# Understanding the Crash Risk Exposure of Low-income Neighborhoods and TANF Recipients

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# Outline

- Introduction
- Literature Review
- Research Questions
- Data
- Methods
- Preliminary Results
- Next Steps

# Introduction

- When controlling for other variables, places with a higher percentage of low income households (labeled as ‘deprived areas’ in a few studies in Europe) tend to have more traffic accidents
- Numerous studies explored the effect of demographic characteristics on crash risks and injury severity, but few focused on area-specific factors (why certain areas have higher crashes than others based on demographic differences)

# Literature Review: Crash Risks and Injure Severity

- Built Environment and Land Use
- Transportation Network and Design Variables
- Traffic Patterns
- Demographic, Cognitive, and Economic Contributors

# Demographic and Economic Contributors

- Income
- School-aged Children
- Seniors
- Teens
- Young Male
- Educational Levels
- Car Ownership
- Total Population
- Employment Density
- Most studies in travel behavior and crash risk analysis use these variables as control or exposure variables; few solely focused on these variables, particularly within certain geographic contexts (e.g. Abdalla et al., 1997; Chichester et al., 1998; Graham et al., 2005). Some attribute the uneven crash risks by class and wealth to environmental (in)justice issues (e.g. Kravetz and Noland, 2012).

# Literature Review

- Most models in travel behavior and safety research use demographic variables as control and exposure variables
- However, studies solely focusing on how demographic variables contribute to crash risks and injury severity in geographic contexts are scanty
- Among those few studies focusing on how socioeconomic variables relate to crash risks and injury severity in certain areas, negative binomial regression models are often used, which did not identify the regulating and mediating factors of certain socioeconomic variables, such as income and wealth
- This study hopes to formulate a different model exploring the mediating effects of income in crash risks and injury severity

# Research Questions

- What are the overall patterns of crash distribution? How are they spatially related to socioeconomic status of households at the Census Block Group level?
- Which socioeconomic variables contribute to increased crash risks? Are neighborhoods with a higher concentration of subsidy recipients associated with elevated crash risks?
- What is the mediating effect of wealth, measured by median household income, in crash risks?

# Data

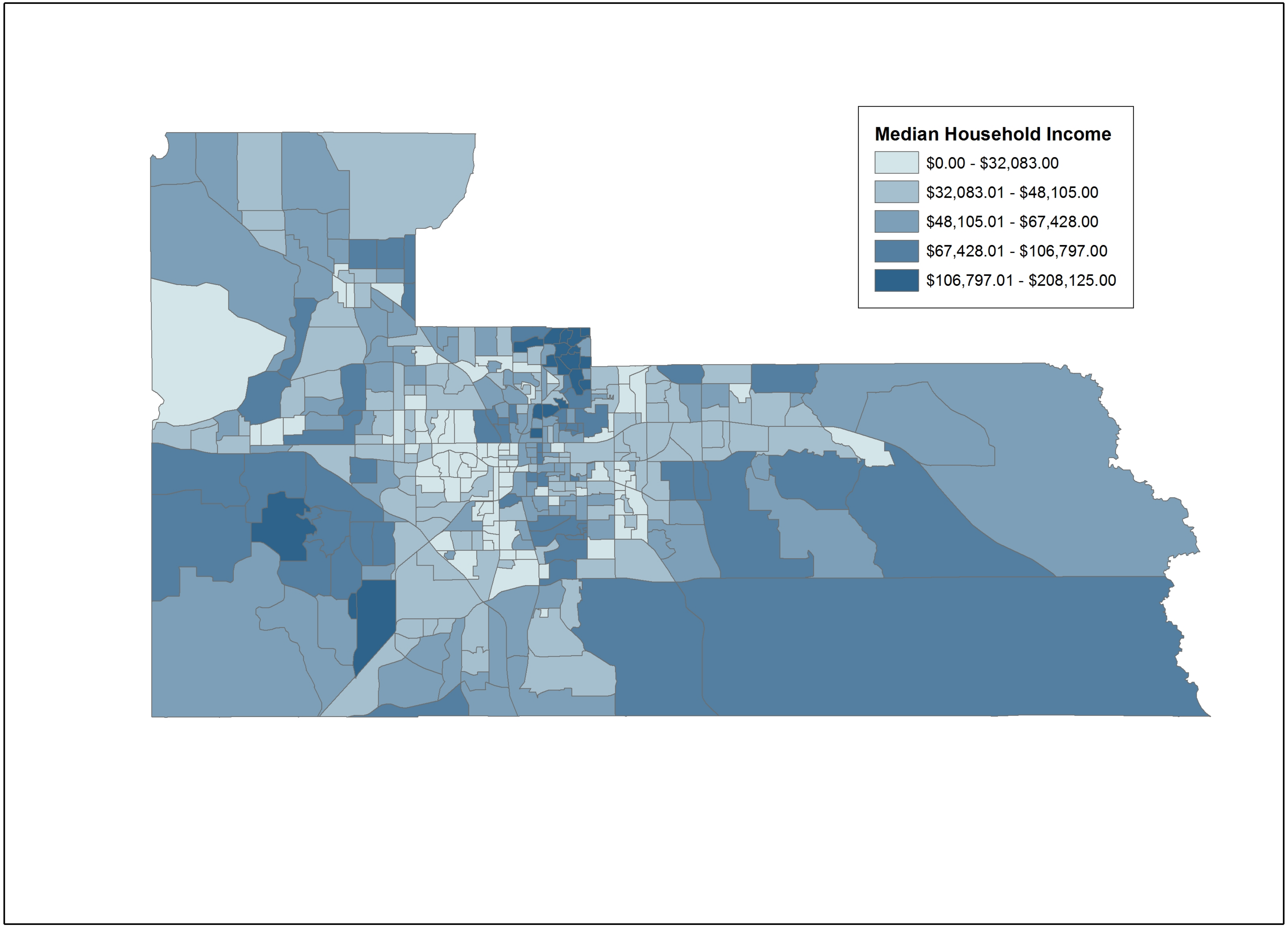
- 2011-2013 crash data in Orange County, FL
- 2011-2014 5-Year American Community Survey data: Race, income, foreign-born status, female-led households, poverty, school enrollment, car ownership, commuting patterns, etc.
- Other variables: Land use, total population, employment density, intersections, sidewalk density, bikelane density, etc.

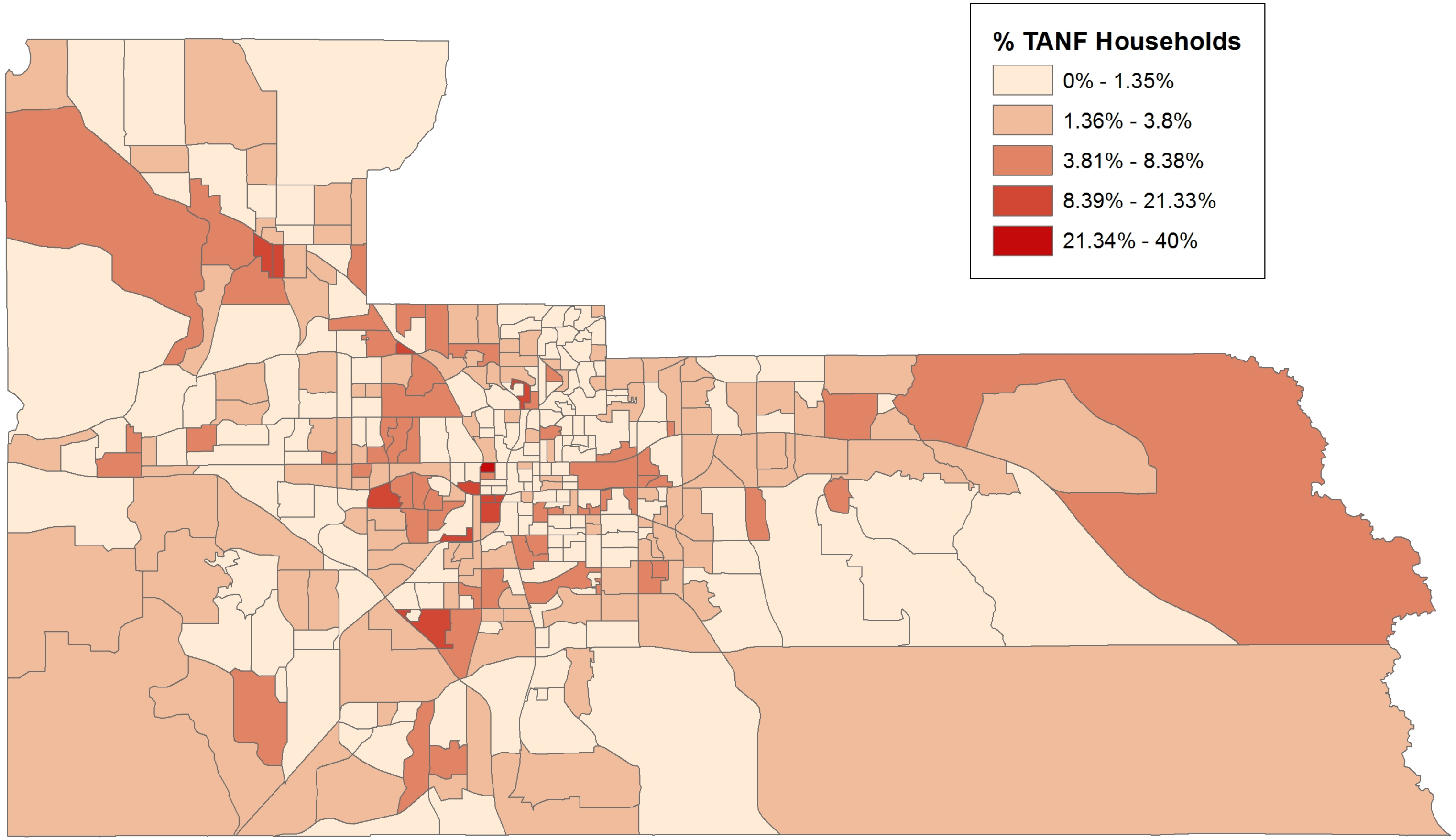
# Methods

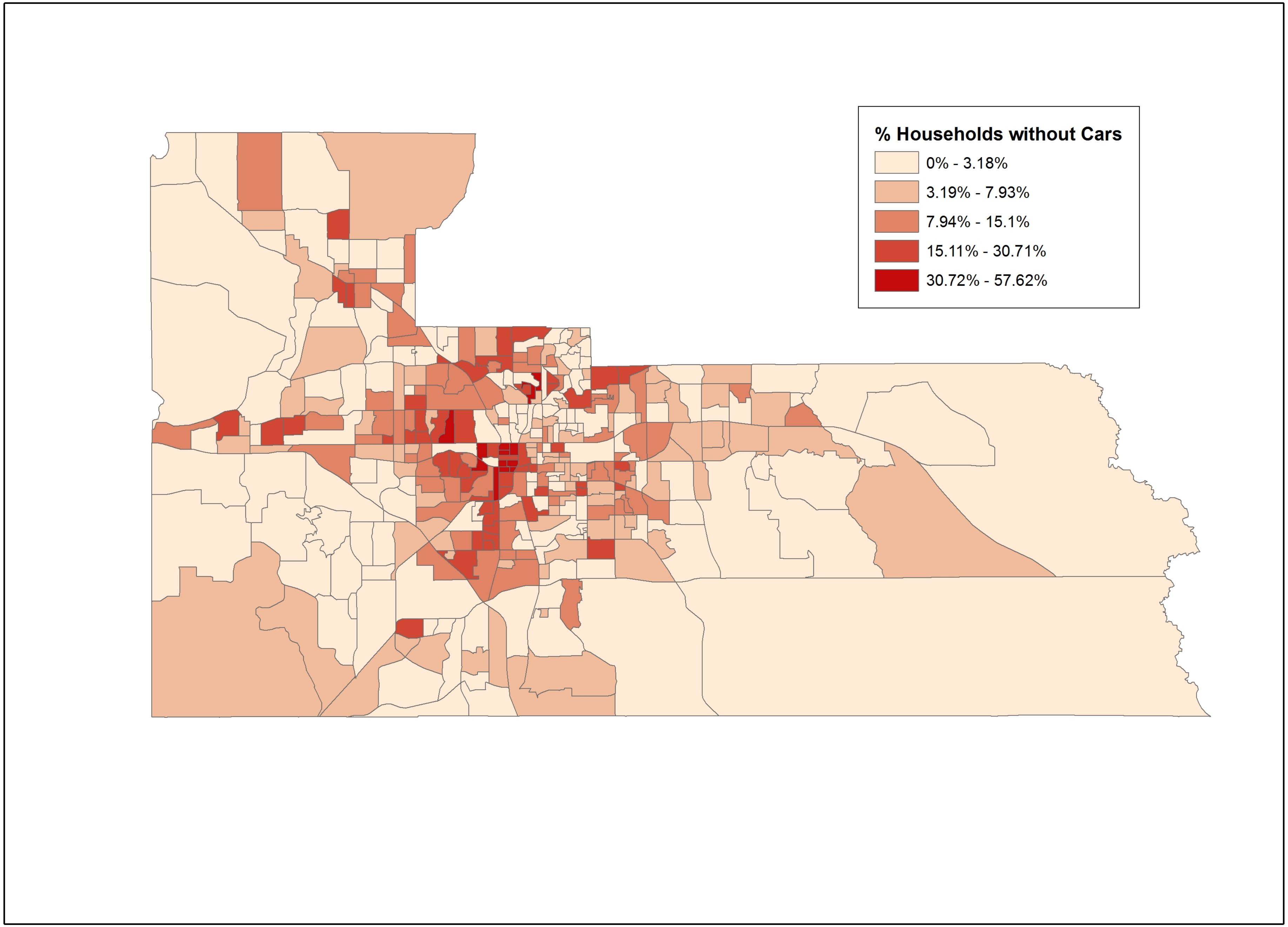
- GIS spatial pattern analysis
- Negative Binomial Regression Models
- Structural Equation Negative Binomial Regression Models (in progress)

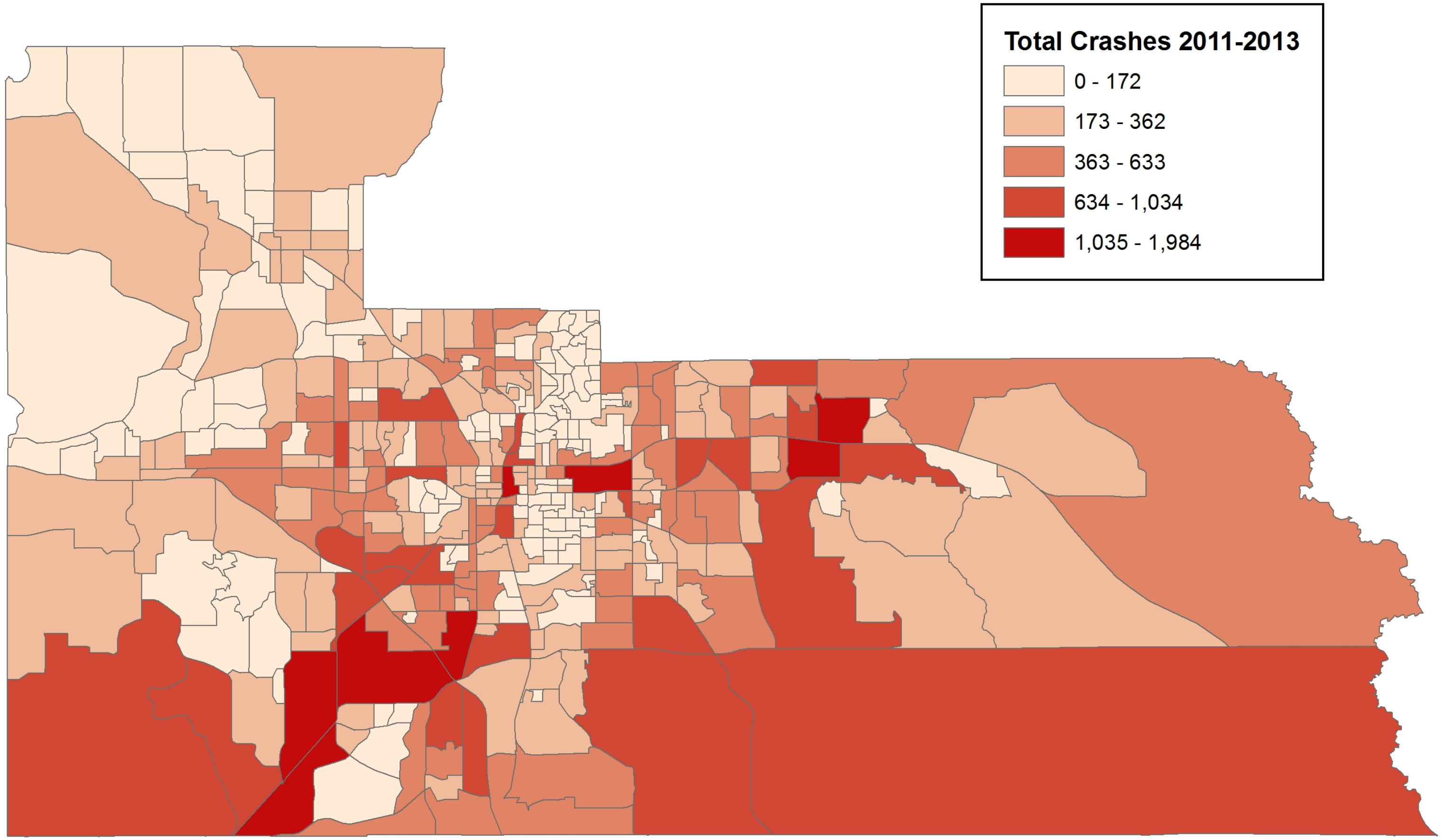
# Preliminary Results

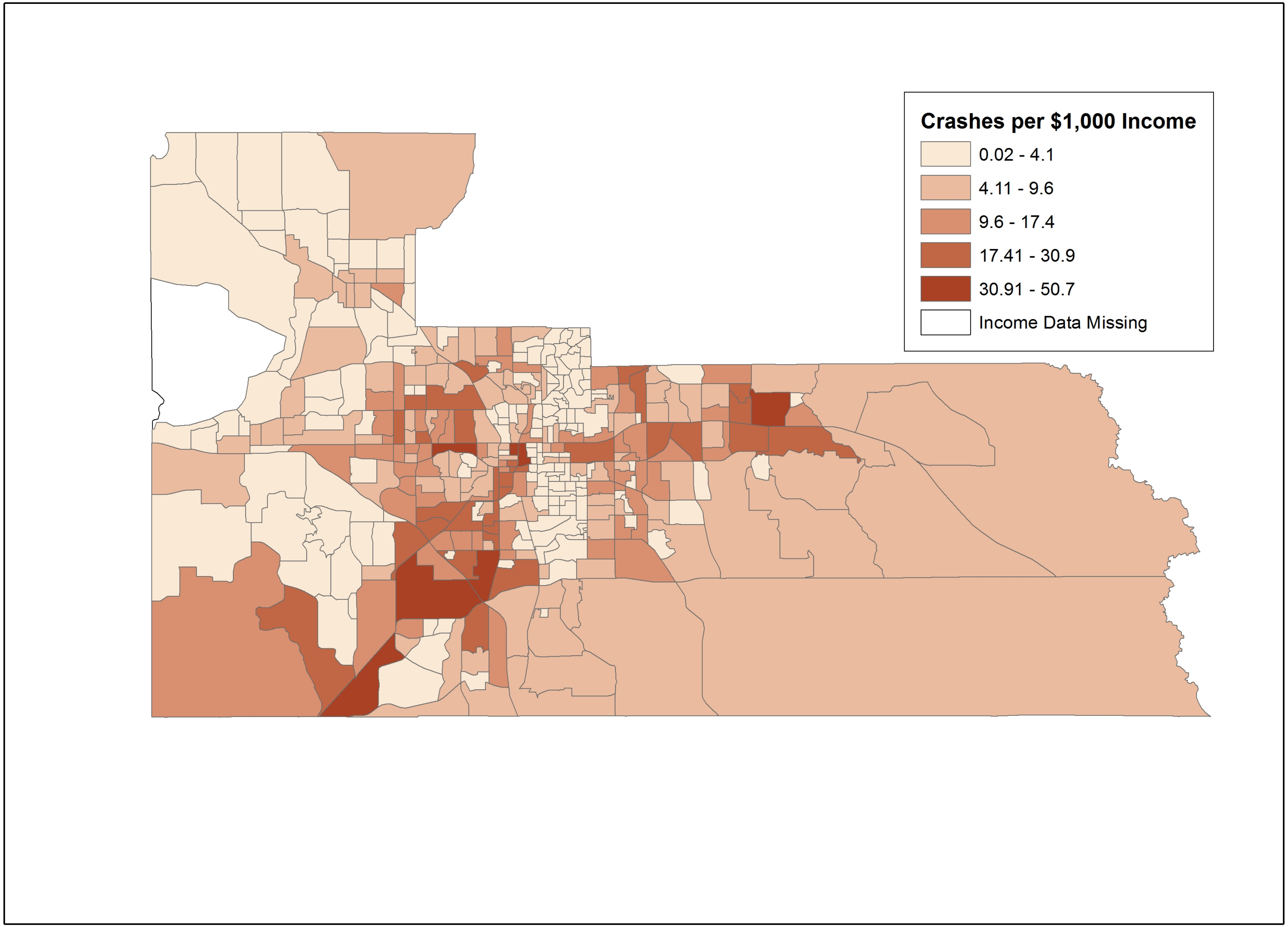
- Spatial Patterns
- Negative Binomial Regression Model
- Structural Equation Negative Binomial Regression Models (Conceptual and in progress)

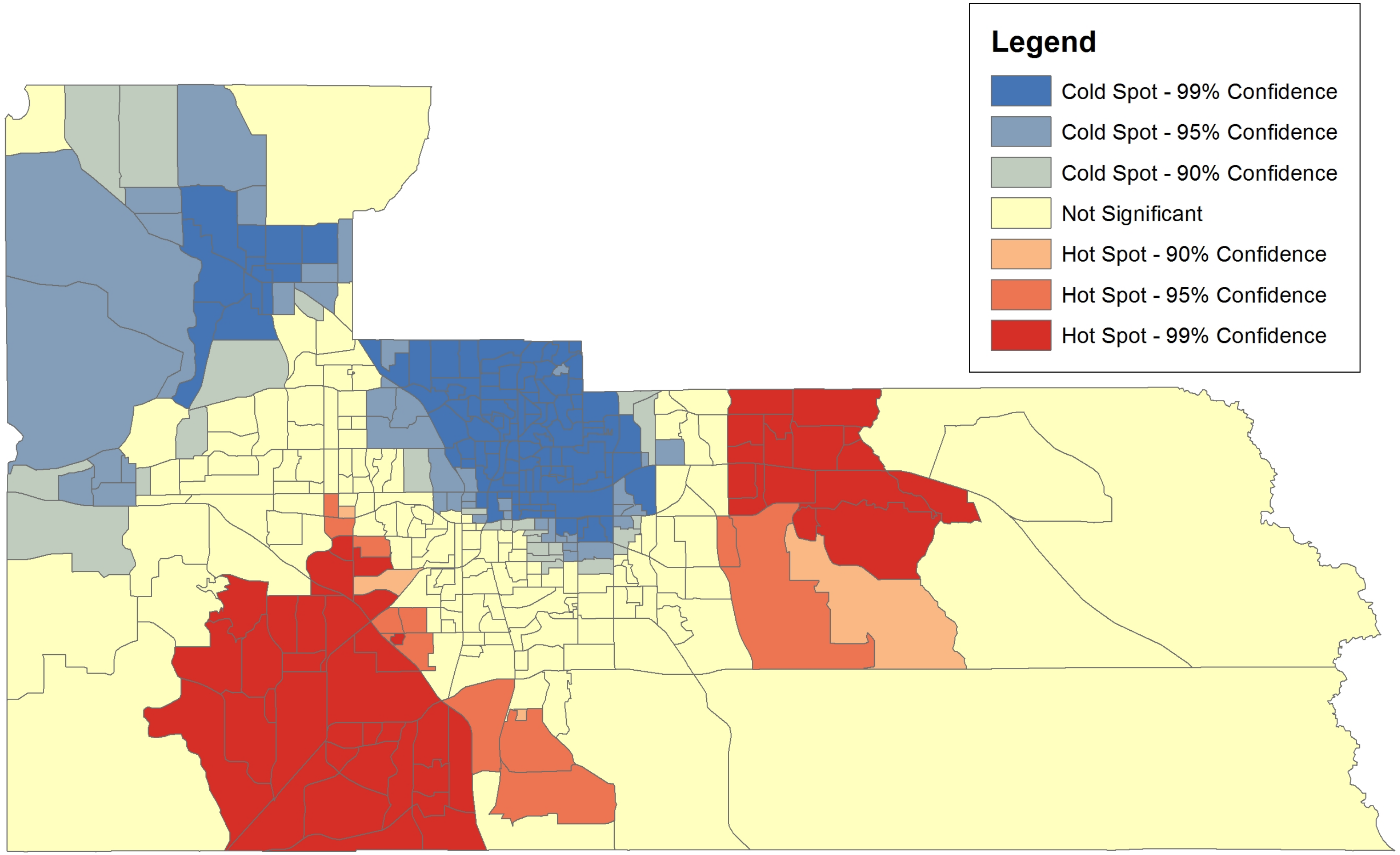

Median Household Income
$0.00 - $32,083.00
$32,083.01 - $48,105.00
$48,105.01 - $67,428.00
$67,428.01 - $106,797.00
$106,797.01 - $208,125.00


% TANF Households
0% - 1.35%
1.36% - 3.8%
3.81% - 8.38%
8.39% - 21.33%
21.34% - 40%


% Households without Cars
0% - 3.18%
3.19% - 7.93%
7.94% - 15.1%
15.11% - 30.71%
30.72% - 57.62%


Total Crashes 2011-2013
0 - 172
173 - 362
363 - 633
634 - 1,034
1,035 - 1,984


Crashes per $1,000 Income
0.02 - 4.1
4.11 - 9.6
9.6 - 17.4
17.41 - 30.9
30.91 - 50.7
Income Data Missing



Legend
Cold Spot - 99% Confidence
Cold Spot - 95% Confidence
Cold Spot - 90% Confidence
Not Significant
Hot Spot - 90% Confidence
Hot Spot - 95% Confidence
Hot Spot - 99% Confidence

- Pearson’s correlation indicates that income is positively and highly associated with college educated, property values, and homeownership rates; negatively associated with female-led households, poverty rate, SNAP recipients, and households without health insurance ($r>0.5$).
- The negative association between income, carless households, and transit uses is mild (r: between -0.5 and -0.4).
- Income is weakly associated with percentage TANF recipients and housing assistance recipients, which might indicate TANF and housing assistance recipients are more scattered in neighborhoods with different socioeconomic characteristics.

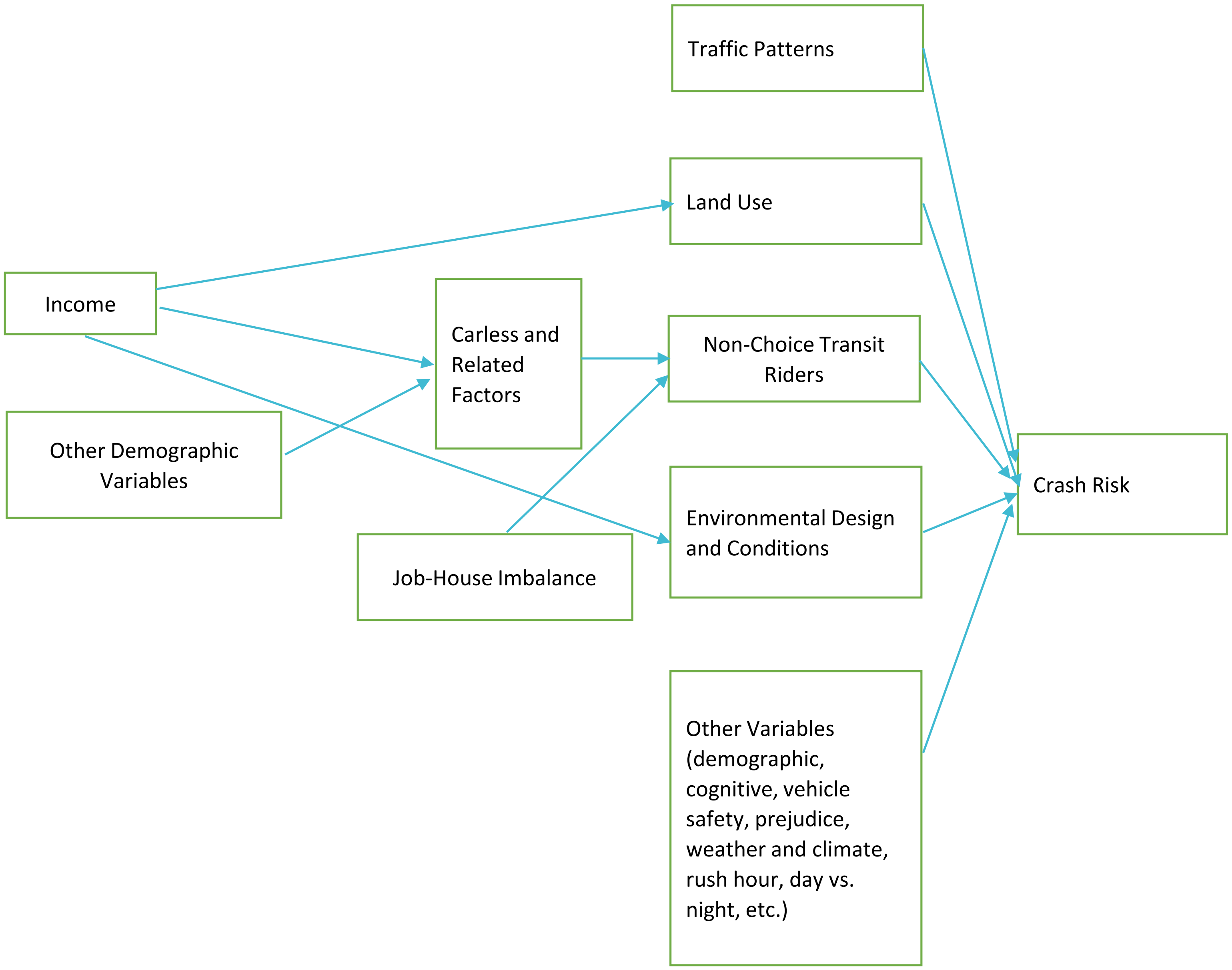
# Preliminary Results

| Variable | Mean | Std Dev | Minimum | Maximum |
|---|---|---|---|---|
| **Total Crashes (2011-2013)** | 294 | 278 | 0 | 1,984 |
| | | | | |
| **Demographic Variables** | | | | |
| Median Household Income (2010-2014) | $ 51,850.0 | $ 27,764.0 | $ - | $ 208,125.0 |
| % TANF Households | 2.2% | 3.3% | 0 | 40.0% |
| # of Public Housing Units | 18 | 28 | 0 | 183 |
| % Households Receiving Housing Choice Vouchers | 2.3% | 5.7% | 0 | 67.6% |
| % Nonwhite Households | 71.4% | 37.4% | 0 | 100.0% |
| % Households not Speaking English at Home | 29.1% | 18.1% | 0 | 84.3% |
| % Households with Children (<18 years old) | 21.1% | 8.6% | 0 | 52.7% |
| % Households with Seniors (>=65 years old) | 12.4% | 8.5% | 0 | 72.3% |
| | | | | |
| **Built Environment and Transportation Variables** | | | | |
| % Freeways | 7.5% | 11.7% | 0 | 53.9% |
| % Artery Roads | 13.4% | 11.3% | 0 | 71.0% |
| Multifamily Land Use (acres) | 37.9 | 51.4 | 0 | 268.9 |
| Commercial Land Use (acres) | 22.7 | 36.6 | 0 | 304.3 |
| Sidewalk Density | 8.0% | 6.8% | 0 | 36.4% |
| # of Transit Stops | 15 | 14 | 0 | 85 |
| Total VMT | 773,766 | 1,271,127 | 0 | 9,639,722 |

# Preliminary Results: Analysis Of Maximum Likelihood Parameter Estimates (DV: Total Crashes 2011-13)

| Parameter | Estimate | Standard Error | Wald 95% Confidence Limits | | Wald Chi-Square | Pr > ChiSq |
|---|---|---|---|---|---|---|
| Intercept | 4.667 | 0.166 | 4.341 | 4.992 | 789.210 | <.0001 |
| | | | | | | |
| **Demographic Variables** | | | | | | |
| Median Household Income (2010-2014) | -0.000 | 0.000 | -0.000 | -0.000 | 15.470 | <.0001 |
| % TANF Households | 0.010 | 0.999 | -1.948 | 1.968 | 0.000 | 0.992 |
| # of Public Housing Units | -0.002 | 0.001 | -0.004 | 0.001 | 2.540 | 0.111 |
| % Households Receiving Housing Choice Voucher | 0.381 | 0.558 | -0.713 | 1.474 | 0.470 | 0.495 |
| % Nonwhite Households | 0.123 | 0.075 | -0.024 | 0.269 | 2.680 | 0.102 |
| % Households not Speaking English at Home | 0.846 | 0.197 | 0.459 | 1.232 | 18.410 | <.0001 |
| % Households with Children (<18 years old) | -0.965 | 0.372 | -1.694 | -0.237 | 6.740 | 0.009 |
| % Households with Seniors (>=65 years old) | -1.005 | 0.360 | -1.711 | -0.300 | 7.800 | 0.005 |
| | | | | | | |
| **Built Environment and Transportation Variables** | | | | | | |
| % Freeways | 1.599 | 0.294 | 1.023 | 2.175 | 29.590 | <.0001 |
| % Artery Roads | 2.153 | 0.311 | 1.543 | 2.762 | 47.960 | <.0001 |
| Multifamily Land Use (acres) | 0.002 | 0.001 | 0.001 | 0.003 | 8.980 | 0.003 |
| Commercial Land Use (acres) | 0.003 | 0.001 | 0.001 | 0.005 | 7.680 | 0.006 |
| Sidewalk Density | 2.305 | 0.510 | 1.306 | 3.304 | 20.450 | <.0001 |
| # of Transit Stops | 0.013 | 0.003 | 0.008 | 0.019 | 22.440 | <.0001 |
| Total VMT | 0.000 | 0.000 | 0.000 | 0.000 | 9.110 | 0.003 |
| Dispersion | 0.266 | 0.020 | 0.230 | 0.308 | | |

# Structural Equation Negative Binomial Regression Models



# Next Steps

- Structural Equational Negative Binomial Regression Models:

  - Total crashes

  - Vehicular crashes

  - Pedestrian crashes

  - Bike crashes

- Case studies of high-crash vs. low-crash neighborhoods

# Thank you!

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