

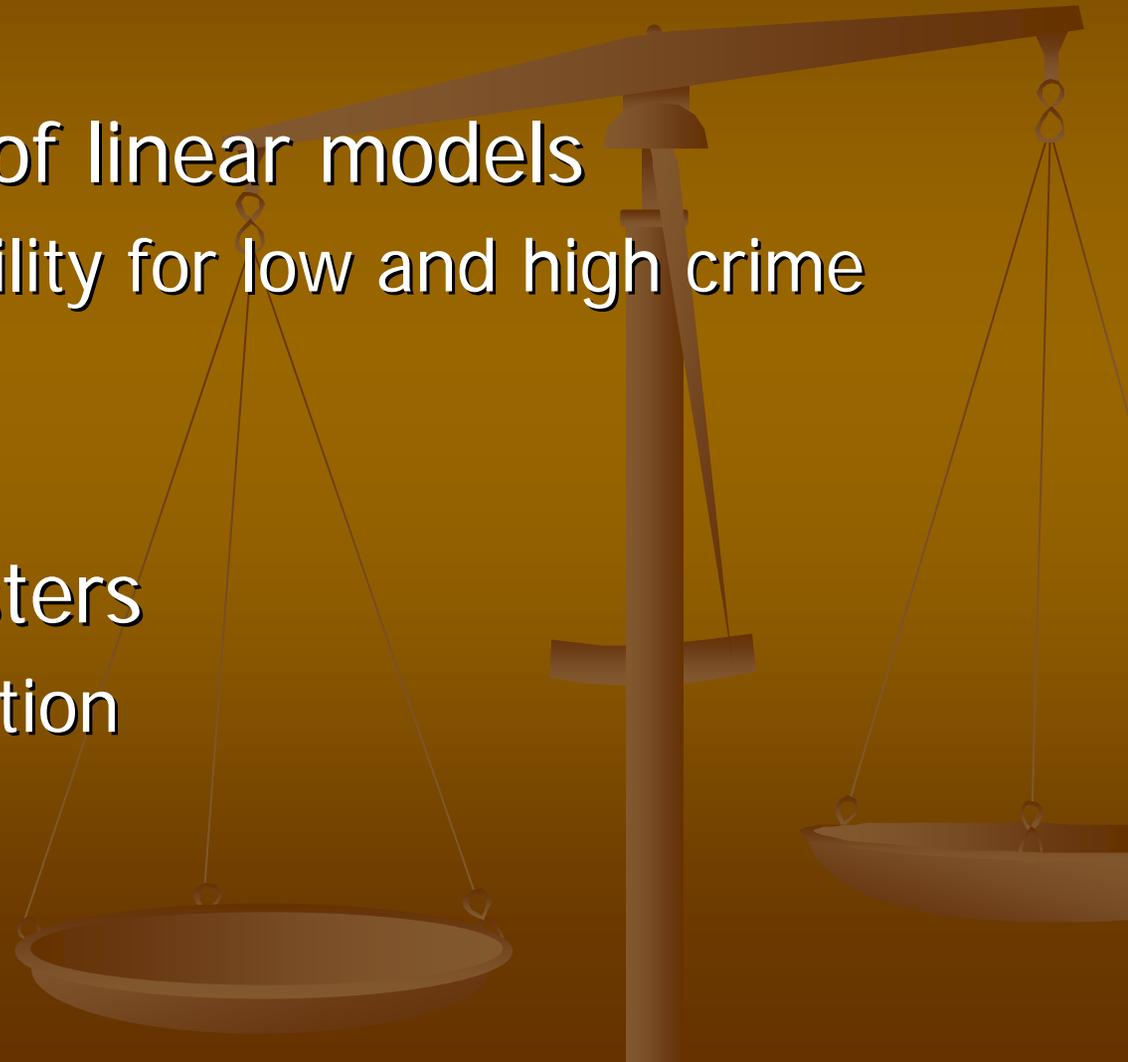
Predicting local crime clusters using a local indicator of spatial association and a discrete choice model



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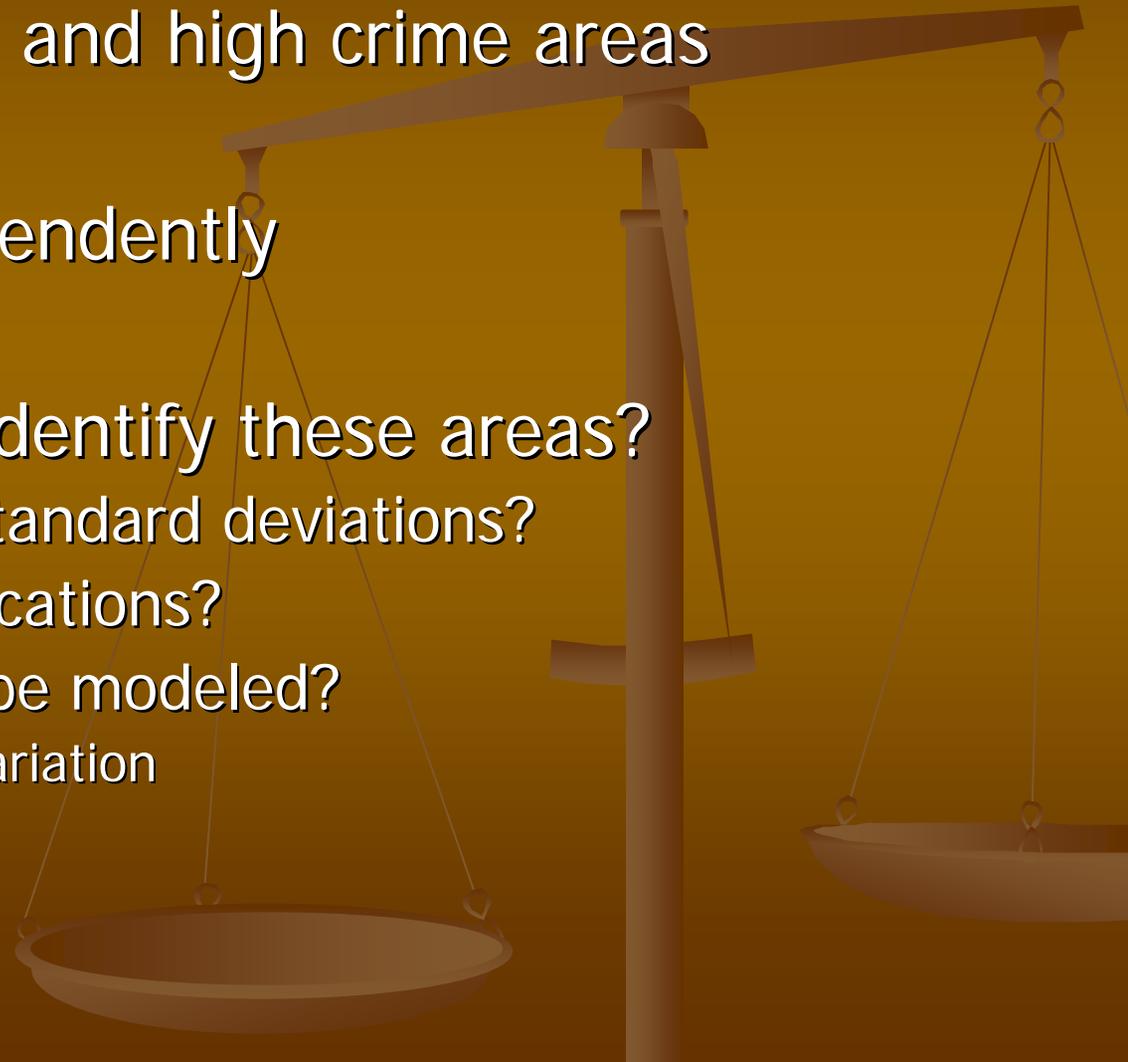
Motivation for this research

- The limitations of linear models
 - Parameter stability for low and high crime areas?
- Local crime clusters
 - A lack of prediction

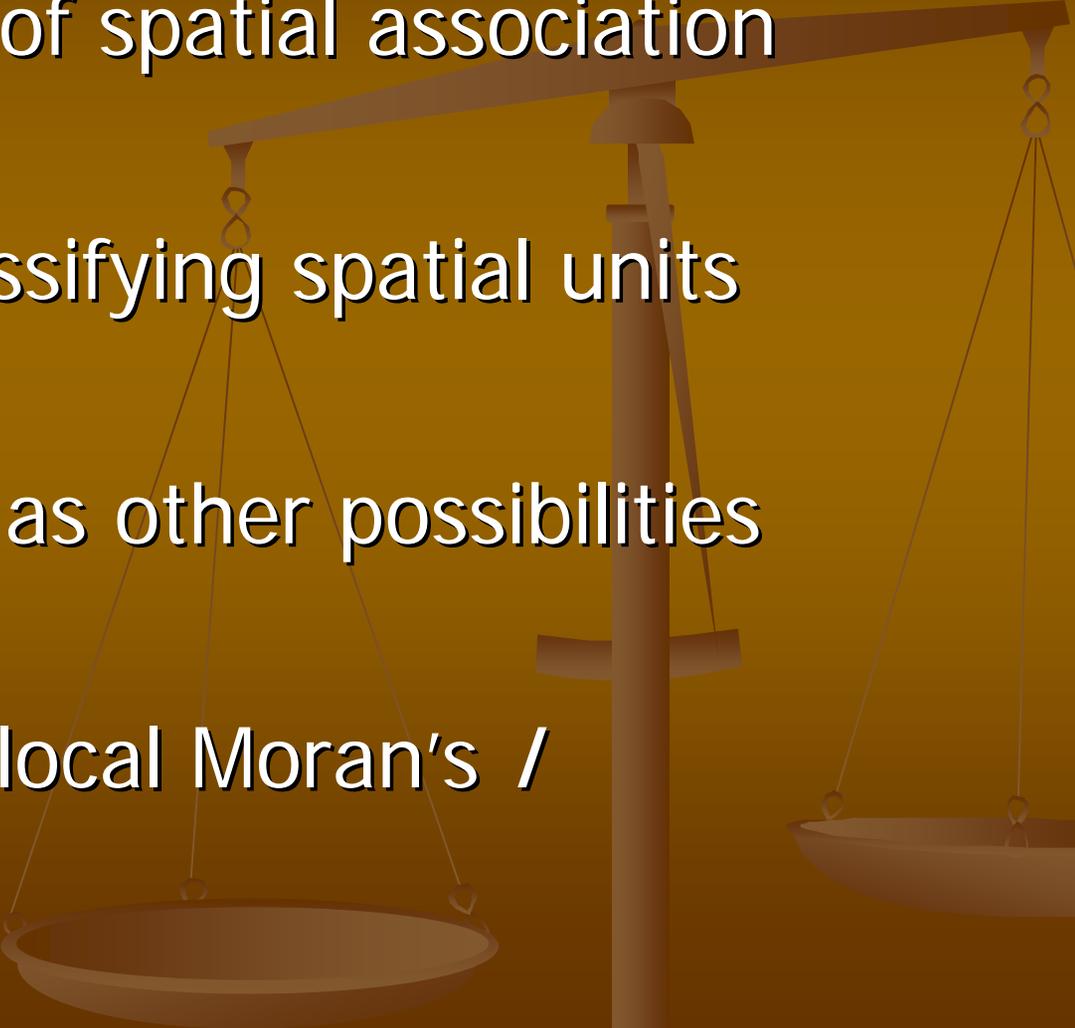


Resolving linearity

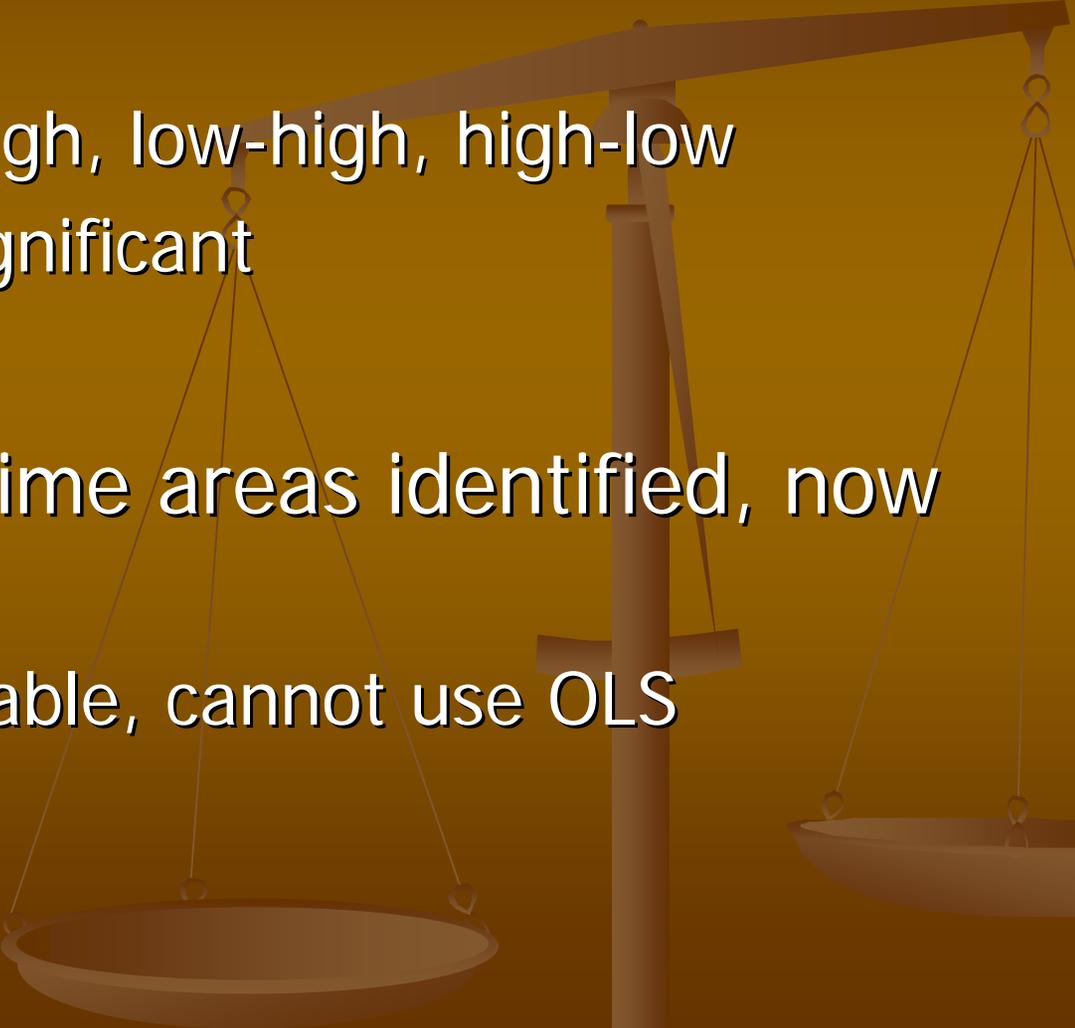
- Identify low crime and high crime areas
- Model them independently
- Problem: how to identify these areas?
 - Natural breaks? Standard deviations?
 - How many classifications?
 - How should they be modeled?
 - Little remaining variation



LISA

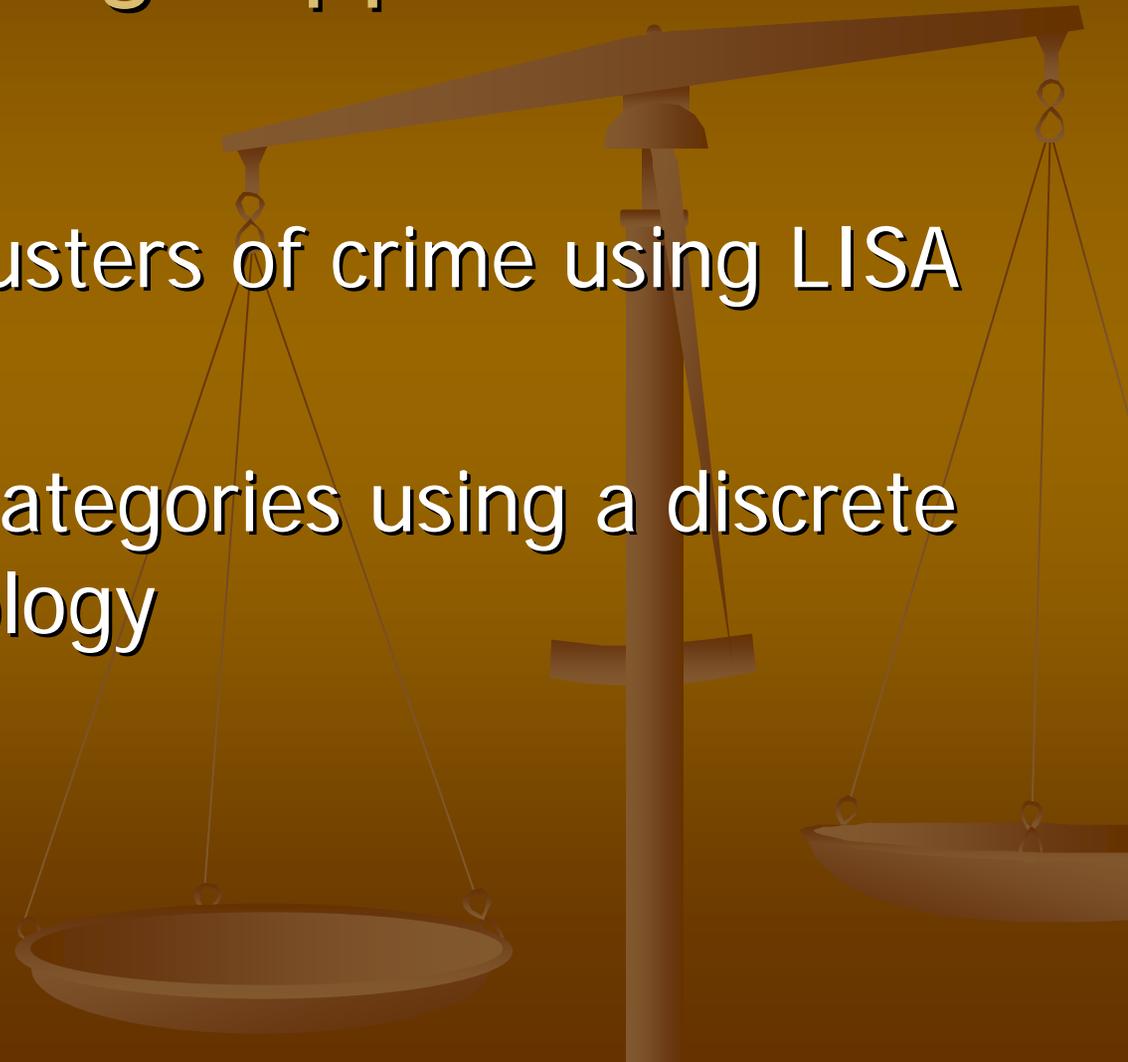
- Local indicators of spatial association
 - A method of classifying spatial units
 - Not as arbitrary as other possibilities
 - Anselin (1995): local Moran's I
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LISA, cont'd

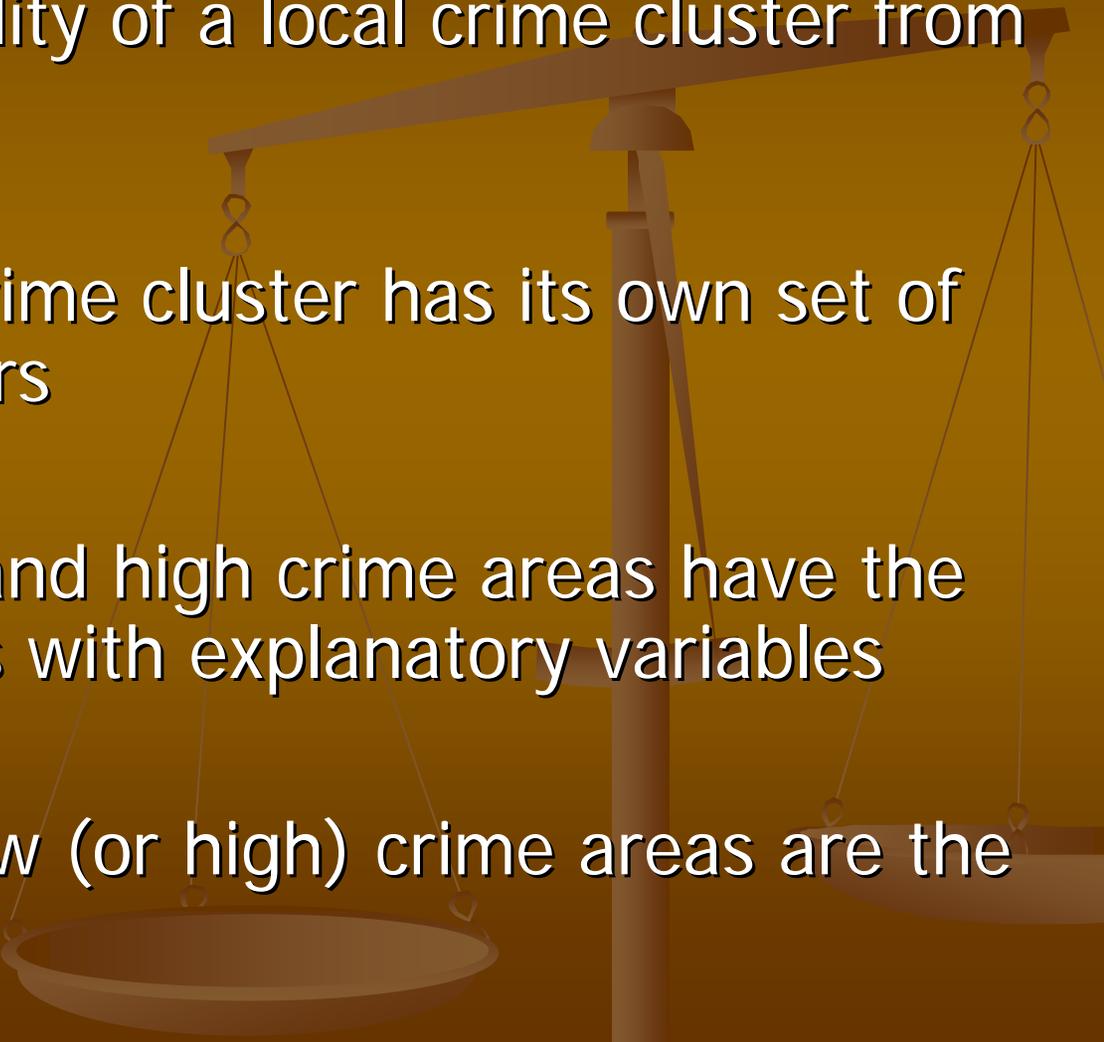
- 5 classifications
 - low-low, high-high, low-high, high-low
 - Statistically insignificant
 - Low and high crime areas identified, now what?
 - Categorical variable, cannot use OLS
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Synthesizing my motivation: a two-stage approach

- Identify local clusters of crime using LISA
- Model these 5 categories using a discrete choice methodology



Multinomial logistic regression

- Predicts the probability of a local crime cluster from occurring
 - Each type of local crime cluster has its own set of estimated parameters
 - Can uncover if low and high crime areas have the "same" relationships with explanatory variables
 - Can uncover if all low (or high) crime areas are the same
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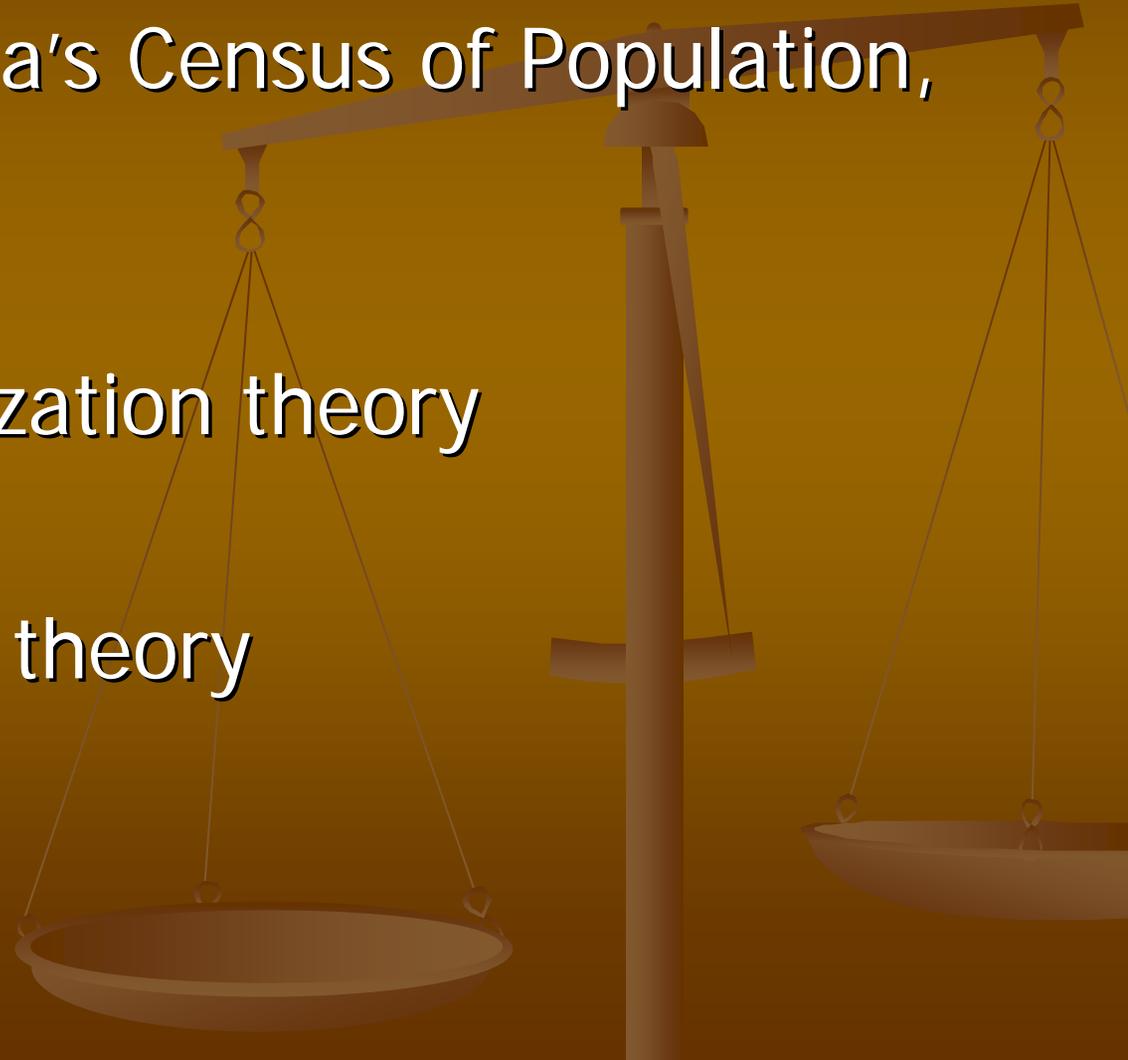
Crime data



- VPD calls for service, 2001
- Automotive theft, burglary, and violent crime
- All crimes measured as rates per 1000

Ecological data

- Statistics Canada's Census of Population, 2001
- Social disorganization theory
- Routine activity theory



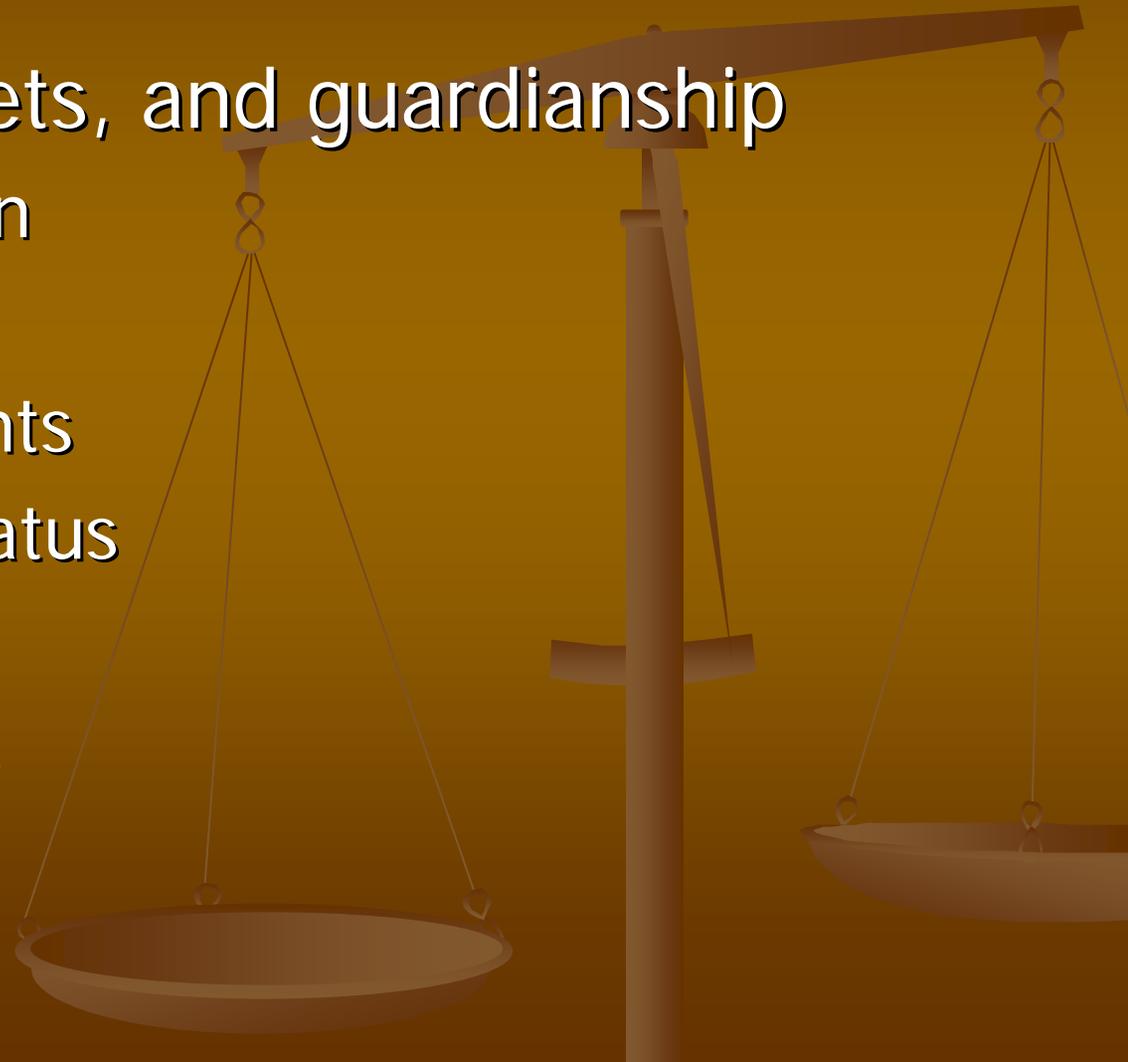
Social disorganization theory

- Ethnic heterogeneity
- Population turnover
- Social and economic deprivation
- Family disruption

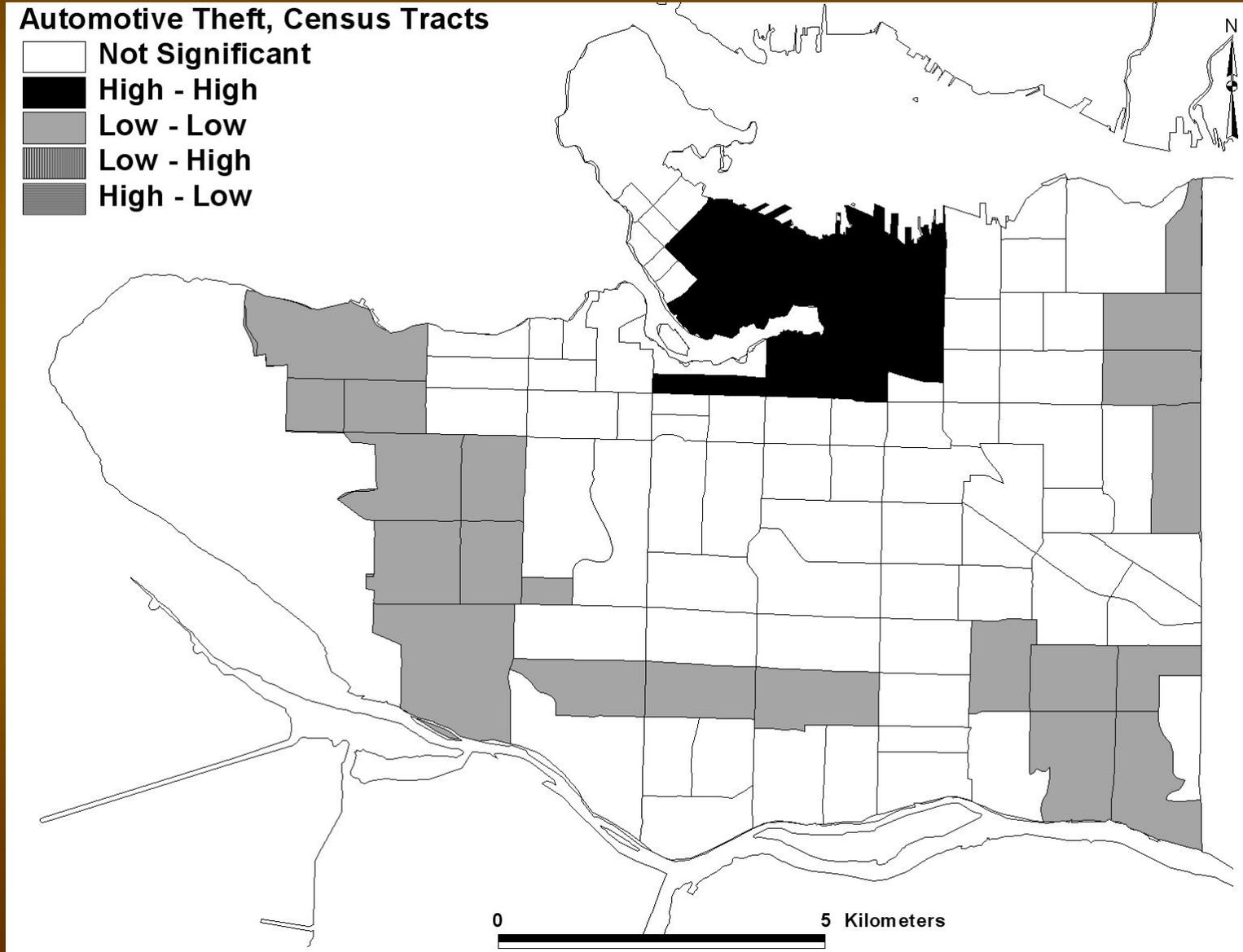


Routine activity theory

- Offenders, targets, and guardianship
 - Age composition
 - Marital status
 - Population counts
 - Employment status
 - Income levels
 - Dwelling values



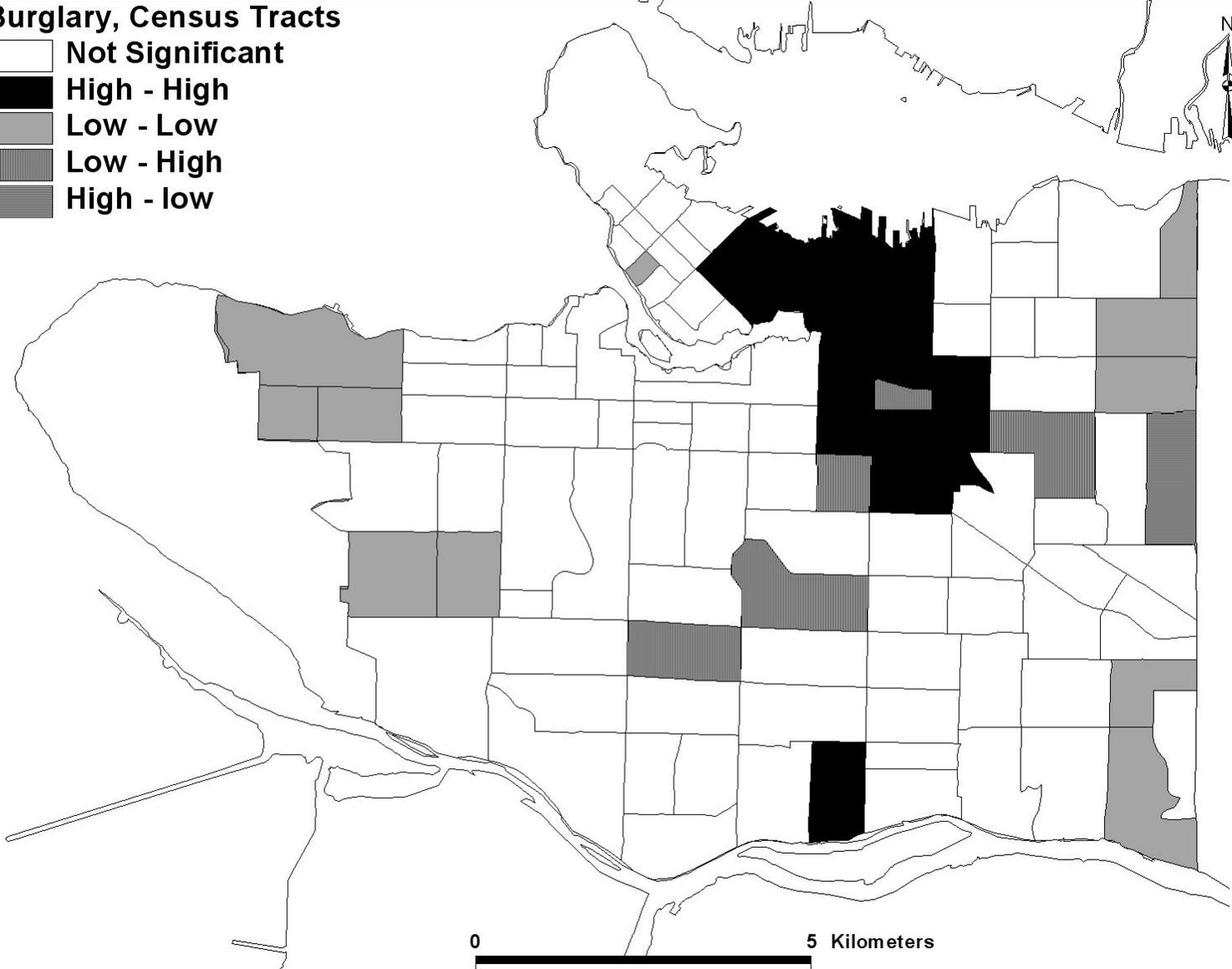
Crime clusters (CTs), automotive theft



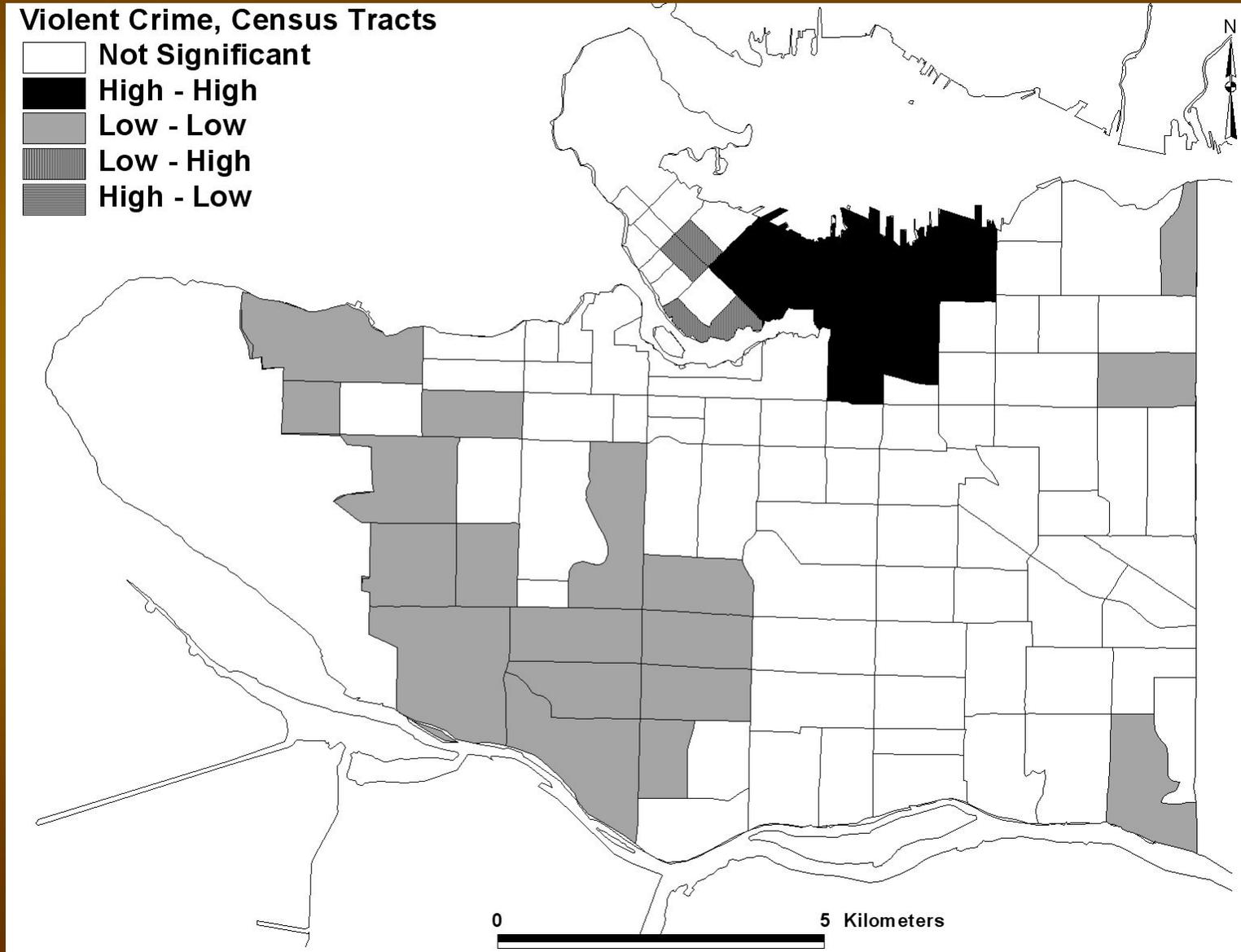
Crime clusters (CTs), burglary

Burglary, Census Tracts

- Not Significant
- High - High
- Low - Low
- Low - High
- High - low



Crime clusters (CTs), violent crime



Local crime clusters, CTs

Table 6. Percentages of cluster types, census tracts, Vancouver, British Columbia, Canada, 2001

| | Cluster Types | | | | |
|------------------|---------------|-----------|---------|----------|----------|
| | Insignificant | High-High | Low-Low | Low-High | High-Low |
| Automotive Theft | 67.3 | 10.9 | 21.8 | 0.0 | 0.0 |
| Burglary | 69.1 | 10.9 | 14.5 | 4.5 | 0.9 |
| Violent Crime | 71.8 | 6.4 | 19.1 | 2.7 | 0.0 |

Source. Vancouver Police Department and Statistics Canada, calculations by the author.

Automotive theft results, CTs

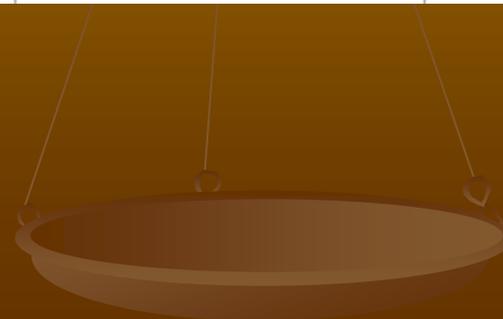
Table 7. Multinomial logistic regression results, census tracts, automotive theft

| | High-High | Low-Low |
|------------------------|---------------|---------------|
| Population Change, % | 0.488 | -2.279 |
| Single Parents, % | -1.560 | 1.386 |
| Unemployment Rate | 1.357 | 1.149 |
| Average Income, 000s | 0.072 | 0.347 |
| Probability of cluster | 2.34 | 12.34 |
| Pseudo - R^2 | 0.337 | |
| Percent Correct | 74.55 | |

Burglary results, CTs

Table 8. Multinomial logistic regression results, census tracts, burglary

| | High-High I | Low-Low | Low-High | High-Low |
|------------------------|----------------|---------------|--------------|----------|
| Population Change, % | 0.353 | -1.462 | 0.038 | -0.098 |
| Single Parents, % | 0.219 | 1.206 | 1.075 | 0.067 |
| Recent Immigrants, % | 0.179 | -1.149 | 0.124 | -0.046 |
| Unemployment Rate | 1.877 | 0.560 | -0.276 | 0.175 |
| Probability of cluster | 3.28 | 8.09 | 0.89 | 0.86 |
| Pseudo - R^2 | 0.308 | | | |
| Percent Correct | 74.55 | | | |

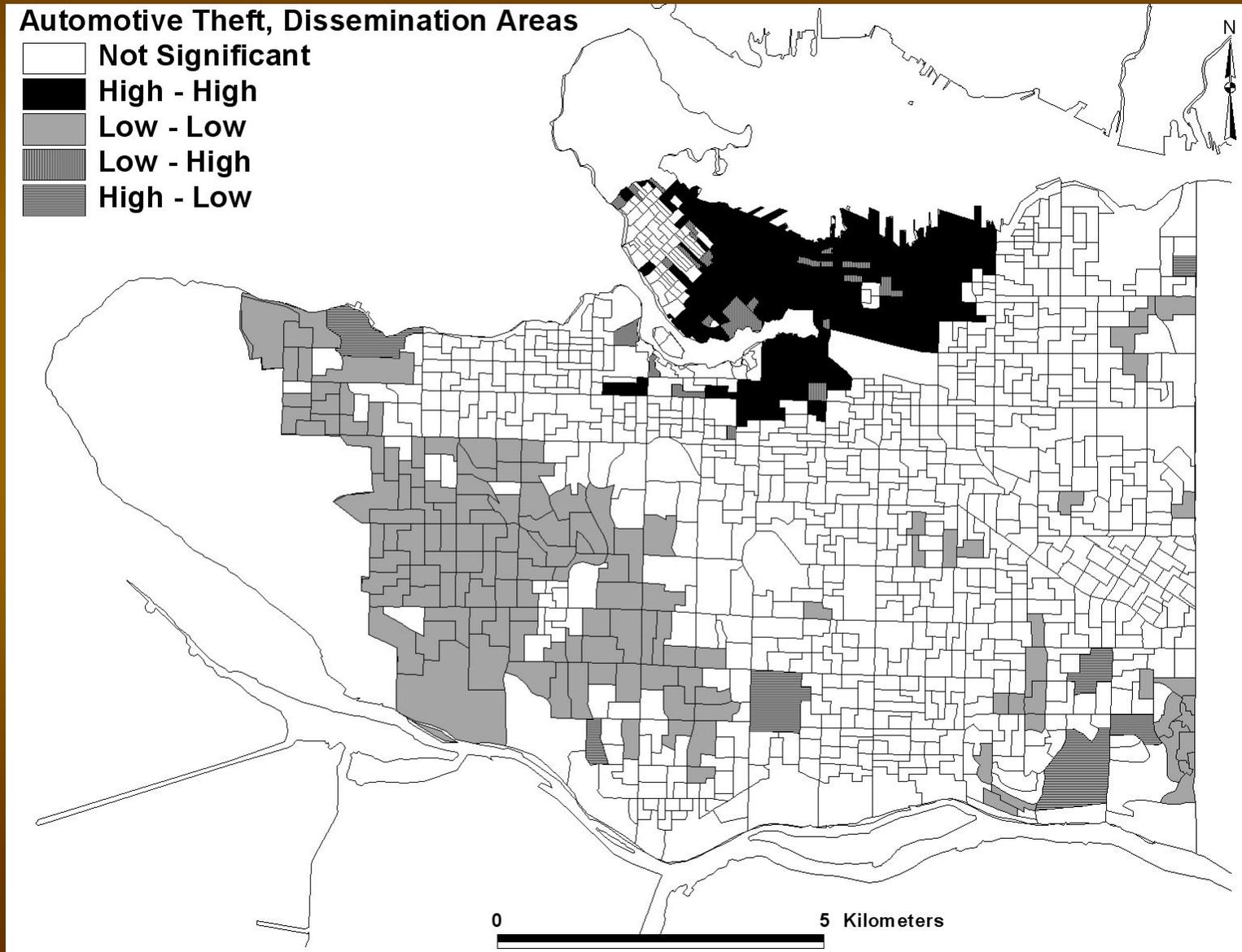


Violent crime results, CTs

Table 9. Multinomial logistic regression results, census tracts, violent crime

| | High-High | Low-Low | Low-High |
|------------------------|--------------|---------------|--------------|
| Population Change, % | 0.078 | -2.099 | 0.047 |
| Unemployment Rate | 0.470 | 2.192 | 0.009 |
| Average Income, 000s | 0.013 | 0.475 | 0.004 |
| Probability of cluster | 0.53 | 8.85 | 0.12 |
| Pseudo - R^2 | 0.476 | | |
| Percent Correct | 83.64 | | |

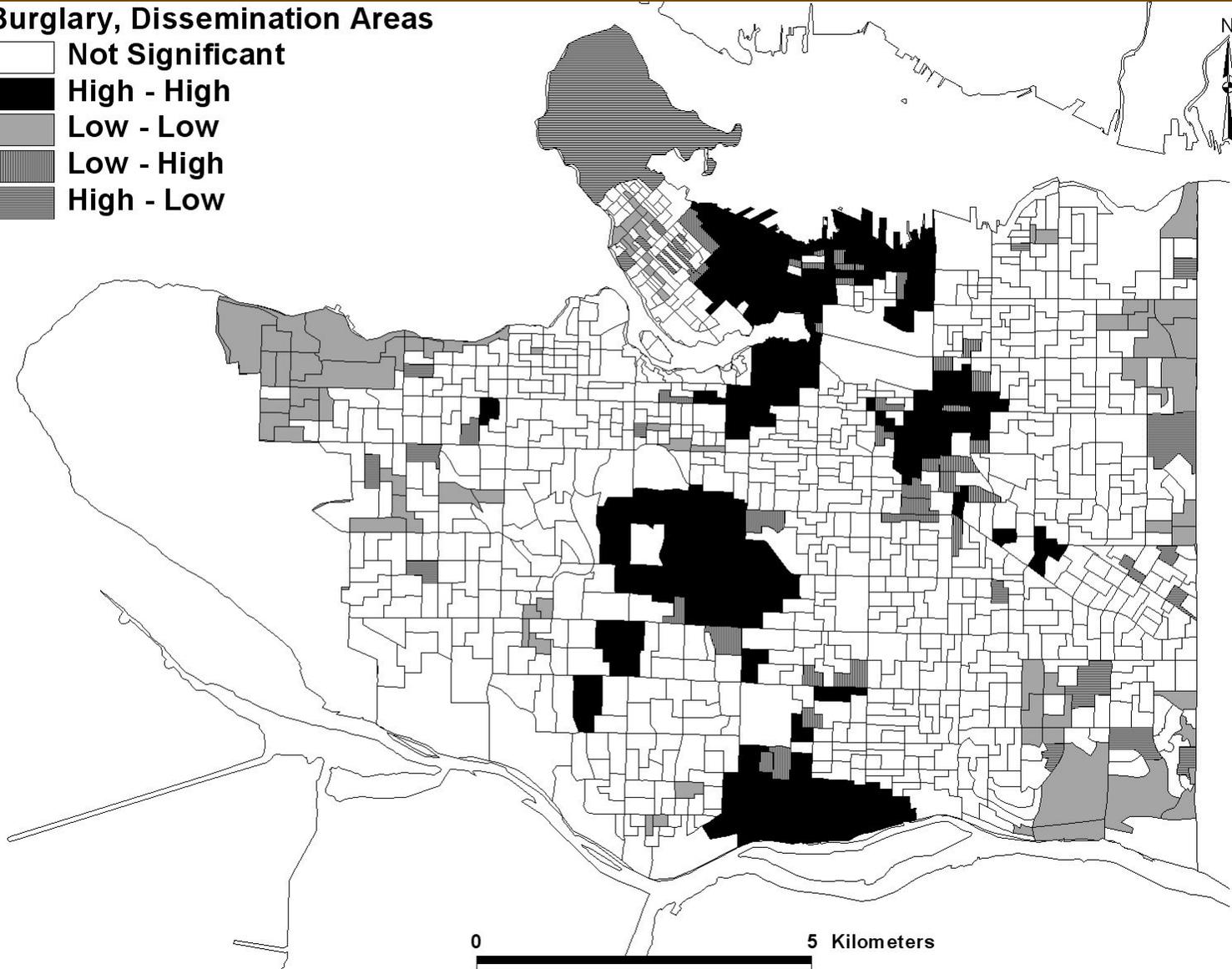
Crime clusters (DAs), automotive theft



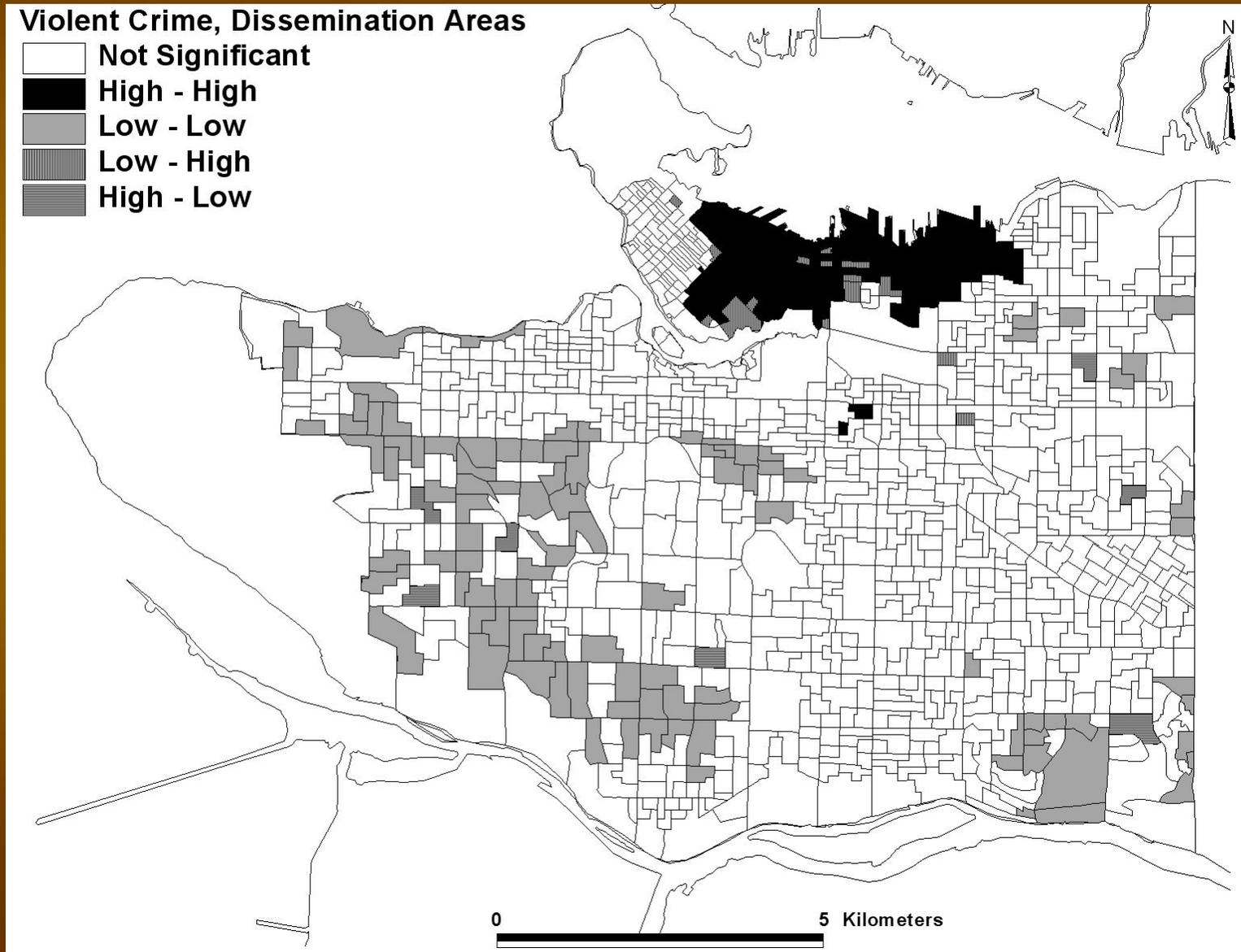
Crime clusters (DAs), burglary

Burglary, Dissemination Areas

- Not Significant
- High - High
- Low - Low
- Low - High
- High - Low



Crime clusters (DAs), violent crime



Local crime clusters, DAs

Table 10. Percentages of cluster types, dissemination areas, Vancouver, British Columbia, Canada, 2001

| | Cluster Type | | | | |
|------------------|---------------|-----------|---------|----------|----------|
| | Insignificant | High-High | Low-Low | Low-High | High-Low |
| Automotive Theft | 77.2 | 5.6 | 14.0 | 2.5 | 0.7 |
| Burglary | 76.7 | 8.6 | 8.3 | 3.9 | 2.5 |
| Violent Crime | 82.9 | 4.0 | 10.7 | 1.6 | 0.7 |

Automotive theft results, DAs

Table 11. Multinomial logistic regression results, dissemination areas, automotive theft

| | High-High | Low-Low | Low-High | High-Low |
|------------------------|---------------|---------------|---------------|---------------|
| Population Change, % | 0.016 | -0.240 | 0.051 | -0.000 |
| Males 15-24, % | -0.119 | 1.533 | -0.180 | -0.000 |
| Single Parents, % | -0.130 | 0.597 | 0.030 | 0.000 |
| Ethnic Diversity | 0.019 | -0.171 | -0.001 | -0.000 |
| Unemployment Rate | 0.105 | 0.163 | 0.114 | 0.000 |
| Post-secondary, % | 0.021 | 0.082 | 0.018 | 0.000 |
| Average Income, 000s | 0.018 | 0.105 | 0.021 | -0.000 |
| Population Density | -0.004 | 0.001 | 0.000 | -0.000 |
| Dwelling Value, 000s | -0.007 | 0.010 | -0.005 | 0.000 |
| Rentals, % | 0.009 | -0.106 | 0.012 | 0.000 |
| Major Repairs, % | -0.060 | -0.349 | -0.023 | -0.000 |
| Probability of cluster | 0.66 | 6.08 | 0.99 | 0.00 |
| Pseudo - R^2 | 0.337 | | | |
| Percent Correct | 82.32 | | | |

Burglary results, DAs

Table 12. Multinomial logistic regression results, dissemination areas, burglary

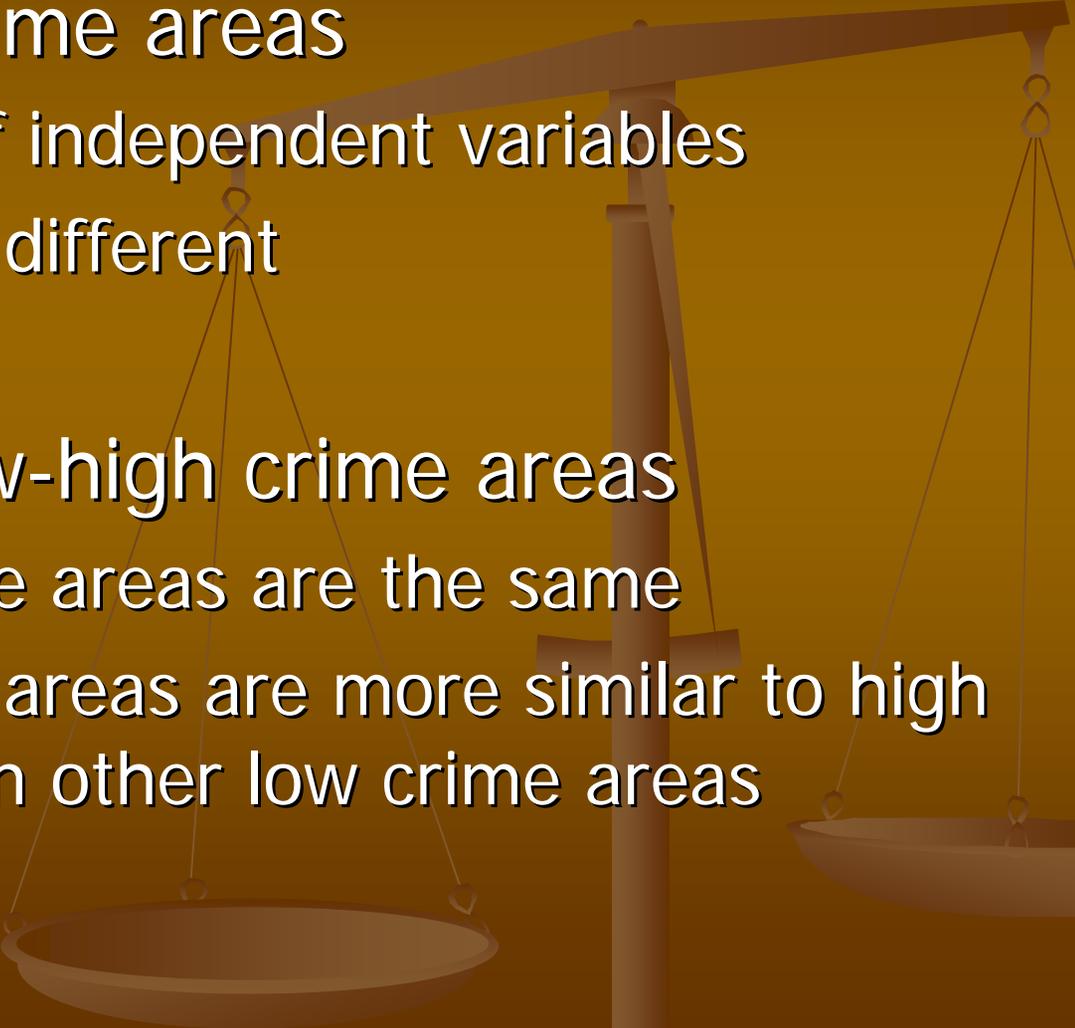
| | High-High | Low-Low | Low-High | High-Low |
|------------------------|--------------|---------------|---------------|---------------|
| Population Change, % | 0.158 | -0.012 | -0.004 | -0.045 |
| Males 15-24, % | -0.329 | -0.181 | -0.255 | 0.379 |
| Recent Immigrants, % | 0.020 | 0.180 | 0.010 | -0.079 |
| Ethnic Diversity | 0.152 | -0.110 | 0.033 | -0.040 |
| Unemployment Rate | 0.435 | 0.022 | 0.153 | -0.012 |
| Dwelling Value, 000s | 0.016 | 0.007 | -0.009 | -0.009 |
| Major Repairs, % | 0.096 | -0.244 | -0.040 | -0.044 |
| Probability of cluster | 6.06 | 5.83 | 2.31 | 1.30 |
| Pseudo - R^2 | 0.074 | | | |
| Percent Correct | 76.67 | | | |

Violent crime results, DAs

Table 13. Multinomial logistic regression results, dissemination areas, violent crime

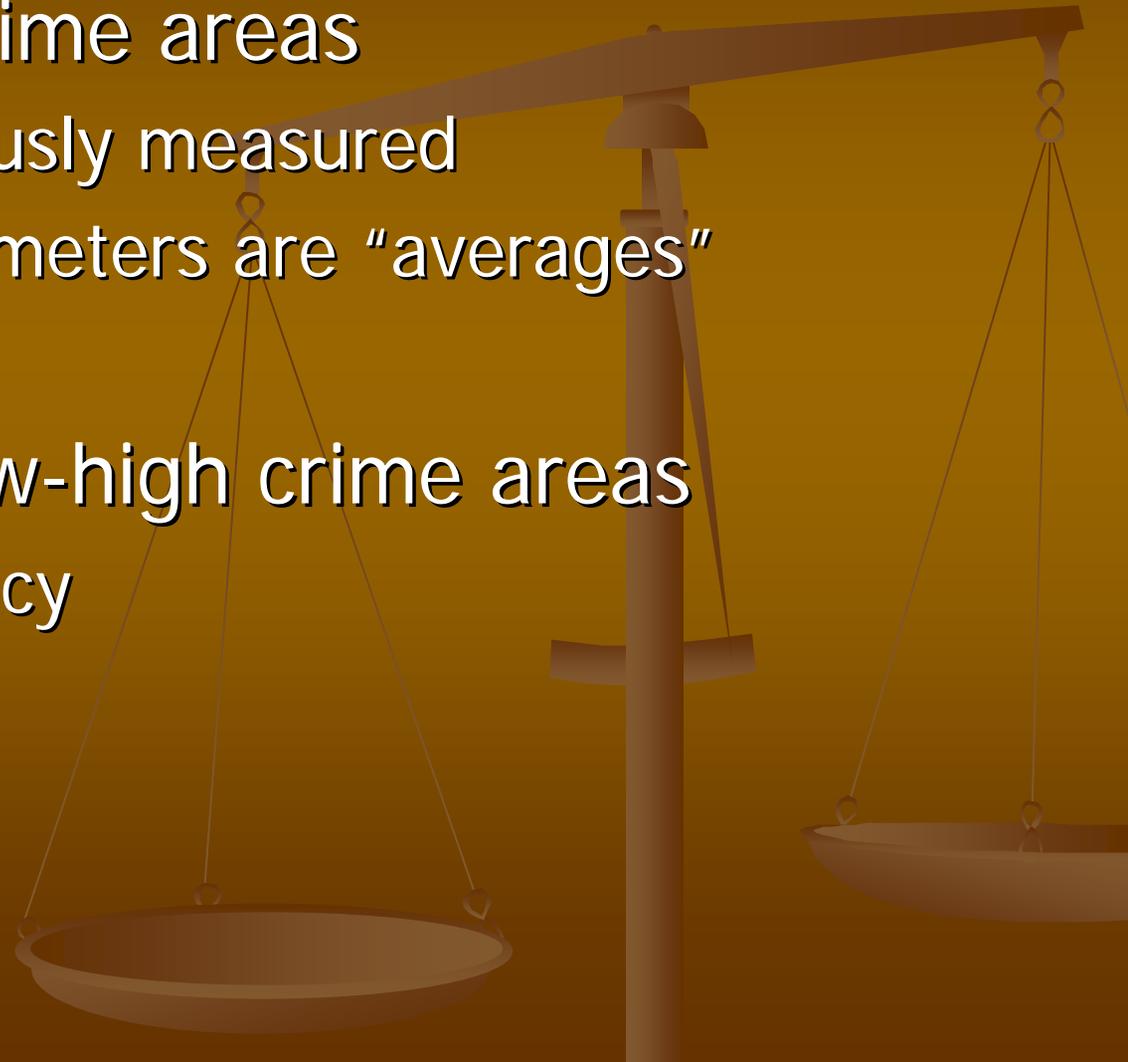
| | High-High | Low-Low | Low-High | High-Low |
|------------------------|---------------|---------------|--------------|---------------|
| Males 15-24, % | -0.041 | 0.719 | -0.115 | -0.000 |
| Single Parents, % | -0.046 | 0.280 | -0.091 | 0.000 |
| Ethnic Diversity | 0.008 | -0.158 | 0.020 | -0.000 |
| Unemployment Rate | 0.038 | -0.299 | 0.066 | 0.000 |
| Average Income, 000s | 0.005 | 0.032 | 0.008 | -0.000 |
| Population Density | -0.001 | 0.002 | -0.000 | -0.000 |
| Dwelling Value, 000s | -0.004 | 0.009 | -0.002 | 0.000 |
| Rentals, % | 0.003 | -0.125 | 0.017 | -0.000 |
| Major Repairs, % | -0.018 | -0.139 | -0.012 | -0.000 |
| Probability of cluster | 0.24 | 6.20 | 0.56 | 0.00 |
| Pseudo - R^2 | 0.255 | | | |
| Percent Correct | 83.43 | | | |

Interesting results

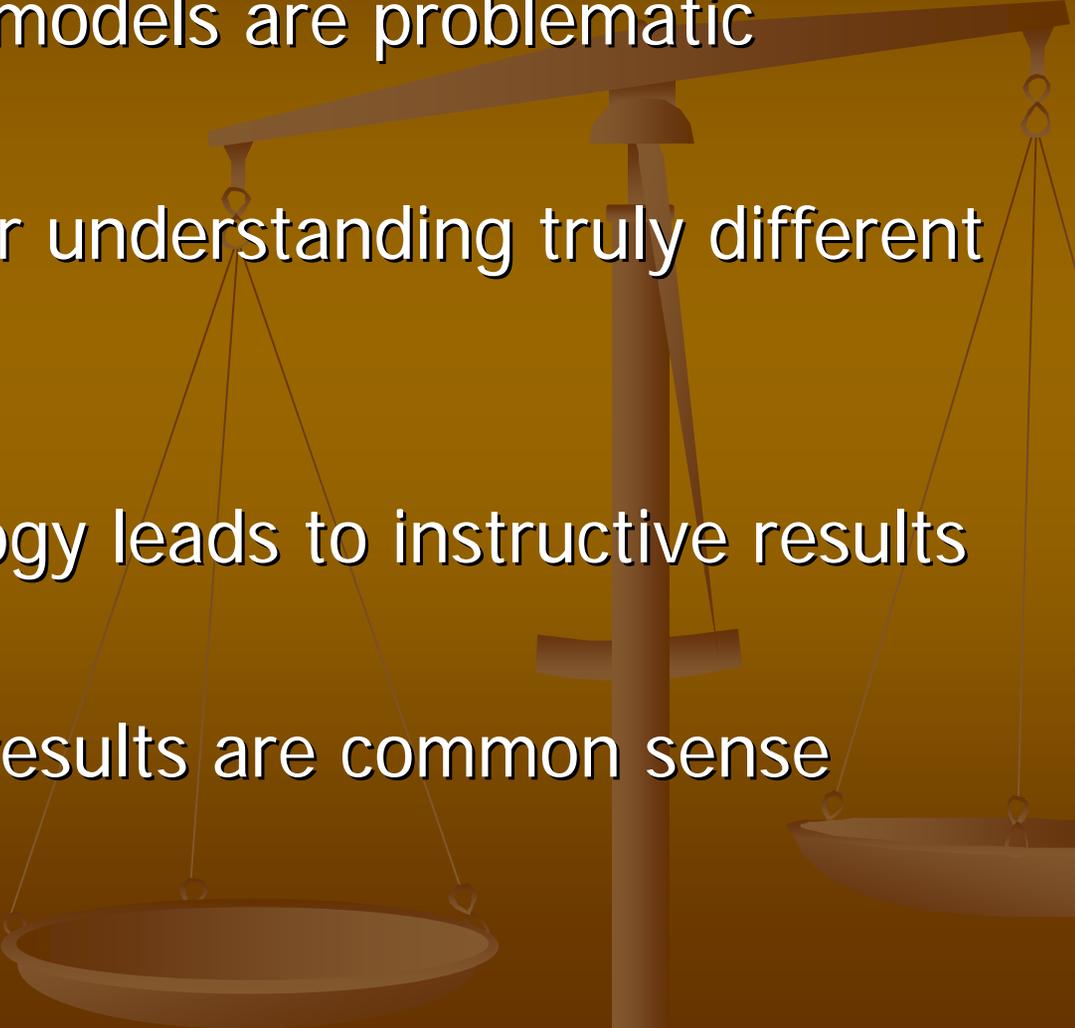
- High and low crime areas
 - Different sets of independent variables
 - Magnitudes are different
 - Low-low and low-high crime areas
 - Not all low crime areas are the same
 - Low-high crime areas are more similar to high crime areas than other low crime areas
- 

Explanations

- High and low crime areas
 - When continuously measured
 - Estimated parameters are “averages”
- Low-low and low-high crime areas
 - Collective efficacy
 - Edges



Conclusions

- Continuous linear models are problematic
 - Of limited value for understanding truly different contexts
 - Current methodology leads to instructive results
 - These instructive results are common sense
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