Crime generators, deterrants, and attractors in micro places:

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Crime Generators, Deterrents, and Attractors in Micro Places

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Introduction

Criminal hotspots are heuristically understood, but seldom well-defined and empirically studied. The primary reason for this is that, historically, criminological research has employed high-level units of analysis such as cities and police districts that overlook subtle differences within regions. In this thesis, I examine the rates at which crime concentrates into micro-geographic hotspots within cities, the stability of crime concentration levels and hotspot locations over time, and the spatial features that may cause high crime rates in specific micro-geographic environments. This research is made possible by a uniquely micro-level unit of analysis: the street segment. Where prior research has been limited by broad units of analysis, street segment-level data allows a city's most problematic spaces to be revealed and studied.

Theory

Routine Activity Theory: Crime is caused at the intersection of the following three factors:

- **Motivated offenders**
- **Easy targets**
- **A lack of capable guardians against crime**

Crime concentrates in the areas where these factors overlap most often in people's everyday activities.

Crime Pattern Theory: Crime is either opportunistic or planned. Local environments contribute to their crime rates through the extent to which they create criminal opportunities. Through this framework, a place can be one or more of the following:

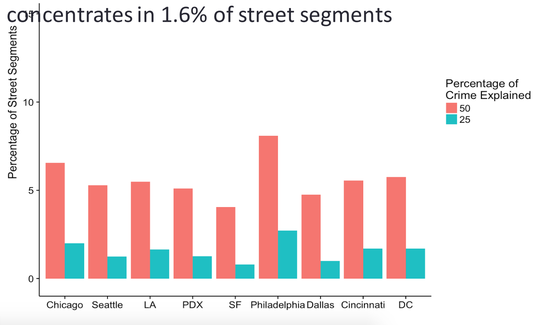
- **Crime generator:** a place creating conditions favorable to crime that turn people's previously-benign intentions criminal
- **Crime attractor:** a place well-known for creating opportunities for planned crime
- **Fear generator:** creates the fear being victimized, whether or not real danger is present
- **Crime neutral:** a place that neither creates common criminal opportunities or attracts willing offenders

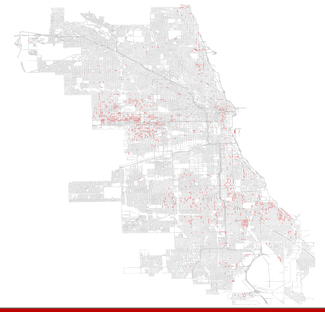
Research Questions

1. To what extent does crime concentrate in small areas within cities?
2. How stable are criminal hotspots over time?
3. How do spatial features, such as storefronts and public services, relate to crime risk?

Crime Concentration in Micro Places Across Cities

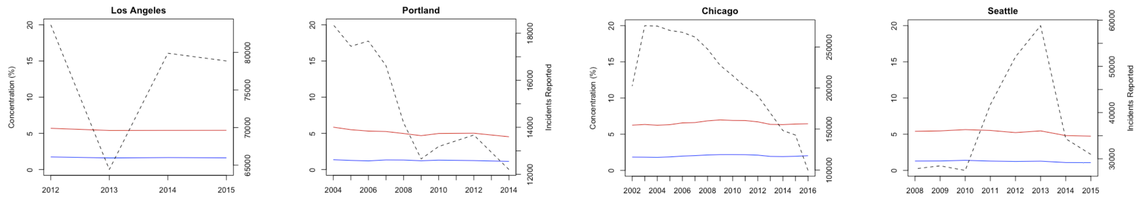
Law of Concentration of Crime at Place: For a defined measure of crime at a specific microgeographic unit, the concentration of crime will fall within a narrow bandwidth of percentages for a defined cumulative proportion of crime
Findings: 50% of crime in major US cities concentrates in just 5.6% of street segments, and 25% of all crime concentrates in 1.6% of street segments





Stability of Criminal Hotspots

- 50% concentration level (red) and 25% concentration level (blue) virtually unaffected by volatile overall crime rates (black) and macroeconomic conditions
- Crime concentrates in roughly the same areas and at roughly the same levels year over year



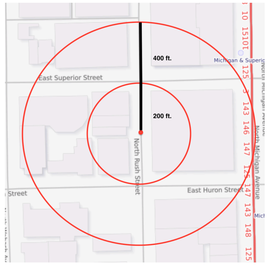
Impact of Spatial Features on Crime

Raw coefficient: expected increase in crime on a street segment when increasing this feature by one

Standardized coefficient: expected standard deviation change in crime count resulting from a one-standard deviation change in this feature

Regression Coefficients (n = 57,427)	Raw Coefficient	Standardized Coefficient	P-Value
Facilities			
Rehab Centers	0.301	0.036	<0.001
Grocery Stores	0.240	0.040	<0.001
Bars	0.117	0.040	<0.001
Liquor Stores	0.135	0.048	<0.001
Gas Stations	0.135	0.025	<0.001
Pawn Shops	0.031	0.002	0.704
Schools	0.369	0.061	<0.001
Performance + Arts Venu	0.057	0.007	0.179
Animal Care Centers	-0.056	-0.008	0.060
Daycare Centers	0.046	0.011	0.015
Other Businesses + Storef	0.003	0.027	<0.001
Spatial Features			
Subway Stations	0.588	0.043	<0.001
Bus Stops	0.014	0.031	<0.001
Graffiti	-0.001	-0.073	<0.001
Log Dist. to City Center	-0.220	-0.064	<0.001
Length	0.001	0.069	<0.001
Socioeconomic Controls			
Per Capita Income	0.000	-0.100	<0.001
Pct. Housing Crowded	0.011	0.013	0.030
Age group controls			

Facility features: count of observations within a set distance of each street segment centroid
Socioeconomic features: provided by Census and City of Chicago at the census tract and community area level



Conclusions

- Roughly 5% of major cities' street segments are responsible for 50% of crime
- Crime concentration levels are robust to changes in macroeconomic conditions and the overall crime rate
- Bars, rehab centers, liquor stores, and other facilities have positive and significant relationships with crime levels in their local environments
- Non-facility spatial features such as bus stops, street length and graffiti presence also have explanatory power over crime level in micro places
- Spatial and facility-based features act as proxies for the unexplainable environments in which they exist
- Income level has the largest standardized impact on crime, with other socioeconomic factors such as housing crowdedness and local population age distribution also being significant indicators of crime

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