# Medellín, Colombia

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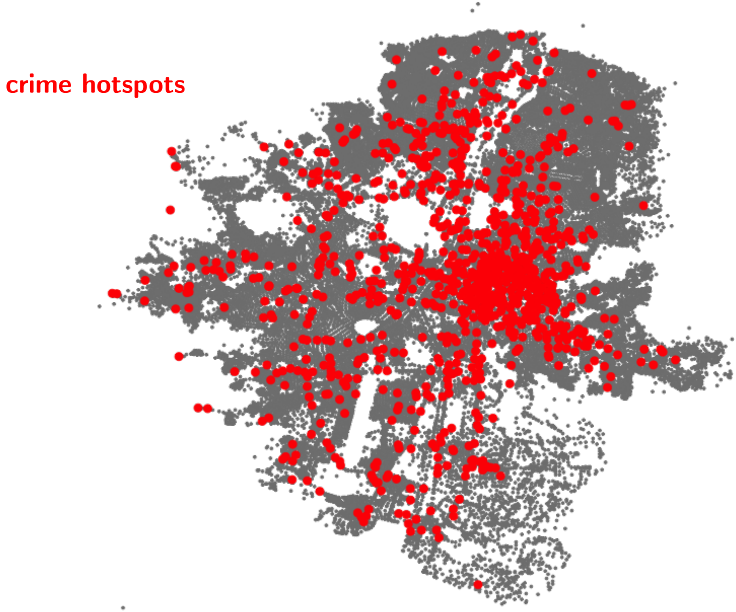
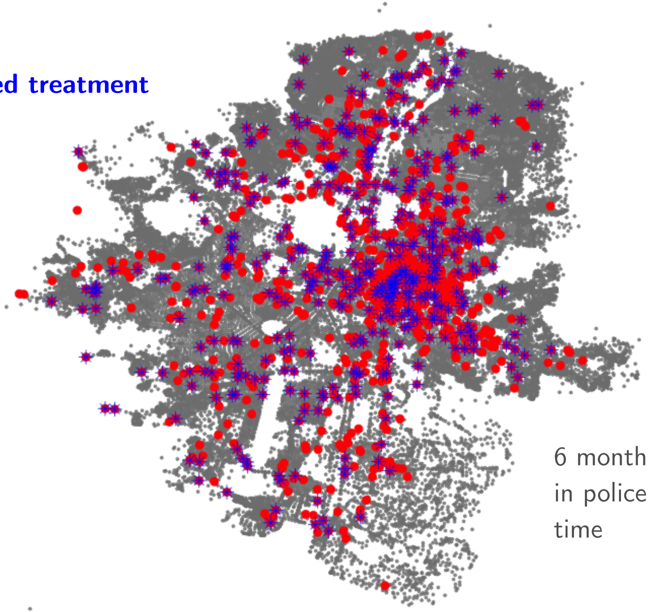


# Medellín, Colombia

**observed treatment**



6 month increase in police patrolling time

# Experiment and data

Units and treatment assignment

- 37,055 total streets (units)
- 967 streets are identified as crime "hotspots"
- 384 are treated with increased police presence

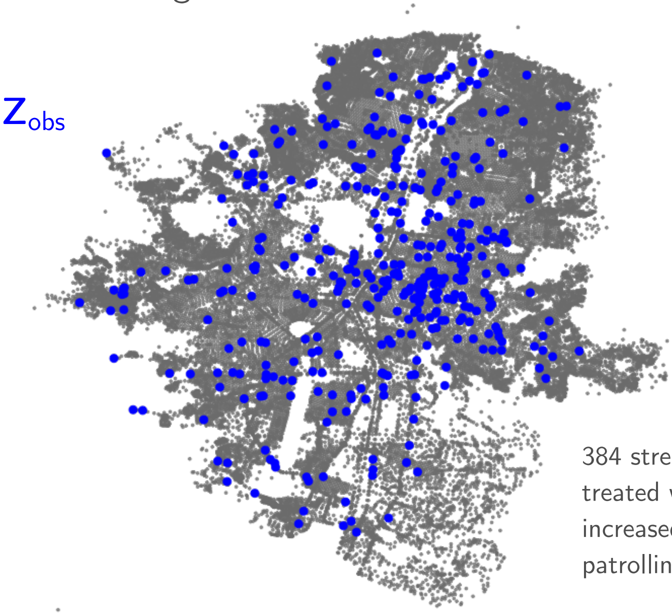
Access to randomizations based on the design, pr($Z$)

Outcomes and covariates

- Crime counts on all streets (murders, car and motorbike thefts, personal robberies, assaults)
- Survey data on hotspot streets
- Characteristics of hotspots (distance from school, bus stop, rec center, church, neighborhood, ...)

# Returning to the map

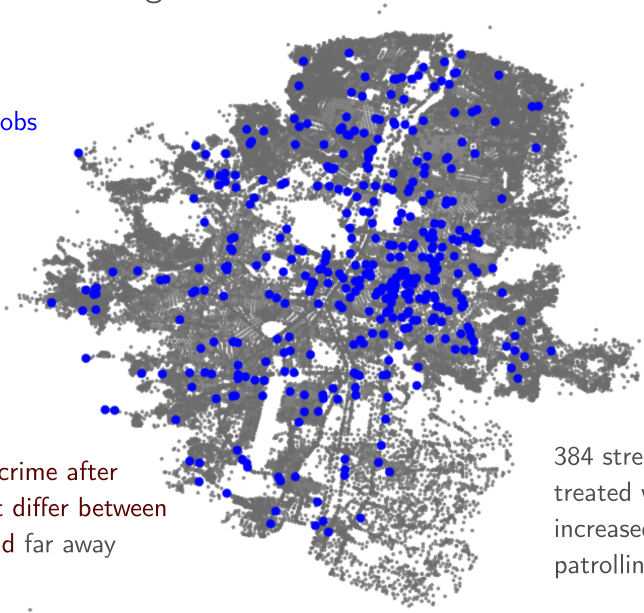
# The observed assignment




384 streets are treated with increased police patrolling

# The observed assignment

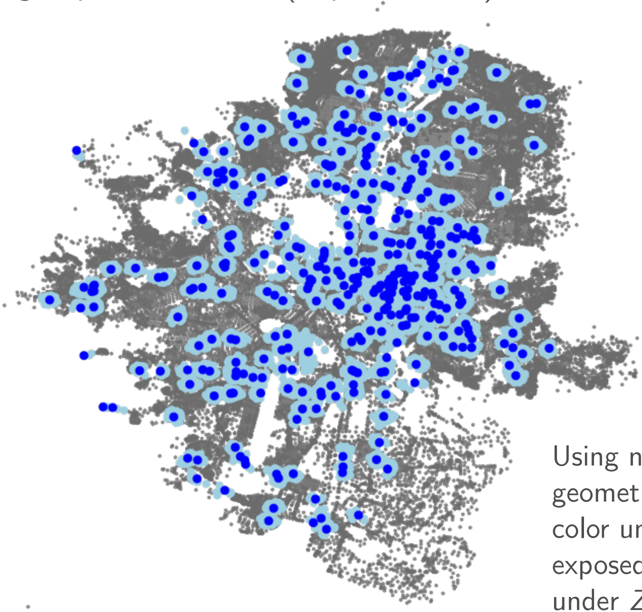
$Z_{obs}$



**Q:** Does crime after treatment differ between nearby **and** far away streets?

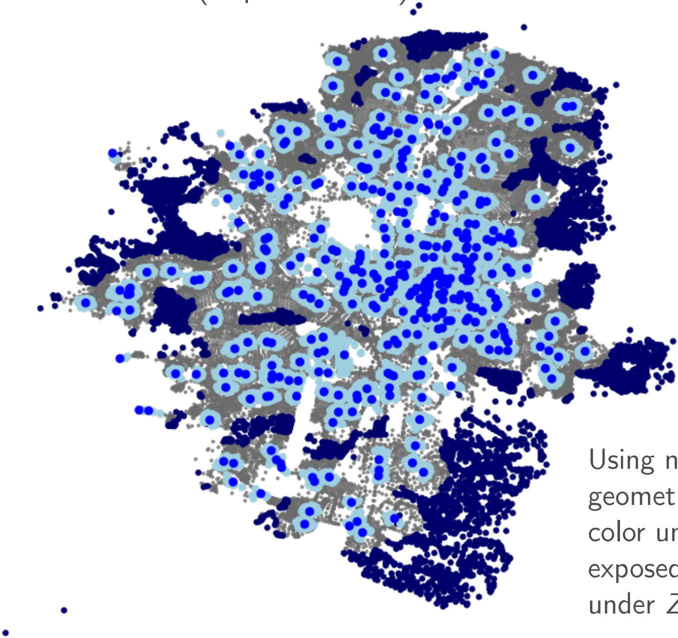
384 streets are treated with increased police patrolling

# Short-range spillover units (exposure “a”)



Using network geometry, color units exposed to “a” under $Z_{\text{obs}}$

# Pure control units (exposure "b")



Using network geometry, color units exposed to "b" under $Z_{obs}$

**We can remake these pictures for every assignment $Z$ drawn from $\mathrm{pr}(Z)$ ...**

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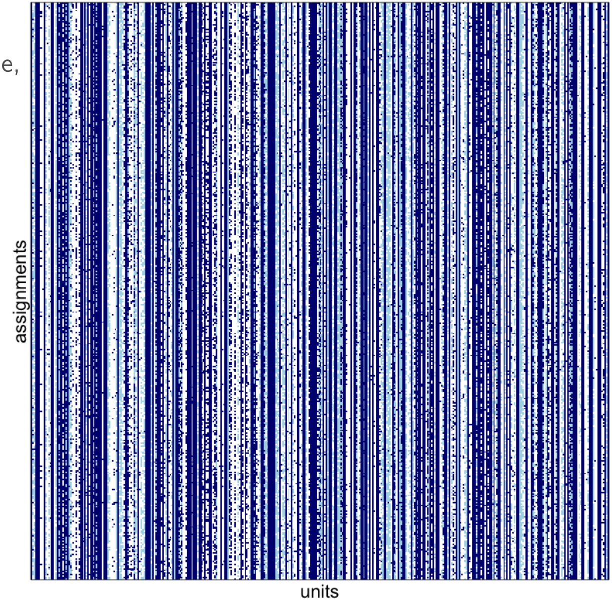
$\rightarrow$ The output is our null exposure graph!

# Null exposure graph

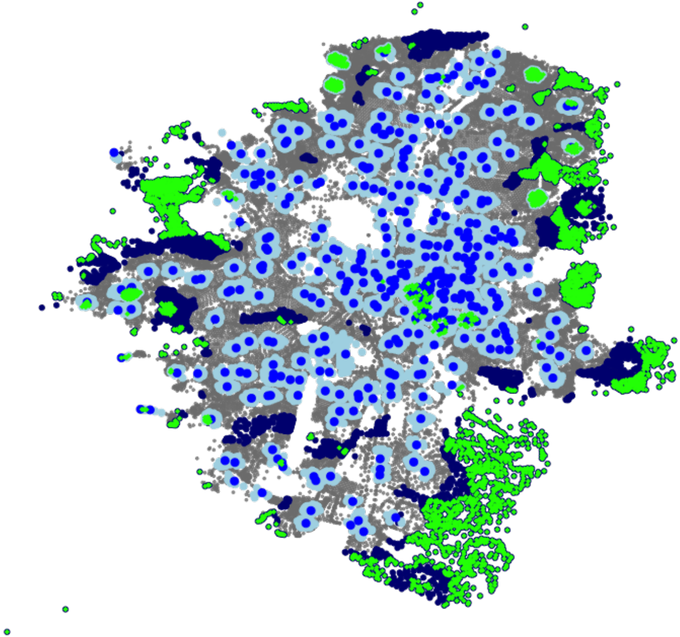
navy, light blue, and white



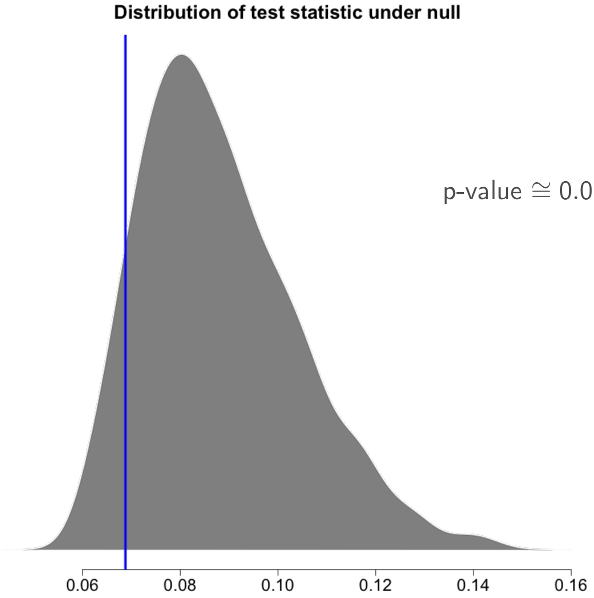
# Biclique containing the observed assignment

only navy and light blue!

# Where are the focal units?



# A test of the null




p-value $\cong$ 0.07

# Concluding thoughts

- New method is presented for testing causal effects under general interference using null exposure graphs and bicliques.
- Structure is placed on null hypothesis through exposure functions.
- Future work: understand power properties; optimized biclique decomposition; more hypotheses.

# Thank You!

Athey, Eckles, Imbens, "Exact p-Values for Network Interference" (JASA, 2018)

Basse, Feller, Toulis, "Randomization tests of causal effects under interference" (Biometrika, 2019)

Aronow, "A general method for detecting interference between units in randomized experiments." (Sociol. Methods Res., 2012)

# Extra slides

# Why is this a valid method?

Clique test statistics: $T_C = T(Y_C, Z_C)$

*$T$ is defined only in $C$ by **condition** step in method

For every $Z, Z'$, we need to show $T(Y', Z') \stackrel{d}{=} T(Y, Z) \mid C$

Proof:

$$T(Y', Z') \stackrel{*}{=} T(Y'_C, Z'_C) \stackrel{H_0}{=} T(Y_C, Z'_C) \stackrel{d}{=} T(Y_C, Z_C) \stackrel{*}{=} T(Y, Z)$$

# Considerations / Other approaches

- Finding bicliques is hard, actually, **NP-hard**[2]

- The method is **constructive**, still needs to be optimized

  i.e., different biclique decompositions will have different power properties, but all are **valid**!

- Other conditional testing methods:

  Aronow 2012, Athey et al. 2018. (Roughly) equivalent to randomly sampling units one one side, then computing the clique that contains those units and obs $Z$.
  $\Rightarrow$ loses power.

  Basse et al. 2019. Biclique sampling can depend on obs $Z$.
  $\Rightarrow$ easier when interference has structure.

[2] We use Binary Inclusion-Maximal Biclustering Algorithm, which uses a divide and conquer method to find bicliques.