledge that doing so may also have the benefit of reducing crime, and thus making transit riders safer.

CHAPTER 7:Conclusions

This project examined associations between the characteristics of transit stop locations and the occurrence of crime in two situations: near (100-m) transit stops to capture exposure while waiting for transit; and in the neighborhood of transit stops (400 m) to capture exposure while walking to and from transit stops. Models were run separately for all stops within the City of Seattle and for stops located in urban villages. The latter stops included almost 90% of the City's ridership and 74 percent of the stops that fall in the highest tertile of crime in the City. We found that amenities at stops had mixed associations with crime, suggesting that amenities serve to provide riders with added comfort but not necessarily more safety. Higher ridership provides safety while waiting for transit, but it exposes riders to more crime as they walk to and from transit. Higher employment densities in neighborhoods around transit stops are protective of crime. In urban villages, sidewalks are associated with a lower likelihood of crime. However, a more connected street network, which characterizes the oldest, most urban areas of Seattle, is associated with more crime.

The project illustrates how novel sets of disaggregated data on both crime and transit ridership can serve to develop models assessing the safety of transit riders at specific locations. Future research should continue to examine how transit riders can be protected from crime while they wait for transit as well as while they walk to and from it.

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