Spatial Aspects of Crime

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Wednesday 21st September, 2022

ECTS2022 Summer School

Crime and Space 1/2

- Almost every paper you will have read on crime will focus on one dimension of crime: the **crime rate of a given area**
  - Areas may be countries, regions, police force area/jurisdictions, districts, cities or boroughs to name a few
  - Note: no citations as I wouldn't know where to start and where to stop..
- There are likely several reasons for this
  1. **Data restrictions**: in the past, district or city-level crime stats may have been as low a level as was available.
  2. Area crime rates are extremely **useful snapshots** of area differences. Depending on our research question, they may be all we need.

Crime and Space 2/2

- **Issue**: Although crime rates give us information about **between** area variation, they tell us nothing about how crime is distributed **within** an area, which may be policy-relevant
  - the **police** will respond to different within-area distributions
  - different within-area distributions will warrant different **public policy** responses
  - the **public** will likely care too [T6, Adda et al. (2014)]
- For instance, if we see an increase in the crime rate in an area, is this because:
  1. Neighbourhood crime rose uniformly within the area?
  2. Crime rose only in the "usual", high crime neighbourhoods?
  3. Crime spread from high crime neighbourhoods to lower crime neighbours due to expansion of criminal enterprise?
- [Schematic]
- The crime rate doesn't help us here

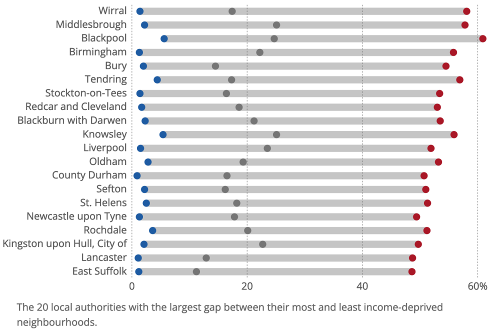
This Lecture

- Take an elliptical path to thinking about small area crime via an ONS piece on small area income statistics
  - key idea here: there are parallels
- Focus on a different dimension of crime – **crime concentration**, which is a within-area measure
- Consider issues inherent in a raw concentration measure, and how to circumvent these
- Take a look at the concentration of crime out in the wild – Giulietti and McConnell [2022]

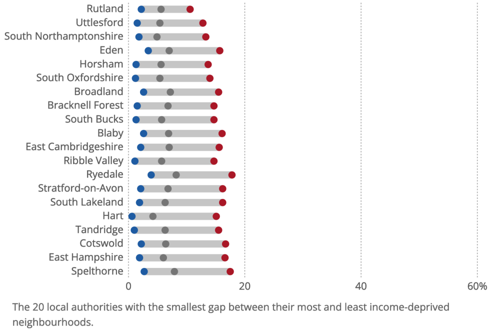
ONS – Within- and Between-Area Measures of Deprivation

- ONS, Exploring local income deprivation, https://www.ons.gov.uk/visualisations/dvc1371/
- explore graphically how to measure within-area deprivation distribution.
- lots of interesting graphs and a variety of methods
- may seem a little prosaic to some of you – these methods are distribution classifications, within-area ranges, Moran's I
- but, we don't see this done too often within the context of crime, even though we now have the data..

ONS – Within-Area Measure 1: Local Deprivation Gaps



(a) Top 20 LDGs



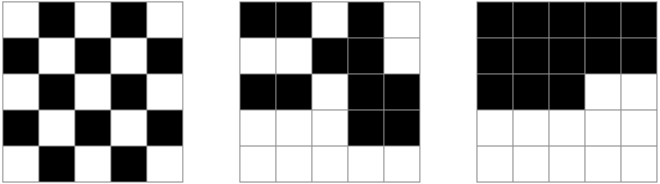
(b) Bottom 20 LDGs

Source: ONS, Exploring local income deprivation, https://www.ons.gov.uk/visualisations/dvc1371/

How income deprivation is clustered

An alternative way of looking at inequality in an area is to measure how inter-mixed the most and least deprived neighbourhoods are.

We can see the extent to which neighbourhoods of the same income level are clustered together using an index called Moran's I.

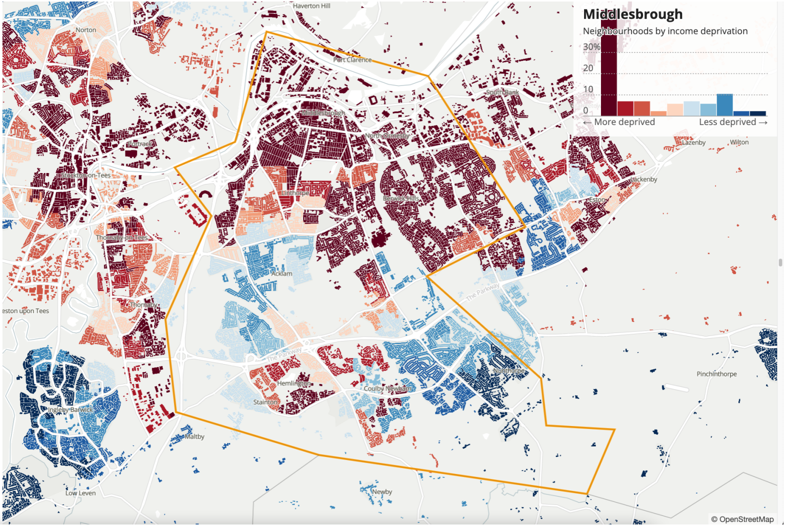


Grids representing the theoretical extremes of Moran's I.
From left to right: Uniform distribution (-1). Random distribution (0). Highly clustered/separated (+1).

Source: ONS, Exploring local income deprivation, https://www.ons.gov.uk/visualisations/dvc1371/

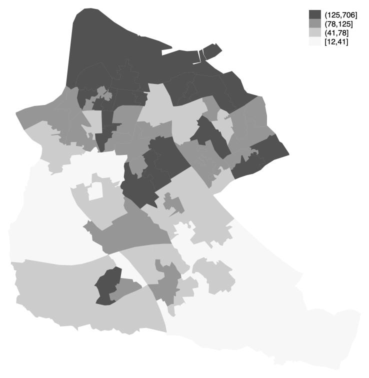
Neighbourhood Income Deprivation – Middlesbrough

Middlesbrough has a very high Moran's I, relatively close to 1. This is clearly identified by the separation of neighbourhoods in the north and south of the local authority, with high and low levels of income deprivation, respectively.

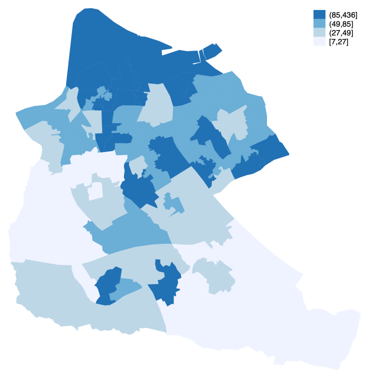


Source: ONS, Exploring local income deprivation, https://www.ons.gov.uk/visualisations/dvc1371/

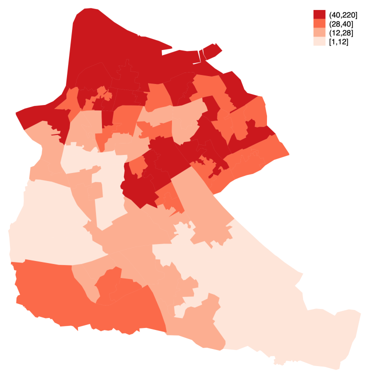
Neighbourhood Crime – Middlesbrough



(a) Total Crime



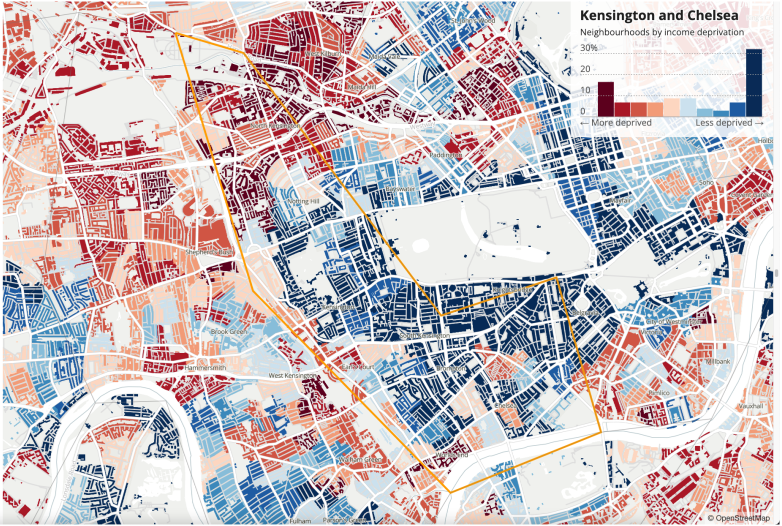
(b) Property Crime



(c) Violent Crime

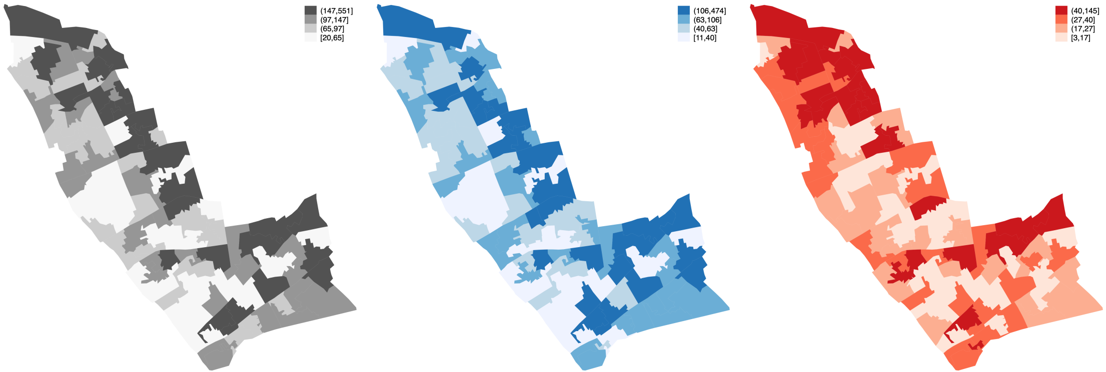
Neighbourhood Income Deprivation – Kensington and Chelsea

Kensington and Chelsea has the highest Moran's I in England. Despite having one of the highest average household incomes in England, the north of Kensington and Chelsea has some of the most income-deprived neighbourhoods. Grenfell Tower is in this more deprived area.



Source: ONS, Exploring local income deprivation, https://www.ons.gov.uk/visualisations/dvc1371/

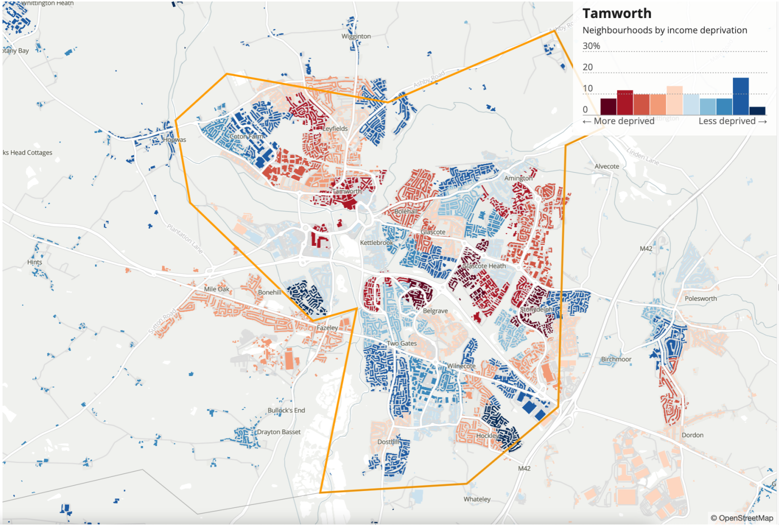
Neighbourhood Crime – Kensington and Chelsea



(a) Total Crime (b) Property Crime (c) Violent Crime

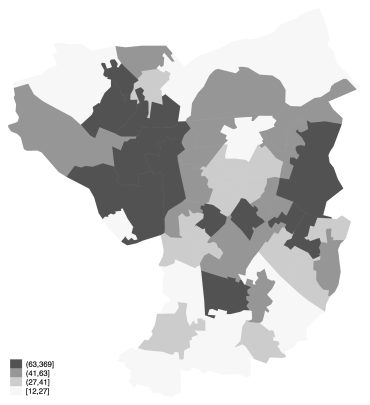
Neighbourhood Income Deprivation – Tamworth

By contrast, **Tamworth**, near **Birmingham**, has a relatively low Moran's I value. High and low deprivation neighbourhoods are more mixed together.

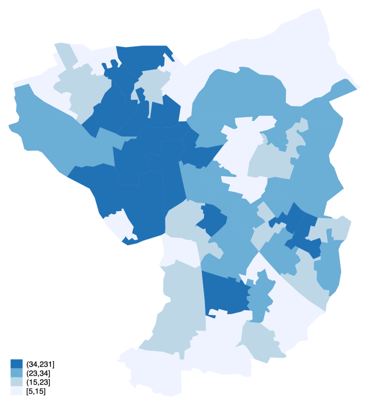


Source: ONS, Exploring local income deprivation, https://www.ons.gov.uk/visualisations/dvc1371/

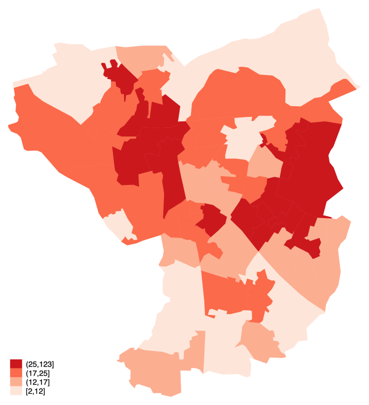
Neighbourhood Crime – Tamworth



(a) Total Crime



(b) Property Crime



(c) Violent Crime

Crime Concentration – Overview

- Weisburd [2015], in his 2014 Sutherland Lecture to the American Society of Criminology:
  - notes that even though crime levels vary greatly across areas, that crime concentration is extremely stable across both space and time
  - shows that across 8 cities in US of different sizes:
    - top 1% of street segments account for 25% of crime
    - top 5% of street segments account for 50% of crime
  - dubs the narrow range of crime concentration across cities "the law of crime concentration"
- Definition: Crime Concentration measures the **proportion of streets that account for k% of crime.**
  - For Weisburd's data, CC 25% is .01 and CC 50% is .05.
  - The smaller the CC number, the more concentrated is crime

Crime Concentration – Problems 1/2

- The standard crime concentration measure is not great when crimes are very rare. Example:
  - Consider a city with 100 murders in a year
  - Each murder occurs on a different street
  - Imagine they are uniformly distributed across a city
  - The city has 10,000 streets
  - Here, 1% of streets account for 100% of all murders
  - reflects difference in magnitude of streets and crimes, **not** that homicides are spatially concentrated per se.

Crime Concentration – Problems 2/2

- The standard crime concentration measure is not great when comparing across areas of different sizes. An example from Giulietti and McConnell [2022], where we want to compare crime concentration across areas:
  - In 2011, the least populated district was Purbeck, with
    - population of 45,165
    - 1,821 crimes
    - 903 street segments
    - crimes/streets = 2.02
  - The most populous district was Birmingham, with
    - a population of 1,061,074
    - 86,935 crimes
    - 8,836 street segments
    - crimes/streets = 9.84
- We want a concentration measure that isn't skewed by these different ratios i.e., one that finds a higher concentration measure in Birmingham due not to an actual higher concentration, but due to the crimes/streets ratio.

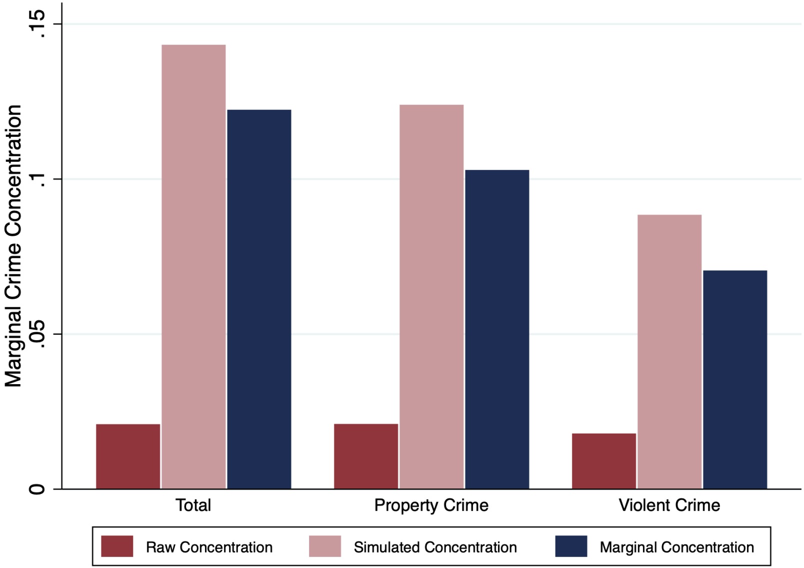
Crime Concentration – Solutions

- These problems have been known for a while now, and different researchers have attempted to solve these in different ways.
    1. Alternative measures:
        - Bernasco and Steenbeek [2017]; O'Brien [2019] – Don't use concentration, use Lorenz Curve or Gini Coefficient instead
    2. Concentration Measure Refinements
        - Levin et al. [2017] – % of streets accounting for k% of crime conditional on a street having at least one crime.
        - Chalfin et al. [2021] – use randomisation to account for ratio of crimes to streets (see next page)
- N.B. So many 2017 references here due to a Journal of Quantitative Criminology Special Issue on the topic of concentration

Chalfin et al. [2021] – Marginal Crime Concentration

1. By crime-type $\times$ district $\times$ year, (uniformly) randomly allocate crimes to streets, and then calculate the k crime concentration statistic for this iteration i – $cc_{i,at}^{k,\text{sim}}$
   - e.g., for a given crime-type $\times$ district $\times$ year, iteration 706 resulted in 14% of streets accounted for 25% of crime.
2. do this N=10,000 times
3. take the average – $(1/N)\sum_i^N cc_{i,at}^{k,\text{sim}} = \overline{cc}_{at}^{k,\text{sim}}$.
   - This simulated average concentration measure is our area and crime specific benchmark (think of the problems we discuss above)
4. $mcc_{at}^k = \overline{cc}_{at}^{k,\text{sim}} - cc_{at}^k$
   - MCC effectively conditions out any dimensions of the crime-area combination that would lead us to spuriously conclude that there was high concentration e.g., the murder example above.
   - Higher MCC means higher concentration

Visualising the MCC



Crime Rates and Crime Concentration 1/2

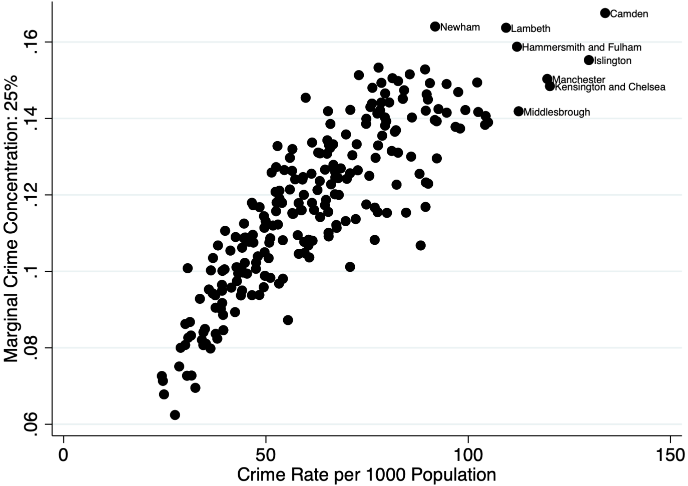
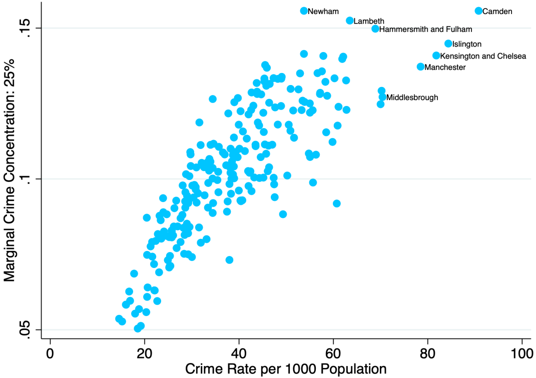
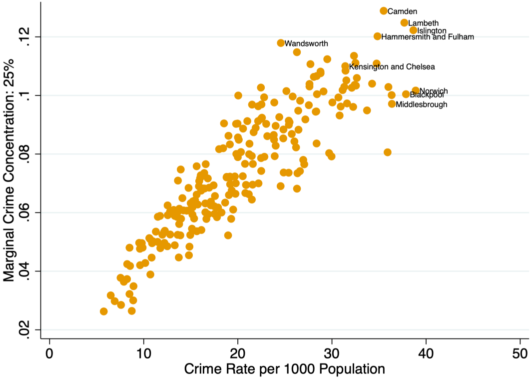


Figure 5: Total Crime

Crime Rates and Crime Concentration 1/2



(a) Property Crime



(b) Violent Crime

Crime Concentration in Action – Giulietti and McConnell [2022]

- In combination with crime rates, we consider crime concentration in an area as an outcome in recent work.
- Question: does austerity intensity impact crime concentration in an area?
- Baseline
  - Continuous: $c_{it} = \beta Post_t \times Austerity_i + X_{it}^{'}\gamma + \pi_{r\times t} + \theta_i + \epsilon_{it}$
  - Discrete: $c_{it} = \beta Post_t \times \mathbb{1}[Austerity_i \geq median] + X_{it}^{'}\gamma + \pi_{r\times t} + \theta_i + \epsilon_{it}$
- Dynamic DD
  - Continuous: $c_{it} = \sum_{j=1}^{3} \beta_j Post_j \times Austerity_i + X_{it}^{'}\gamma + \pi_{r\times t} + \theta_i + \epsilon_{it}$
  - Discrete: $c_{it} = \sum_{j=1}^{3} \beta_j Post_j \times \mathbb{1}[Austerity_i \geq median] + X_{it}^{'}\gamma + \pi_{r\times t} + \theta_i + \epsilon_{it}$
- Timing
  - Pre-Period - 2011 and 2012 Fiscal Years
  - Post-Period - 2013-2015 Fiscal Years

Key Finding 2 - Austerity Causes ↑ Crime Concentration [Continuous D]

Table 1: Austerity Increases the Concentration of Crime in Districts, Notably Property Crime

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline DD			**Dynamic DD**		
		Crime Categories			**Crime Categories**	
	Total Crime	Property Crime	Violent Crime	Total Crime	Property Crime	Violent Crime
A. Continuous Treatment						
Post × Austerity	.00062**	.00077**	.00037			
	(.00029)	(.0003)	(.00036)			
Post_1 × Austerity				.0006***	.00091***	.00058**
				(.00021)	(.00023)	(.00028)
Post_2 × Austerity				.00079***	.001***	.00068*
				(.00028)	(.00032)	(.00034)
Post_3 × Austerity				.00022	.00071**	.00012
				(.0003)	(.00035)	(.00042)
$\overline{Y}_{\text{pre-period}}$	.124	.094	.0674	.124	.094	.0674
Districts	234	234	234	234	234	234
Observations	1,170	1,170	1,170	1,170	1,170	1,170
Proportion of Total Crime	1	.66	.26	1	.66	.26

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at district level. The dependent variable is the Marginal Crime Concentration.

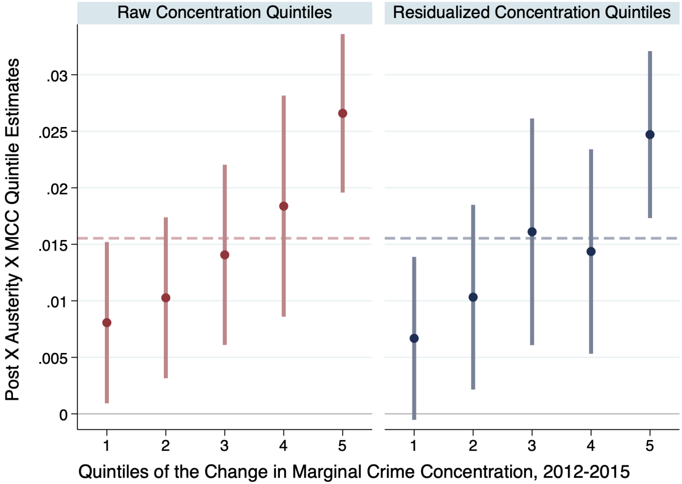
Key Finding 2 - Austerity Causes ↑ Crime Concentration [Binary D]

Table 2: Austerity Increases the Concentration of Crime in Districts, Notably Property Crime

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline DD			**Dynamic DD**		
		Crime Categories			**Crime Categories**	
	Total Crime	Property Crime	Violent Crime	Total Crime	Property Crime	Violent Crime
B. Binary Treatment						
Post × $\mathbb{1}$[Austerity Impact Above Median]	.00131**	.00153**	.0012			
	(.00058)	(.00064)	(.00074)			
$Post_1$ × $\mathbb{1}$[Austerity Impact Above Median]				.0014***	.00191***	.00133*
				(.00049)	(.00057)	(.00071)
$Post_2$ × $\mathbb{1}$[Austerity Impact Above Median]				.00159***	.00195***	.00188**
				(.00061)	(.00073)	(.00085)
$Post_3$ × $\mathbb{1}$[Austerity Impact Above Median]				.00066	.00165**	.0003
				(.00068)	(.00082)	(.00104)
$\overline{Y}_{\textbf{pre-period}}$	.124	.094	.0674	.124	.094	.0674
Districts	234	234	234	234	234	234
Observations	1,170	1,170	1,170	1,170	1,170	1,170
Proportion of Total Crime	1	.66	.26	1	.66	.26

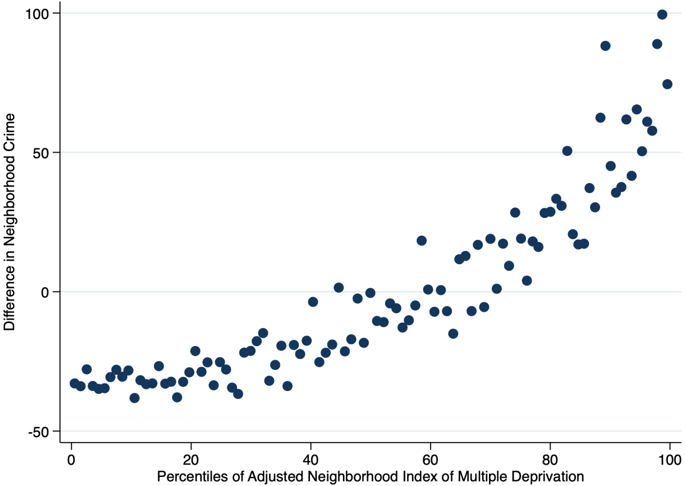
Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at district level. The dependent variable is the Marginal Crime Concentration.

Districts That Experience ↑ Crime are Same That Experience ↑ Concentration



Specification: $c_{it} = \sum_{q=1}^{5} \beta_q Post_t \times Austerity_i \times MCC\ Quintile_{iq} + X_{it}^{'}\gamma + \pi_{r \times t} + \theta_i + \epsilon_{it}$

Key Finding 3 - Within-district impact



Summary

- Common to consider within-area distrubution, and changes of this distribution, when analysis income/poverty/deprivation.
- Less so with crime
- We work through how to calcuate concentration, and some of the inherent issues
- Use the concentration metric as an outcome variable in parallel with crime rate – gives us a within-area understanding of crime to complement the between-area understanding.

Additional Results

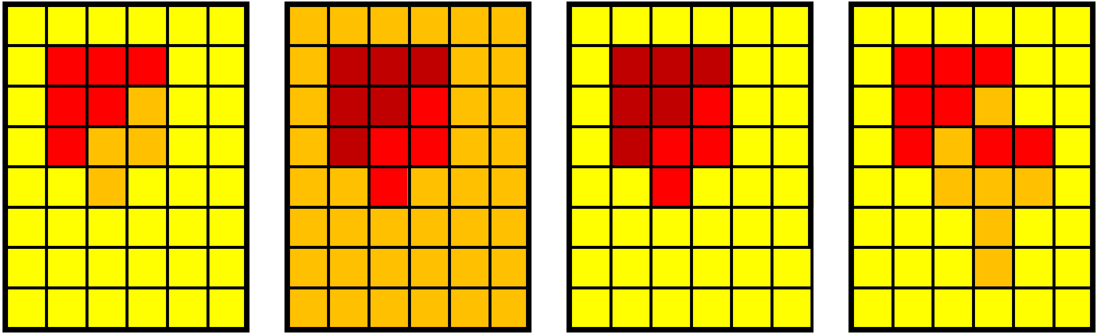
DDD estimates from Adda et al. [2014]

Table 6: The Effect of Depenalizing Cannabis on House Prices

Dependent Variable: Log (zip code-quarter mean house price, deflated to 1995 Q1 prices)

	(1) Baseline	(2) Time Trends	(3) Ex Post Hotspot	(4) Ex Ante Hotspot	(5) Higher Level Clustering
Lambeth x Policy Period	.026**	-.028	.022	-.021	.022
	(.013)	(.019)	(.037)	(.021)	(.016)
Policy Period	.004	-.025***	-.054***	-.036**	-.054***
	(.006)	(.006)	(.011)	(.014)	(.013)
Lambeth x Post-Policy Period	-.050***	-.126***	-.016	-.011	-.016
	(.016)	(.034)	(.030)	(.031)	(.029)
Post-Policy Period	.033***	-.046***	-.111***	-.108***	-.111***
	(.010)	(.011)	(.015)	(.017)	(.028)
Lambeth x Policy Period x Hotspot			-.062*	-.009	-.062***
			(.036)	(.021)	(.012)
Lambeth x Post-Policy Period x Hotspot			-.134***	-.135***	-.134***
			(.022)	(.020)	(.021)
Zip code and Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Borough-Specific Linear Time Trend	No	Yes	Yes	Yes	Yes
Socio-demographic Controls	Yes	Yes	Yes	Yes	Yes
Observations	17331	17331	17331	17331	17331

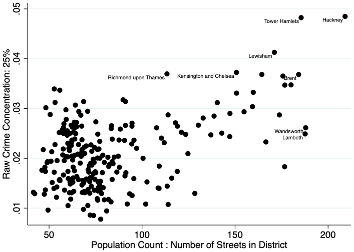
Schematic



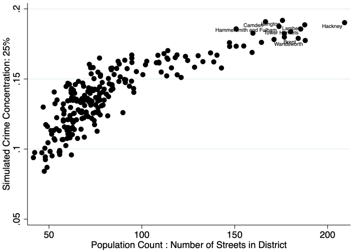
A.) T=1 (Baseline) B.) T=2, Scenario 1 B.) T=2, Scenario 2 C.) T=2, Scenario 3

MCC Elements and Street Ratios – Population/Streets

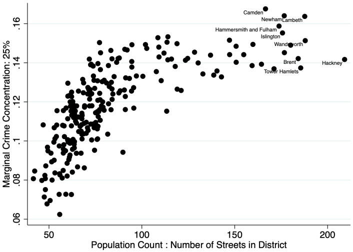
▸ Visualising the MCC



(a) Raw CC

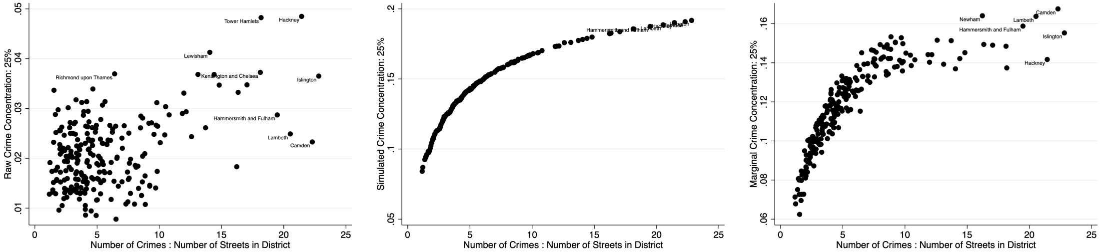


(b) Simulated CC



(c) Marginal CC

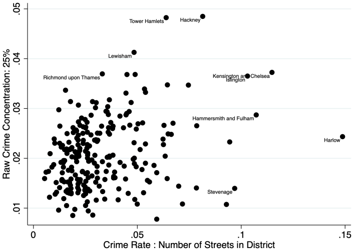
MCC Elements and Street Ratios – Crime/Streets



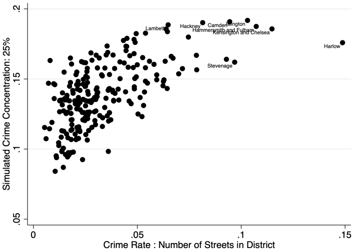
(a) Raw CC (b) Simulated CC (c) Marginal CC

MCC Elements and Street Ratios – Crime Rate/Streets

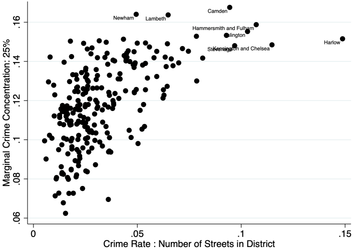
Visualising the MCC



(a) Raw CC



(b) Simulated CC



(c) Marginal CC

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