Administrative and Open Data

Lecture Week 4

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GV4L3

Overview

What do we mean by...?

- Administrative data: Created when people interact with government or public services
  - E.g., tax records, vital record (births and deaths)
- "Open data": Published by governments on online portals; publicly available and accessible
  - Urban data: open data about cities (e.g., 311 data)
  - Open administrative data
- Can be about individuals, businesses, government agencies, etc.
- Can sometimes be linked to other data

Some examples of administrative data

- Voter files
- Tax records
- Health records
- Criminal justice records
- Property transactions

Overview

Administrative data example: “voter files”

- Social scientists increasingly rely on “voter files” where available
- Lists of registered voters indicate whether or not someone voted in a given election (not whom they voted for)
- Typically include voter name, address, DOB, gender
  - May also include party affiliation (US); can be supplemented with other data (e.g., commercial data, imputed race/ethnicity)
- Used by campaigns, pollsters, journalists, academic researchers
- But, data quality varies (e.g., due to highly decentralized election administration)
  - Commercial vendors sell clean, augmented files

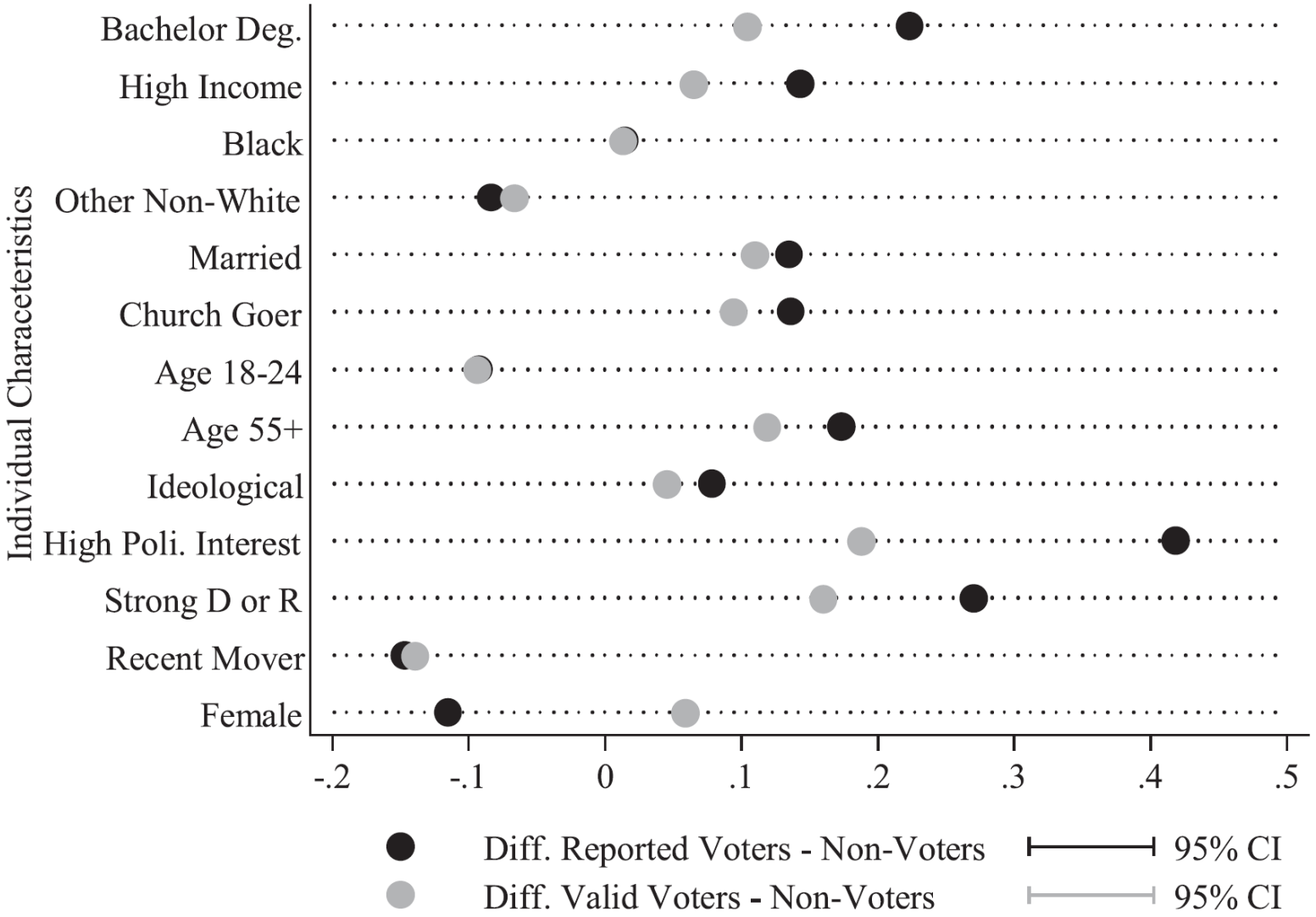
Example: validation (Ansolabehere & Hersh 2012)

- Survey respondents regularly misreport their voting history
  - Misremember
  - Lie
    - Social desirability: "People who are under the most pressure to vote are the ones most likely to misrepresent their behavior when they fail to do so." (Bernstein, Chaha, and Montjoy 2001)
- Ansolabehere & Hersh (2012) conduct 50 state vote validation
  - Link voter file from private vendor to survey data
    - One approach is fuzzy string matching
    - in `R`, see packages `stringdist`, `tidystringdist`, `fuzzyjoin`, `inexact`, `refinr`, `fuzzywuzzyR`
  - Compare self-reports (on survey) to actual voting (in voter file)

Ansolabehere, Stephen, and Eitan Hersh. "Validation: What big data reveal about survey misreporting and the real electorate."

Political Analysis 20, no. 4 (2012): 437-459.

Correlates of reported & validated turnout (Ansolabehere & Hersh 2012)



Side note on race / ethnicity imputation

Predicting individual race from voter registration records (Imai & Khanna 2016)

- Uses Bayes' Rule to estimate $Pr(R_i = r|S_i = s, G_i = g)$, or the conditional probability that voter i belongs to racial group r given his/her surname s and geolocation g.
  - Requires $Pr(R_i = r|S_i = s)$, the racial composition of frequently occurring surnames, $Pr(R_i = r|G_i = g)$, the racial composition of each geolocation (e.g., Census blocks and voting precincts), and $Pr(G_i = g)$, the population proportion of each geolocation.

  $\longrightarrow$ Gives a probabilistic prediction of individual race / ethnicity.

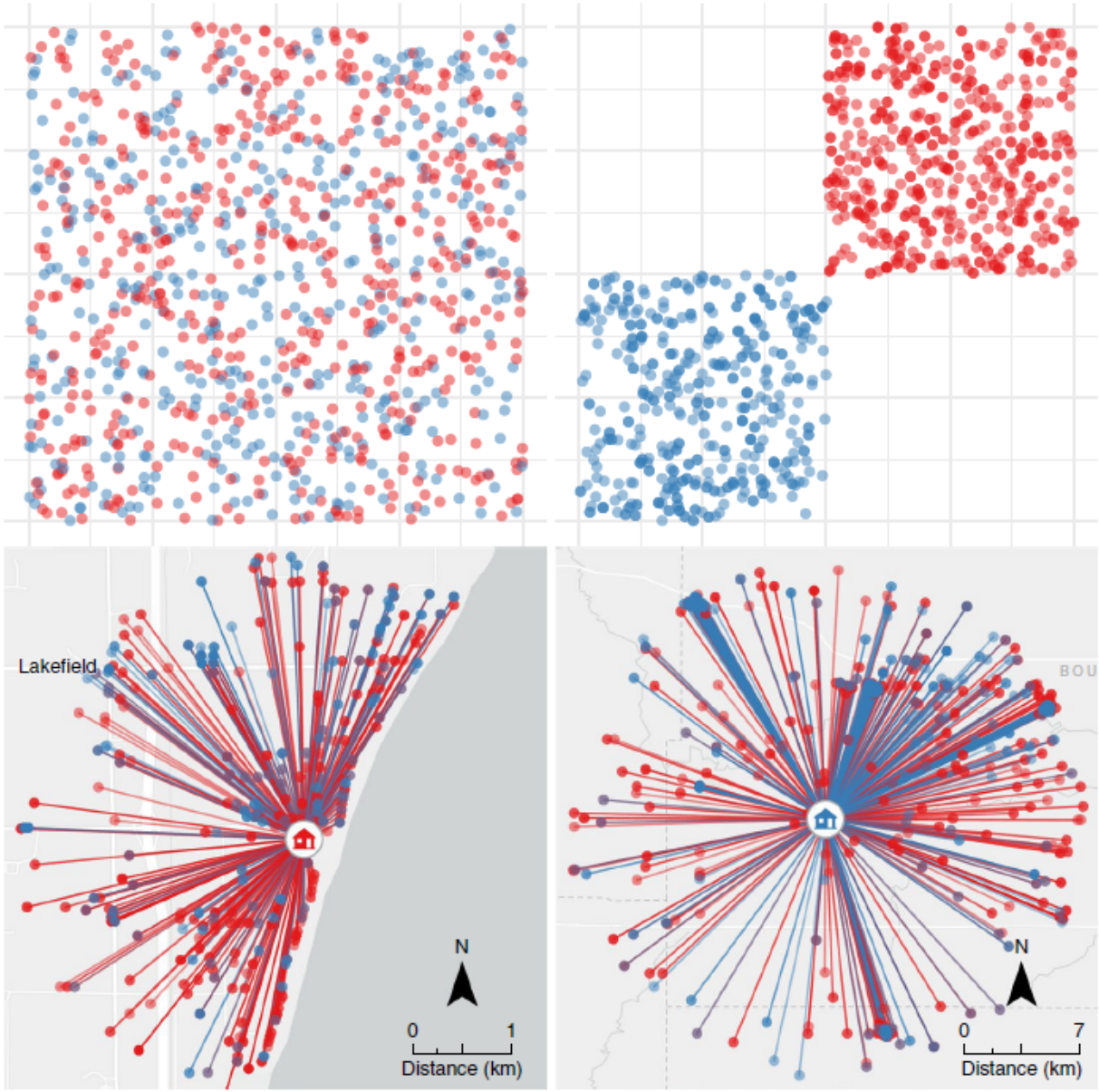
- `R` package, `wru: Who Are You? Bayesian Prediction of Racial Category Using Surname and Geolocation`

Imai, K., & Khanna, K. (2016). Improving ecological inference by predicting individual ethnicity from voter registration records. *Political Analysis*, 24(2), 263-272.

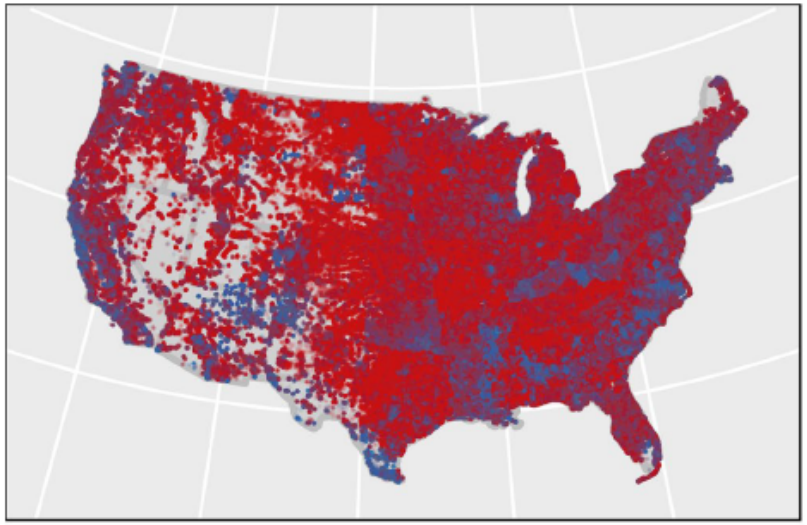
Partisan segregation (Brown & Enos 2021)

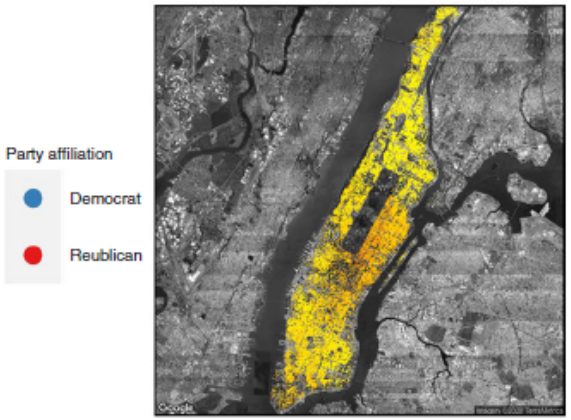
- Partisan geographic clustering prevalent in many countries, with consequences for representation and polarization
- Use individual-level administrative data to measure partisan residential segregation (isolation or exposure)
- **Data**: exact residential address of every registered voter (more than 180 million individuals) in the U.S., and their partisanship
- **Approach**: For each individual, measure distance to their k = 1,000 nearest neighbours; create a weighted (by inverse distance) average of exposure to out-partisans
- **Finding**: Partisans are extremely isolated from one another; this persists within cities and neighborhoods and is not explained by racial/ethnic segregation

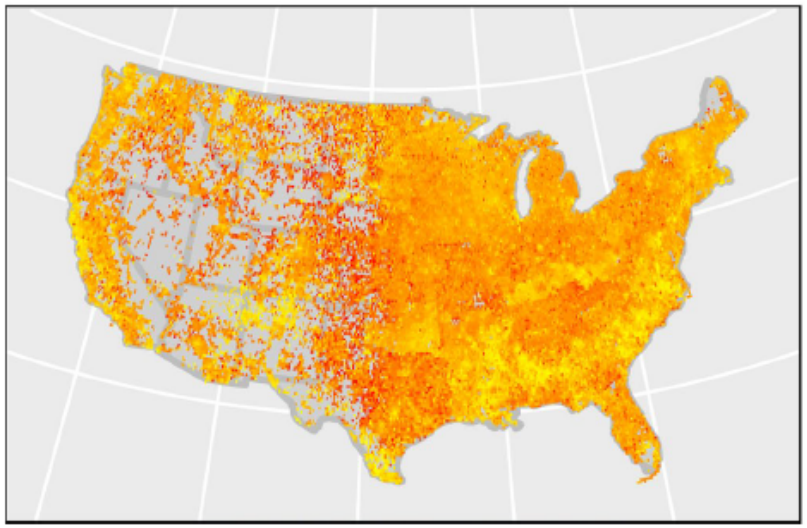
Spatial & aspatial segregation (Brown & Enos 2021)



Measuring spatial exposure (Brown & Enos 2021)







Overview

UK Open Data: https://data.gov.uk/

Find open data

Find data published by central government, local authorities and public bodies to help you build products and services

Search data.gov.uk

Business and economy
Small businesses, industry, imports, exports and trade

Crime and justice
Courts, police, prison, offenders, borders and immigration

Defence
Armed forces, health and safety, search and rescue

Education
Students, training, qualifications and the National Curriculum

Environment
Weather, flooding, rivers, air quality, geology and agriculture

Government
Staff numbers and pay, local councillors and department business plans

Government spending
Includes all payments by government departments over £25,000

Health
Includes smoking, drugs, alcohol, medicine performance and hospitals

Mapping
Addresses, boundaries, land ownership, aerial photographs, seabed and land terrain

Society
Employment, benefits, household finances, poverty and population

Towns and cities
Includes housing, urban planning, leisure, waste and energy, consumption

Transport
Airports, roads, freight, electric vehicles, parking, buses and footpaths

Digital service performance
Cost, usage, completion rate, digital take-up, satisfaction

Government reference data
Trusted data that is referenced and shared across government departments

Two dimensions of data openness

Legally open

Data are legally open when they are:

- in the public domain, or
- released under an open licence with minimal restrictions

(In the UK, this is often the Open Government License)

Technically open

Data are technically open when they are:

- machine-readable and non-proprietary (e.g., CSV/JSON, not locked PDFs)
- publicly accessible (no paywall, password, or firewall)
- accompanied by metadata so others can find and reuse them

Many organisations publish through open data catalogues.

Open data usually means both: legal permission to reuse and practical ability to access and work with the files.

Benefits & limitations of open data

Benefits

- Transparency
- Public service improvement
- Innovation and economic value
- Efficiency

Limitations

- Privacy
- Completeness
- Accessibility
- Accuracy

Non-democracies & data (Carlitz & McLellan 2021)

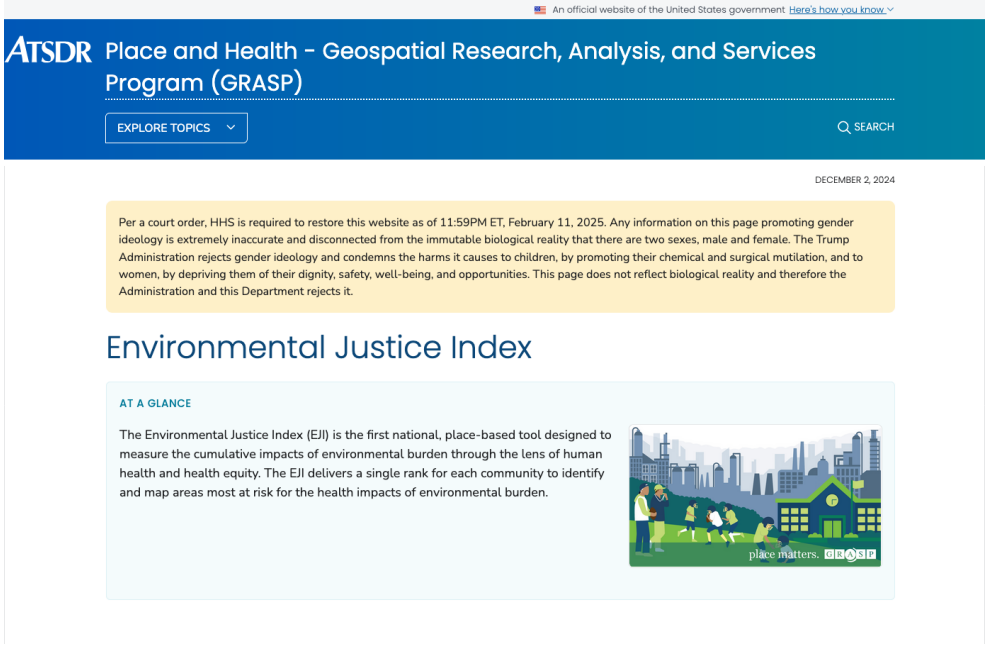
- Authoritarian regimes manipulate official data to legitimize their authority
- Systematically missing or biased data may jeopardize research integrity and lead to false inferences
- Official statistics may...
  - Exaggerate development progress (Sandefur & Glassman 2015)
  - Reflect politicized population counts (Akinyoade, Appiah and Asa 2017; Elemo 2018)
  - Reflect politicization of macroeconomic indicators (Martinez 2019; Rawski 2001; Tsai 2008; Wallace 2016)
- Why release data?
  - Rewarded by voters (Maerz 2016; Little 2017)
  - Ensure future access to government information (Berliner 2014)
  - Discredit opposition parties (Carlitz & McLellan 2021)

FEDERAL

Trump administration withdraws U.S. from global open government initiative

The General Services Administration cited the organization's support for "LGBTQ+ advocacy, feminism, and climate alarmism" among its reasons the nation dropped its membership.

BY MADISON ALDER • JANUARY 30, 2026



2025 U.S. federal online resource removals

- Beginning in Jan 2025, multiple federal agencies deleted, modified, or relabelled online pages and datasets following new administration executive actions.
- Scale (reported): $>$8,000 web pages and $\sim$3,000 datasets changed across $>$12 government websites.
- Most affected (reported):
  - Center for Disease Control (CDC): $>$3,000 pages altered/removed
  - Census Bureau: $\sim$3,000 pages of research materials removed
- Topics disproportionately affected: DEI; gender identity; public health (e.g., long COVID, HIV/AIDS, vaccines); environmental justice/climate; foreign aid; emergency management; employment; Jan 6th.
- Some content removed entirely; other pages remained but were scrubbed of terminology (e.g., “climate change”$\rightarrow$“climate resilience”, “LGBTQ”$\rightarrow$“LGB”, “pregnant people”$\rightarrow$“pregnant women”).
- Aftermath: some content later restored; removals prompted legal challenges and debate.

Example: Contested Boundaries

Where is neighbourhood conflict most likely to occur? (Legewie & Schaeffer 2016)

The paper argues that conflict is not driven by diversity per se, but by poorly defined (fuzzy) boundaries between two otherwise homogeneous ethnoracial communities.

Authors combine large-scale administrative and open data sources:

- 4.7 million geo- and time-coded 311 service requests from New York City (2010, 2014)
- Census block and tract characteristics from the U.S. Census and ACS

Neighbourhood conflict is measured using complaint calls about noise, public drinking, and blocked driveways, and related to spatial variation in ethnoracial composition at the census-block level.

Legewie, J. & Schaeffer, M. (2016). Contested boundaries: Explaining where ethnoracial diversity provokes neighborhood conflict. *American Journal of Sociology*, 122(1): 125–161.

Detecting ethnoracial boundaries

FIG. 2.—Illustration of edge detection algorithm applied to the proportion of black residents in each census block in New York City with inset of gray-scale image.

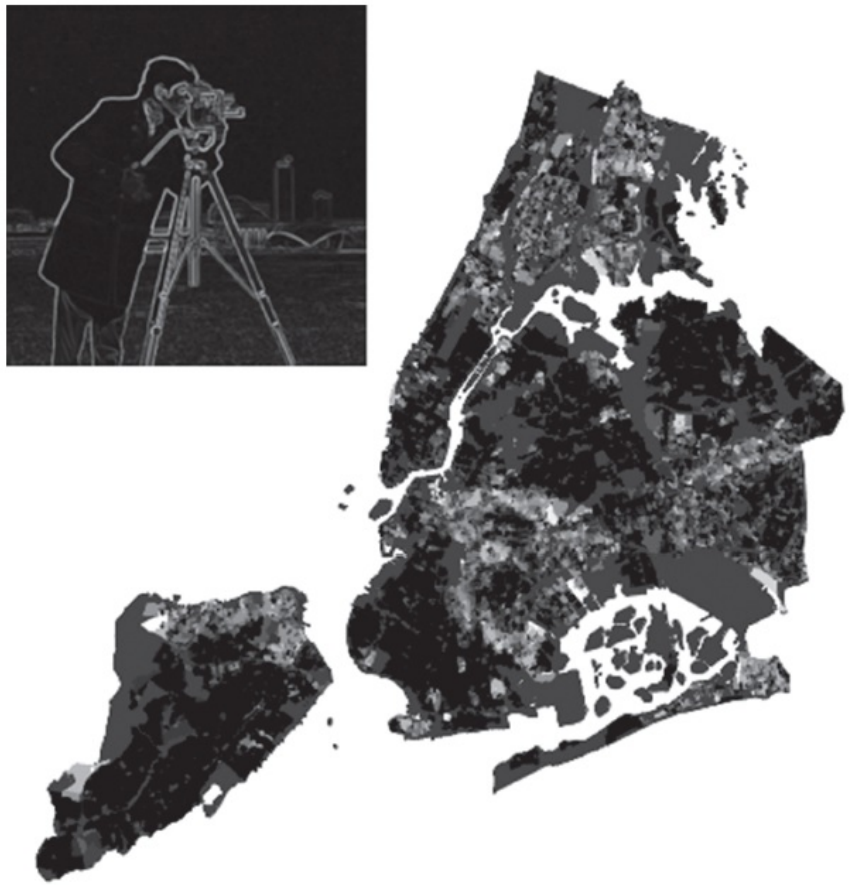


FIG. 2 (*Continued*)

Edge detection algorithms from computer vision identify points where pixel brightness changes sharply. Here, census blocks play the role of pixels, and ethnoracial composition plays the role of brightness.

Edge intensity in Crown Heights, Brooklyn

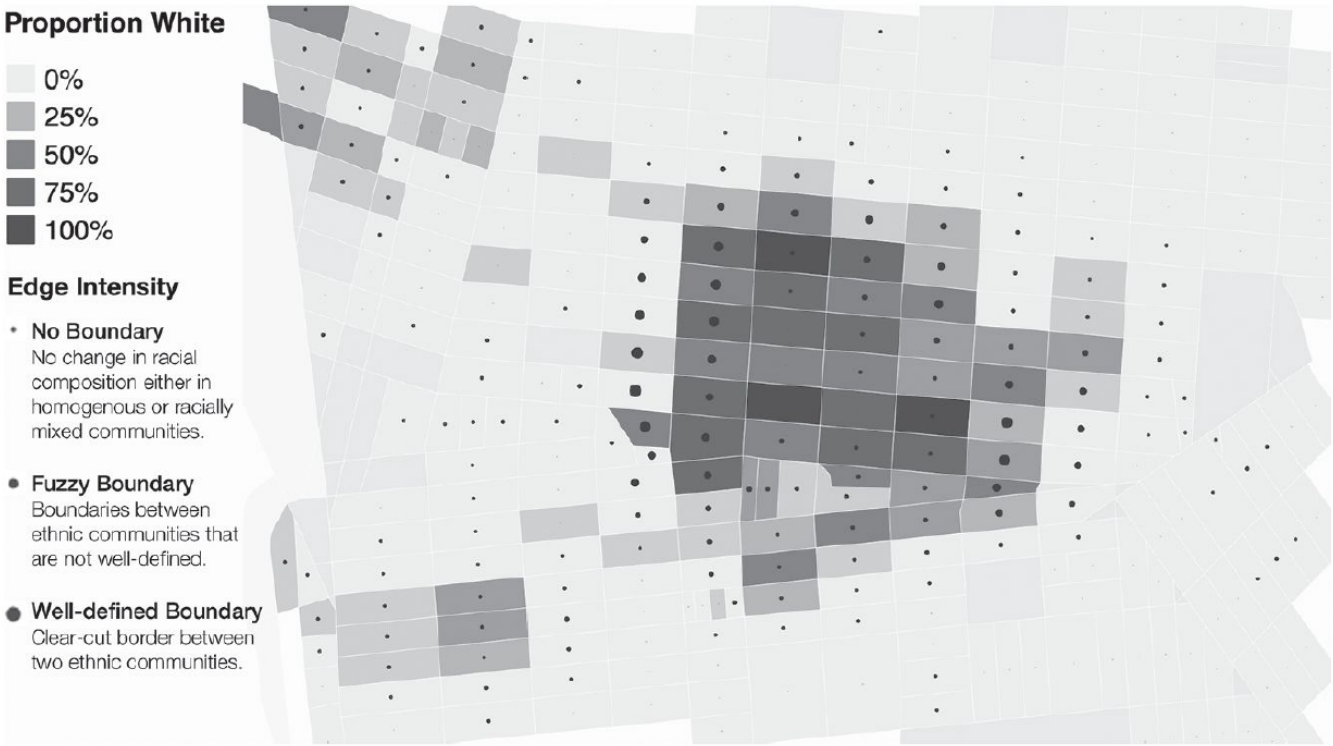


FIG. 1.—Edge intensity in Crown Heights South, Brooklyn (2010). White residents occupy an area of 24 city blocks surrounded by largely African-American residents. The edges are well defined on the west side of the enclave but fuzzy on the northeast side.

Well-defined vs. fuzzy boundaries between ethnically homogeneous communities.

Neighbourhood conflict follows an inverted U-shaped relationship with edge intensity. At the highest levels of edge intensity, predicted complaints are about 46% higher than in areas with low edge intensity, consistent with greater conflict at fuzzy boundaries between homogeneous groups.

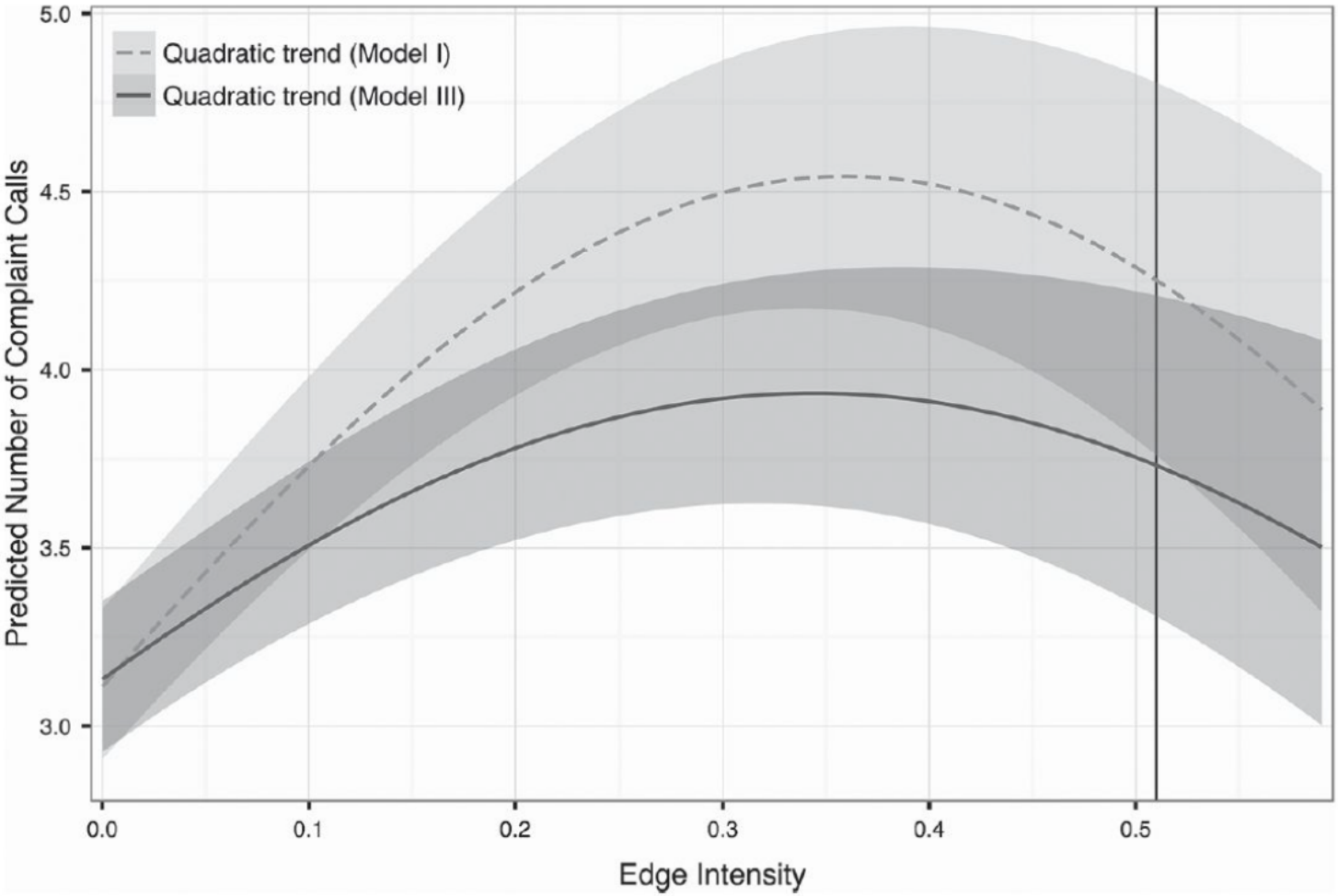


FIG. 3.—Number of complaint calls by edge intensity. The figure shows the predicted number of complaint calls as a function of edge intensity based on the quadratic specification from model 1 (dashed line) and model 3 (solid line) in table 2. The vertical line indicates the empirically observed range for edge intensity in New York City.

Example: “open data” on racially biased policing

MPs rebuke police for ‘systemic failure’ to improve record on race

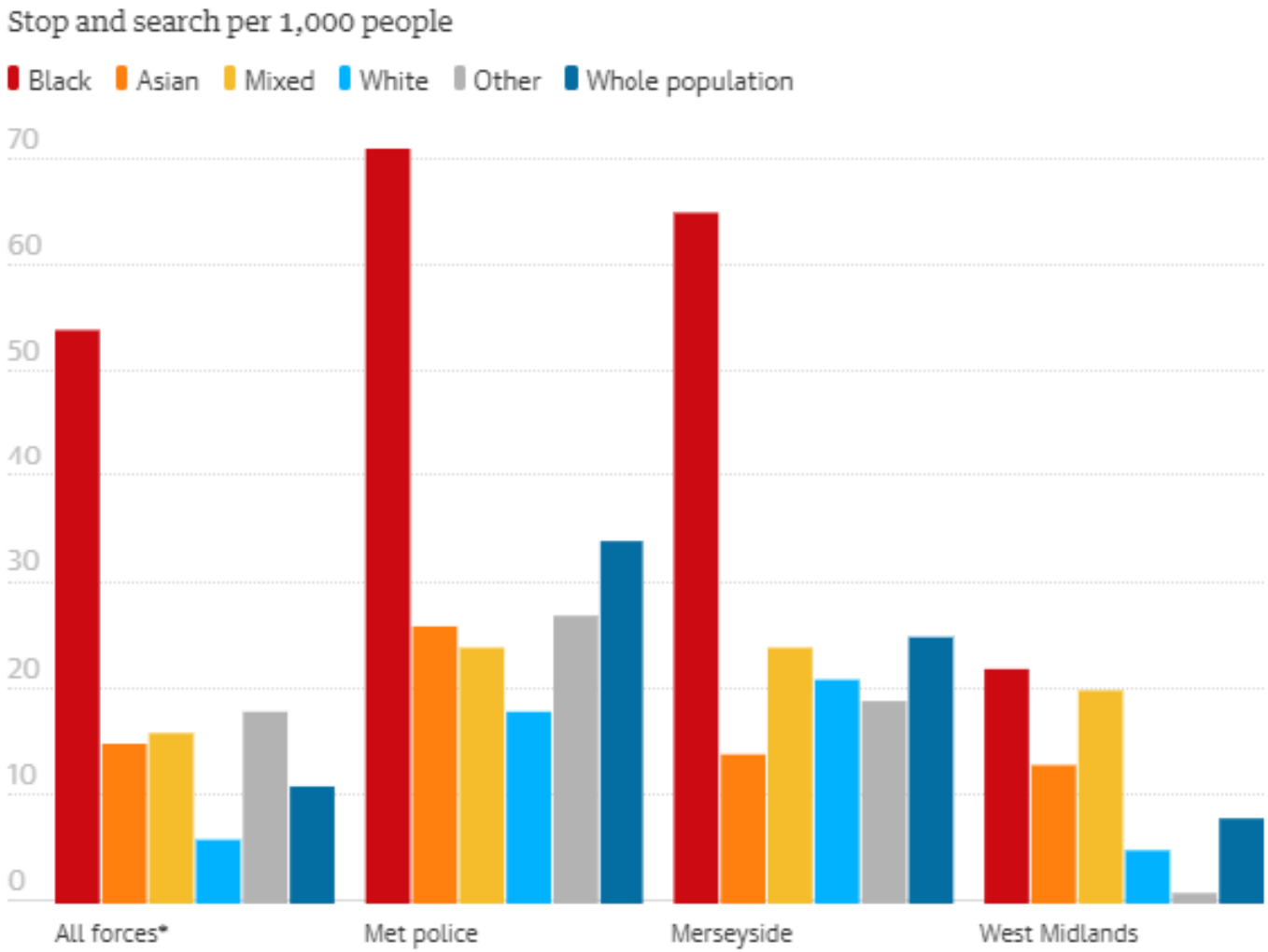
Failings have led to ‘unjustified inequalities’, says landmark report that finds little progress in 22 years since Macpherson

Analysis: failure at the top of police and of governments Tory and Labour

Black people are nine times more likely than white people to face stop and search, with most

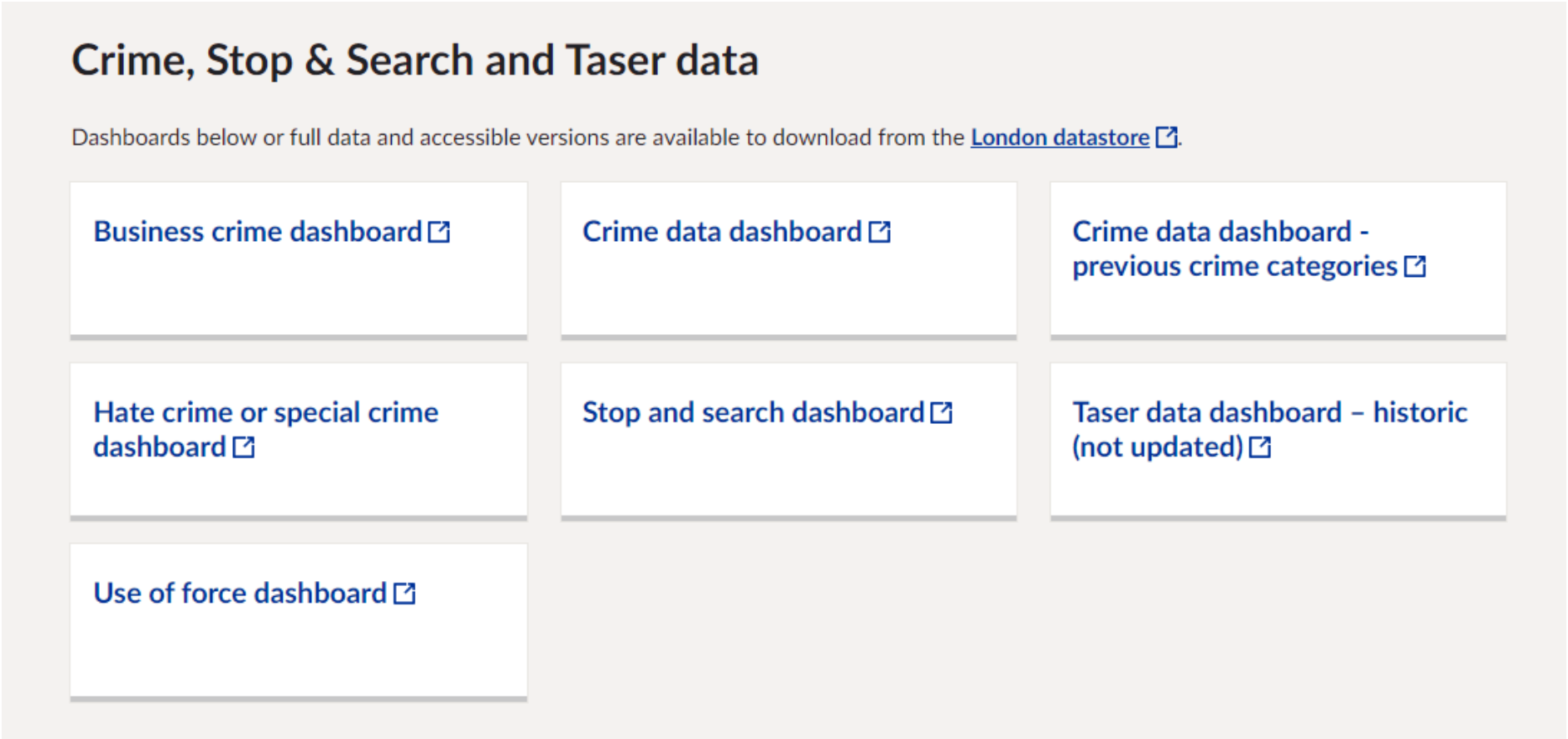
Example: “open data” on racially biased policing

Police carried out 54 stop and searches for every 1,000 black people in England and Wales in 2019-20



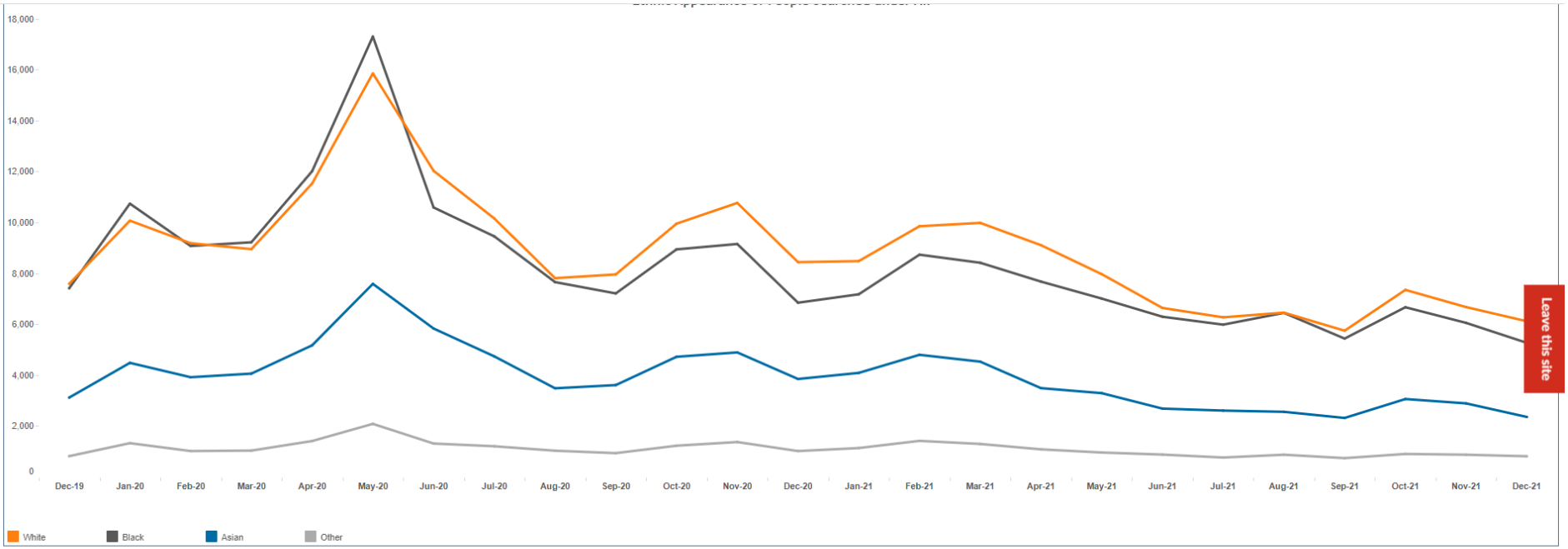
Guardian graphic | Source: The Macpherson report. Note: data unavailable for Greater Manchester, City of London and British Transport Police. * Includes BTP but excludes Greater Manchester. Selected forces shown

Metropolitan Police Dashboards (London Open Data)



https://www.met.police.uk/sd/stats-and-data/

Stop & search by ethnicity (London Open Data)

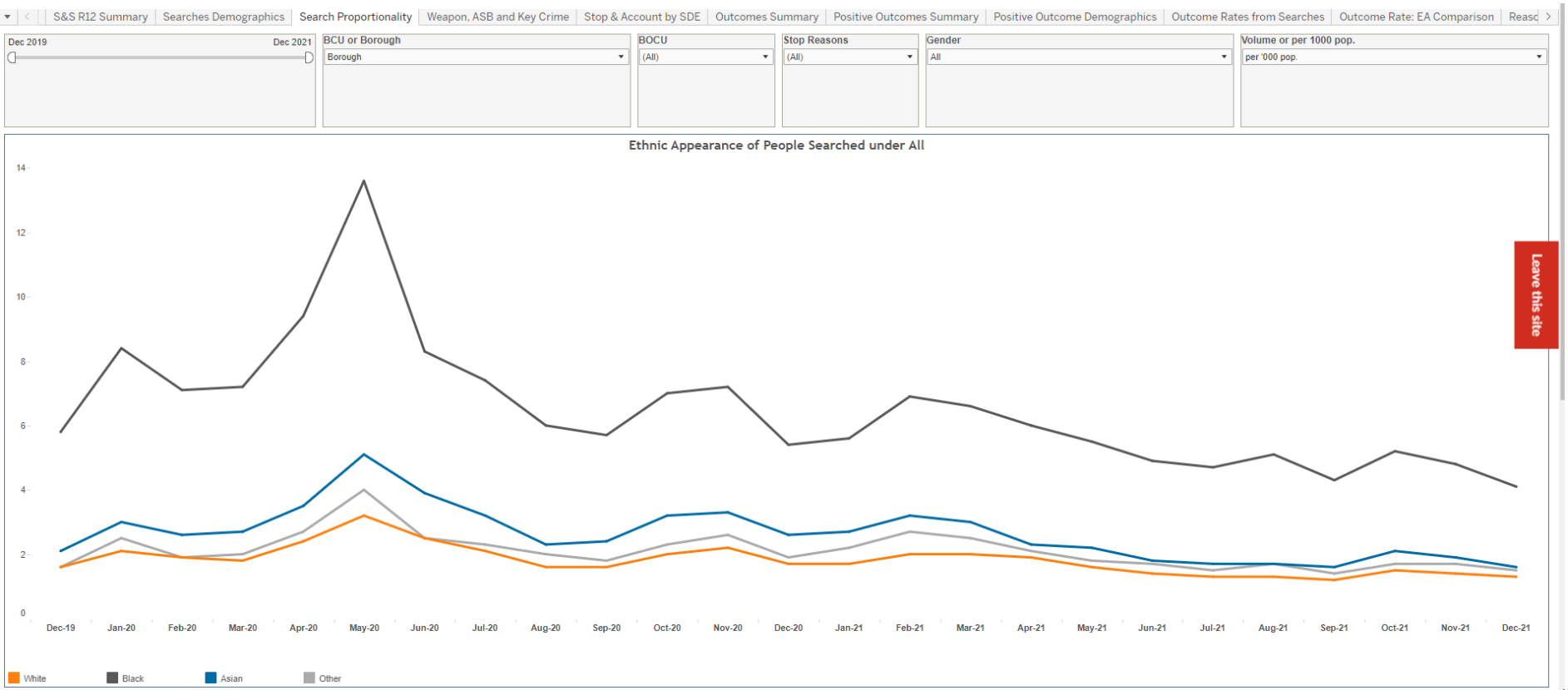


EA	Dec 2019		Jan 2020		Feb 2020		Mar 2020		Apr 2020		May 2020		Jun 2020		Jul 2020		Aug 2020		Sep 2020		Oct 2020		Nov 2020		Dec 2020		Jan 2021		Feb 2021		Mar 2021		Apr 2021	
	Search Volume	Search per '000 pop.	Search Volume	Search per '000 pop.	Search Volume	Search per '000 pop.	Search Volume	Search per '000 pop.	Search Volume	Search per '000 pop.	Search Volume	Search per '000 pop.	Search Volume	Search per '000 pop.	Search Volume	Search per '000 pop.	Search Volume	Search per '000 pop.	Search Volume	Search per '000 pop.	Search Volume	Search per '000 pop.	Search Volume	Search per '000 pop.	Search Volume	Search per '000 pop.	Search Volume	Search per '000 pop.	Search Volume	Search per '000 pop.	Search Volume	Search per '000 pop.	Search Volume	Search per '000 pop.
White	7,583	1.6	10,065	2.1	9,180	1.9	8,946	1.8	11,523	2.4	15,851	3.2	12,024	2.5	10,151	2.1	7,806	1.6	7,953	1.6	9,947	2	10,761	2.2	8,435	1.7	8,476	1.7	9,846	2	9,978	2	9,102	1.9
Black	7,407	5.8	10,734	8.4	9,070	7.1	9,216	7.2	12,006	9.4	17,300	13.6	10,584	8.3	9,448	7.4	7,651	6	7,206	5.7	8,937	7	9,149	7.2	6,841	5.4	7,172	5.6	8,729	6.9	8,411	6.6	7,671	6
Asian	3,113	2.1	4,479	3	3,914	2.6	4,056	2.7	5,167	3.5	7,582	5.1	5,828	3.9	4,733	3.2	3,479	2.3	3,605	2.4	4,717	3.2	4,889	3.3	3,845	2.6	4,084	2.7	4,795	3.2	4,526	3	3,485	2.3
Other	813	1.6	1,324	2.5	1,014	1.9	1,032	2	1,407	2.7	2,082	4	1,309	2.5	1,202	2.3	1,027	2	932	1.8	1,224	2.3	1,368	2.6	1,013	1.9	1,132	2.2	1,414	2.7	1,293	2.5	1,081	2.1
All	18,916	2.3	26,602	3.3	23,178	2.8	23,250	2.8	30,103	3.7	42,815	5.2	29,745	3.6	25,534	3.1	19,963	2.4	19,696	2.4	24,825	3	26,167	3.2	20,134	2.5	20,864	2.6	24,784	3	24,208	3	21,339	2.6

Ethnic Appearance of People Searched, total volume.

Source: `https://www.met.police.uk/sd/stats-and-data/met/stop-and-search-dashboard/`

Stop & search by ethnicity (London Open Data)



Ethnic Appearance of People Searched, per 1,000 population.

Source: `https://www.met.police.uk/sd/stats-and-data/met/stop-and-search-dashboard/`

Stop & Search in the UK (Vomfell & Stewart 2021)

- The majority of officers over-search Asian and Black people relative to the ethnic composition of crime suspects and of the areas they patrol.
- Due to both over-patrolling (targeting areas based on ethnic composition) and over-searching (targeting individuals based on ethnic appearance)

Vomfell, L., Stewart, N. Officer bias, over-patrolling and ethnic disparities in stop and search. *Nature Human Behaviour* 5, 566–575 (2021).