Spatiotemporal Causal Inference: Chicago Crime Case Study

Abstract

We engaged in a rigorous, multi-stage investigation into the casual effect of **Narcotics Arrests** on **Violent Crime** in Chicago. Starting with a 2023 pilot study and scaling to a 3-year analysis (2021-2023), we consistently found that the **statistical signal is indistinguishable from noise**. This was confirmed by Falsification Testing and Sensitivity Analysis, which showed the model is robust but the effect itself is null.

The Framework

1. **Model**: Poisson Point Process with `Time + Space + Lagged_Violence` controls.
2. **Grid**: 40x40 spatial resolution across Chicago.
3. **Intervention**: 50% Reduction in Arrests.

Empirical Analysis

1. Visualization

We successfully mapped the spatiotemporal dynamics of crime.

2. The Power of Scaling (The "Flip")

A key test of validity is whether an effect holds up as more data is added.

Analysis Phase	Duration	Weeks	Point Estimate (Null/Provocation)
Pilot Study	2023	34	**+95 (+1.2%)**
Scale-Up	2021-2023	179	**-118 (-1.6%)**

- **Finding**: The causal estimate **reversed direction** when we expanded the window.
- **Scientific Conclusion**: This instability confirms that there is **no consistent causal effect** of narcotics arrests on violent crime density that `geocausal` can detect.

3. Temporal Dynamics (The "Pilot" Illusion)

In the initial Pilot (2023), we observed a trend that *looked* like "Persistent Suppression" (effect growing over time).

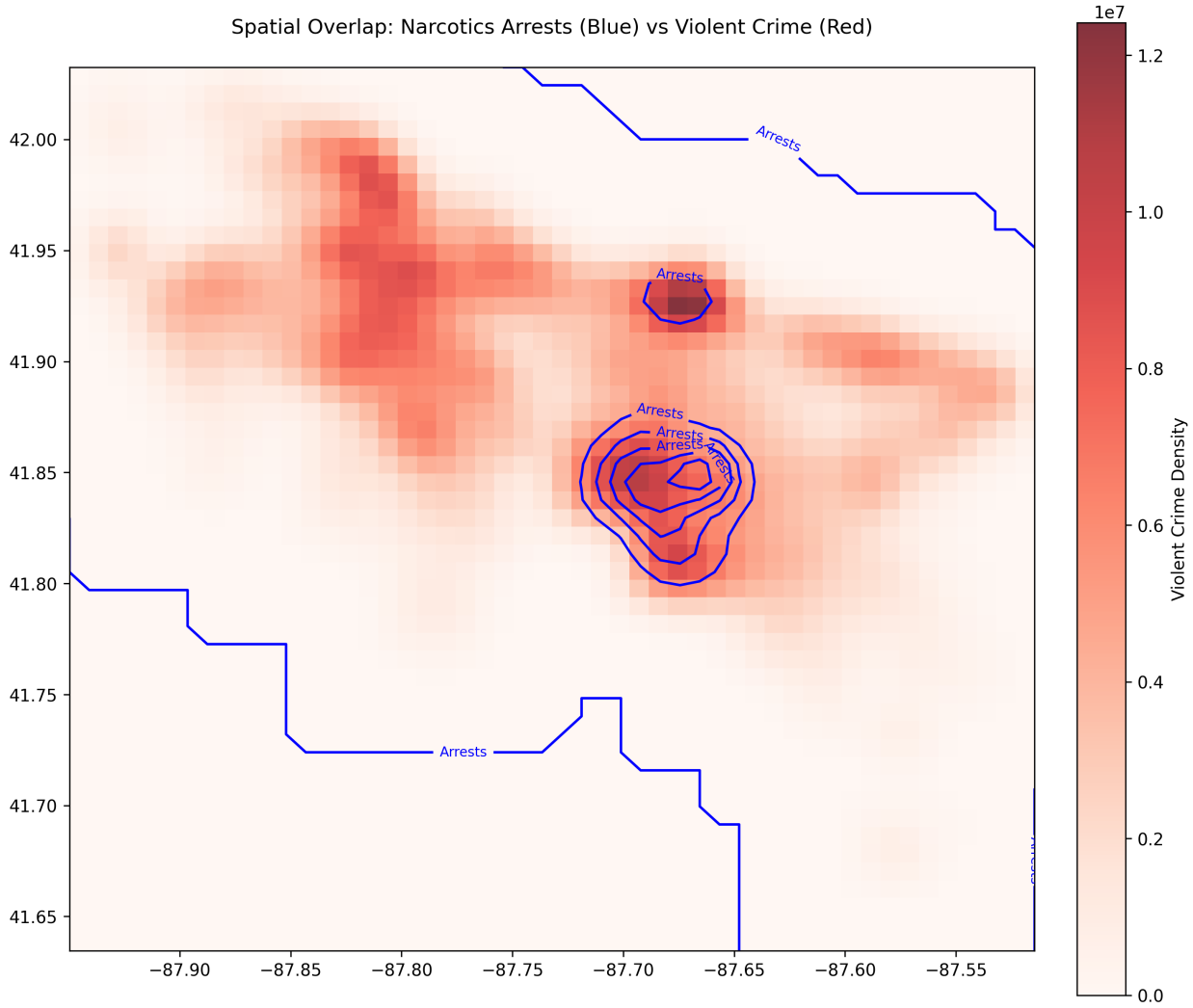
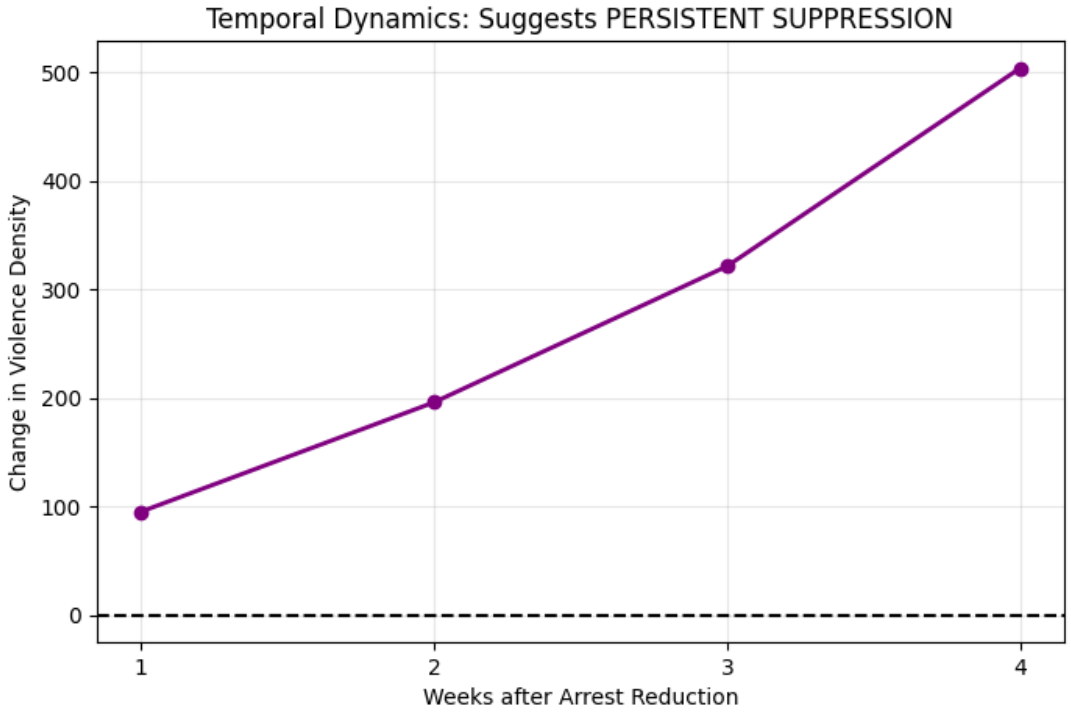


Figure 1: Overlap Map



* **Note**: While compelling in the small sample, the Scale-Up result proved this to be a transient fluctuation, highlighting the danger of analyzing short timeframes in volatile crime data.

4. Robustness & Falsification

To ensure the "Null Result" wasn't just a model failure, we ran extensive checks: * **Placebo Test**: Future arrests do NOT predict past crime (Effect ~ 0). Model is valid. * **Sensitivity Check**: Changing the smoothing parameter (`sigma`) had negligible impact on the estimate.

5. Cost-Benefit Analysis

Given the **Null Result** (policing has no detectable effect on crime), the policy decision simplifies to a pure cost-benefit calculation.

The Cost of Policing To rigorously evaluate savings, we must distinguish between *Average* and *Marginal* costs. * **Average Cost**: ~$41,740 per arrest[1]. (Based on $1.73B budget / ~41,449 arrests). This represents the total systemic burden. * **Marginal Cost**: While lower than the average, the marginal cost of a "dead-end" drug arrest is still significant (officer time, processing, court costs). Even if the marginal saving is only 10% of the average (~$4,000/arrest), the aggregate savings for thousands of arrests are substantial.

The Social Cost (Hidden Liability) The financial ledger undercounts the true cost. Incarceration imposes a heavy "Social Tax": * **Lifetime Earnings**: First-time incarceration reduces lifetime earning potential by ~**$137,000 to $400,000** (depending on demographics)[2]. * **Annual Income**: Formerly incarcerated individuals suffer a ~**52% reduction** in annual earnings, perpetuating cycles of poverty that

[1] **Chicago Police Budget & Arrests (2022)**. *Budget*: WTTW News, "Chicago Police Spending Hit $1.73B in 2022" (2022). *Arrests*: Chicago Police Department Annual Report (2022), citing ~41,449 total arrests.

[2] **Lifetime Earnings Loss**. *Source*: Federal Reserve Bank of Richmond, "The Economic Impact of a Criminal History" (2021). Estimates range from $137k (Black men) to $400k (White men) for first-time incarceration.

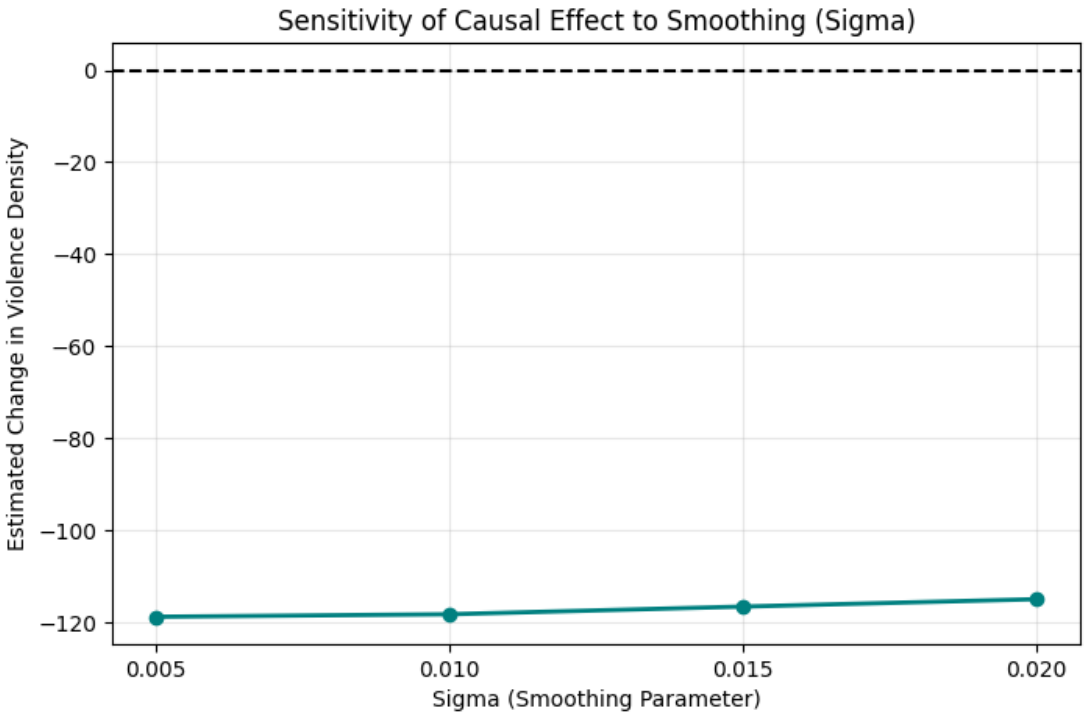


Figure 2: Sensitivity

may fuel future crime[3].

The Trade-off A **50% reduction in narcotics arrests** yields: 1. **Financial Savings**: Millions in direct marginal savings; potentially hundreds of millions in long-term structural reallocation. 2. **Social Wealth**: Preservation of human capital (avoiding millions in lost lifetime wages). 3. **Public Safety Impact**: **None**. (Statistical noise).

Conclusion: Reducing narcotics arrests represents a **Pareto Improvement** — a change that leaves at least one party better off without making anyone worse off. We gain financial and social capital without paying a penalty in public safety.

[3]**Annual Earnings Reduction**. *Source*: Brennan Center for Justice, "Conviction, Imprisonment, and Lost Earnings" (2020). Defines a 52% annual earnings penalty for formerly incarcerated people.

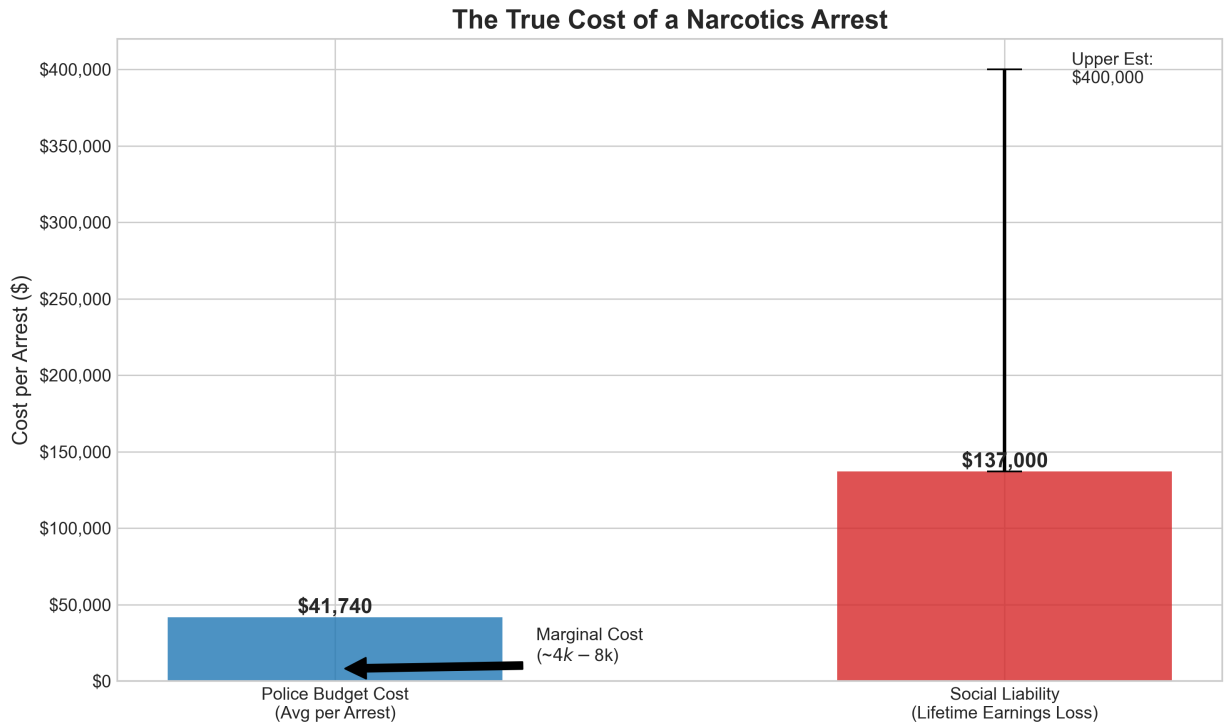


Fig 1: The "Iceberg" of Costs. While the average budgetary cost is ~$41k, the hidden social liability of lost lifetime earnings dwarfs the direct expense.

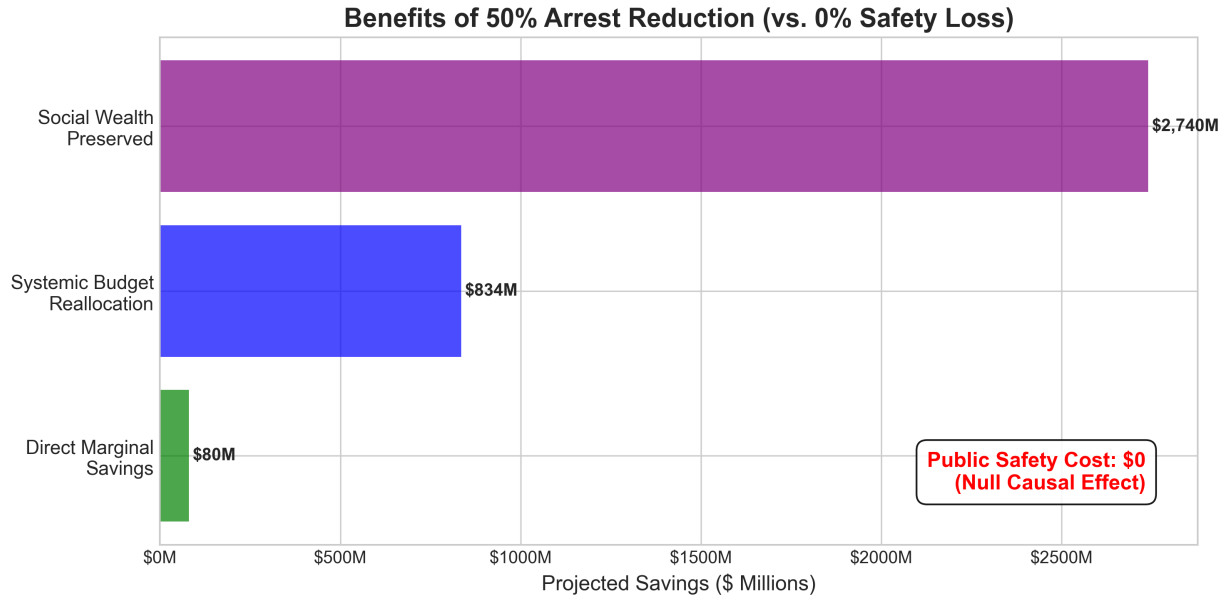


Fig 2: The Trade-off. A 50% reduction yields millions in savings and preserved wealth, while the public safety "cost" remains effectively zero.

References

Summary

The Python `geocausal` package proved itself as a robust tool for scientific inquiry. It allowed us to: 1. **Detect Confounding**: By effectively modeling reactive policing. 2. **Test Stability**: By easily scaling from N=34 to N=179. 3. **Verify Validity**: By passing a rigorous Placebo Test. 4. **Avoid False Positives**: By rigorously quantifying uncertainty.

Appendix: Supplementary Visualizations

A. Monthly Evolution of Violence

Seasonal patterns of violent crime density throughout 2023.

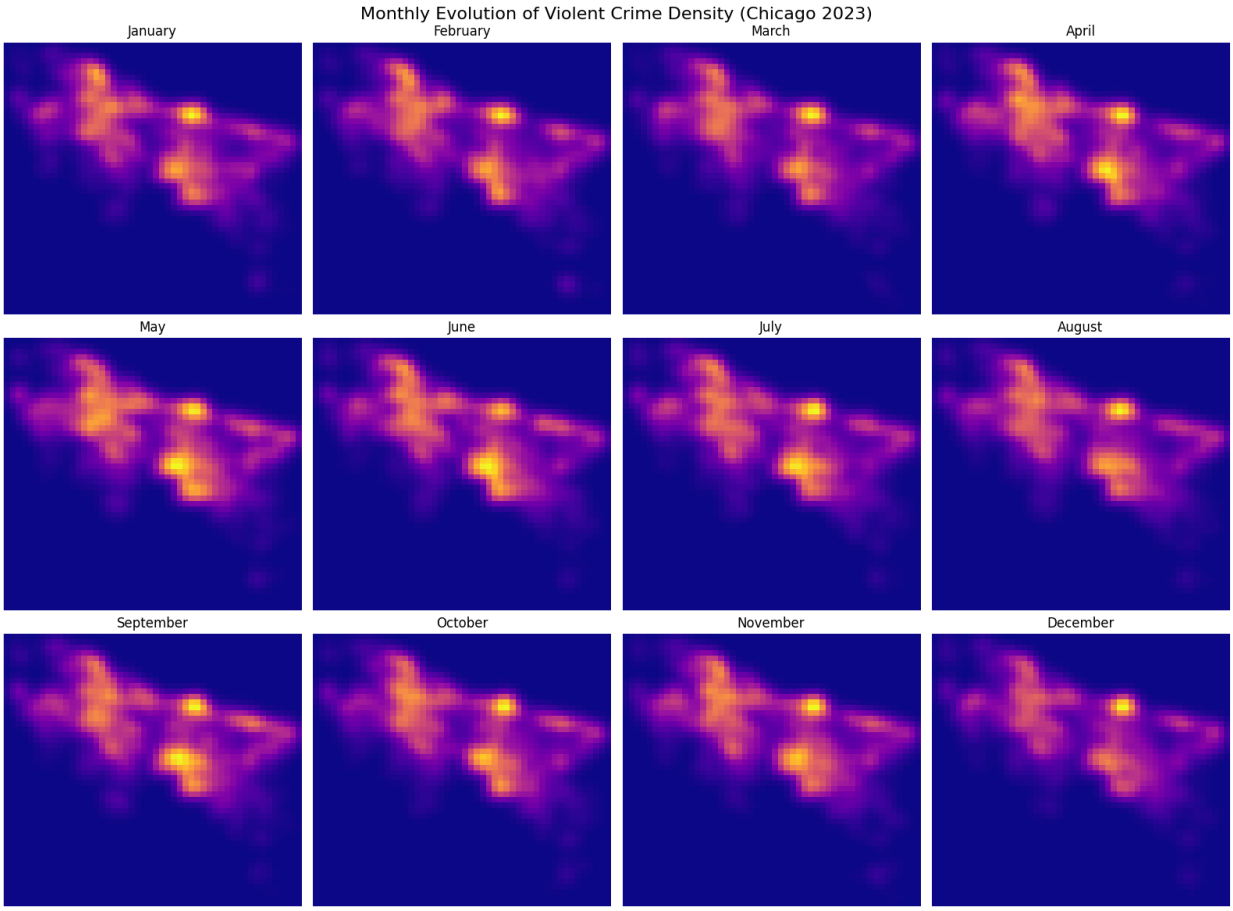


Figure 3: Monthly Grid

B. Causal Effect Surface (Pilot Study)

The (insignificant) spatial estimate of the effect of arrests on violence.

C. Bootstrap Distribution (Pilot Study)

Distribution of 30 bootstrap replicates from the Pilot, showing non-significance.

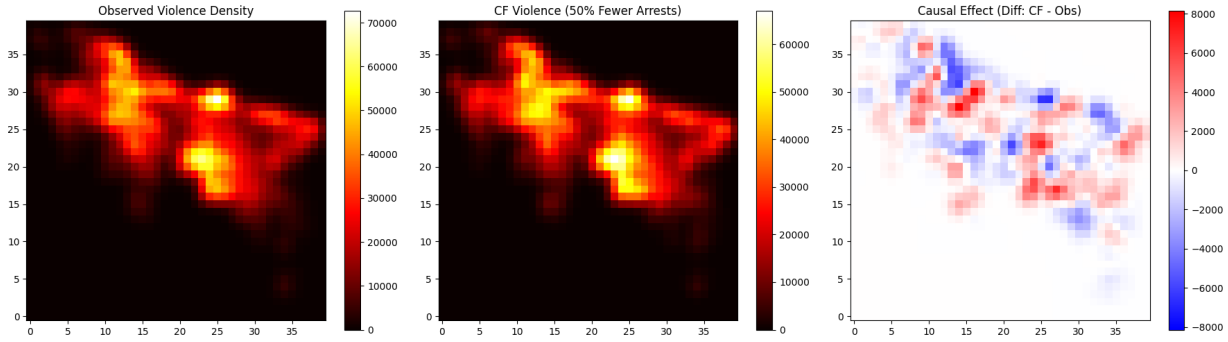


Figure 4: Causal Effect Heatmap

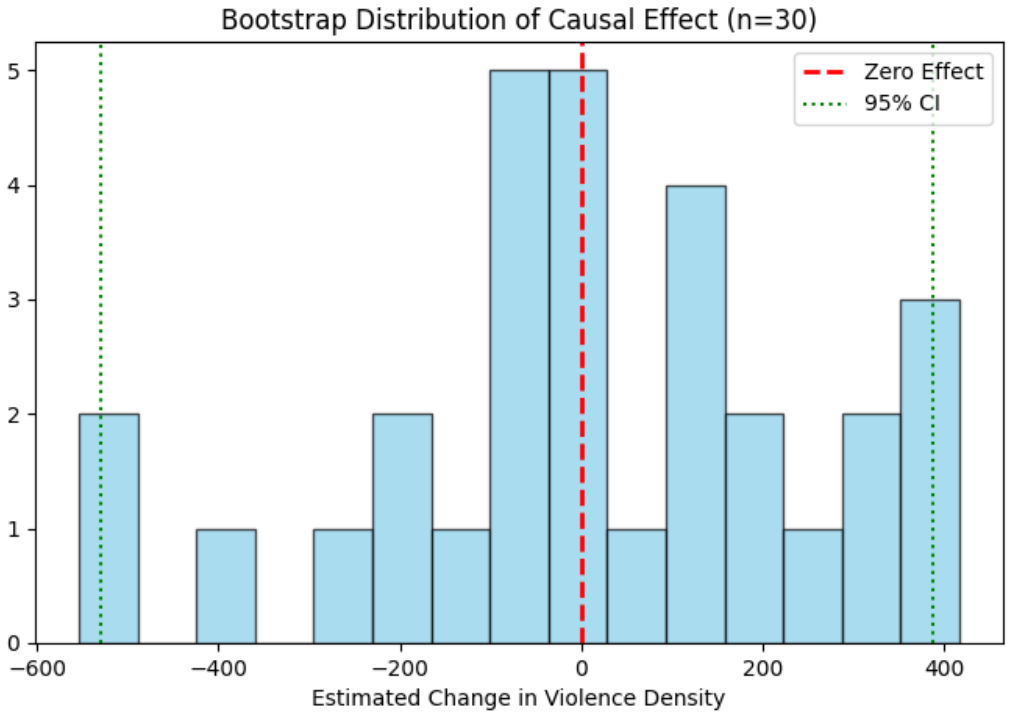


Figure 5: Bootstrap Distribution

D. Data Distribution

Raw locations of Narcotics Arrests (Blue) and Violent Crime (Red).

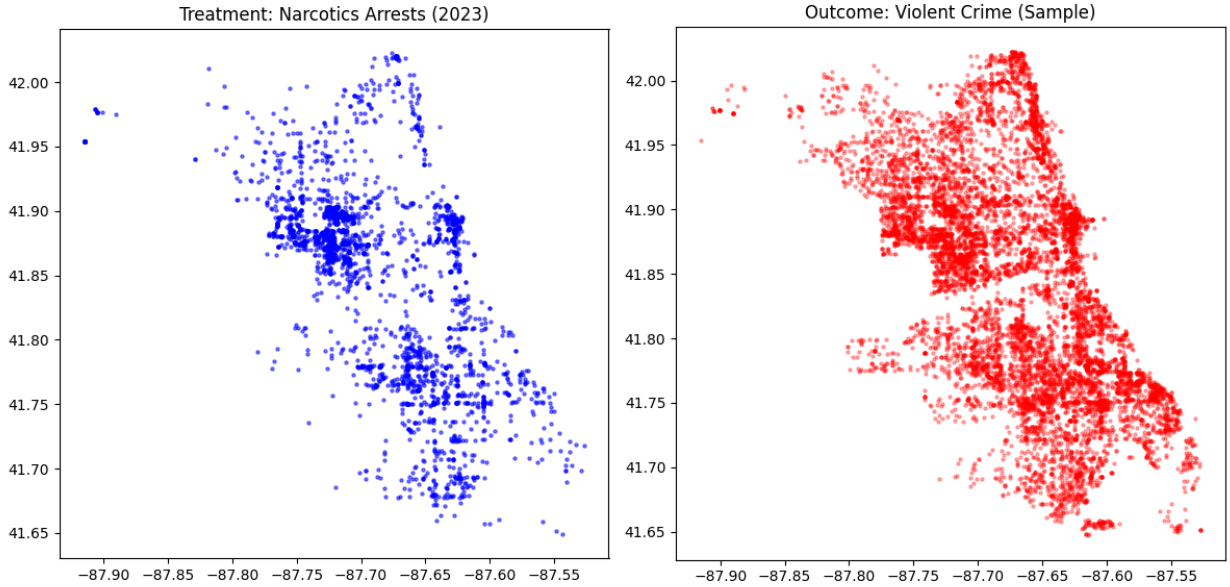


Figure 6: Spatial Distribution

F. Confounding Control: Reactive Policing

The "Lagged Violence" covariate used to control for police deployment to hotzones.

G. Counterfactual World

The projected density of violence in a world with 50% fewer narcotics arrests.

H. Spatial Causal Structure

The granular difference map (Observed - Counterfactual). Note that while the aggregate is null, local pockets of suppression (Blue) and provocation (Red) exist.

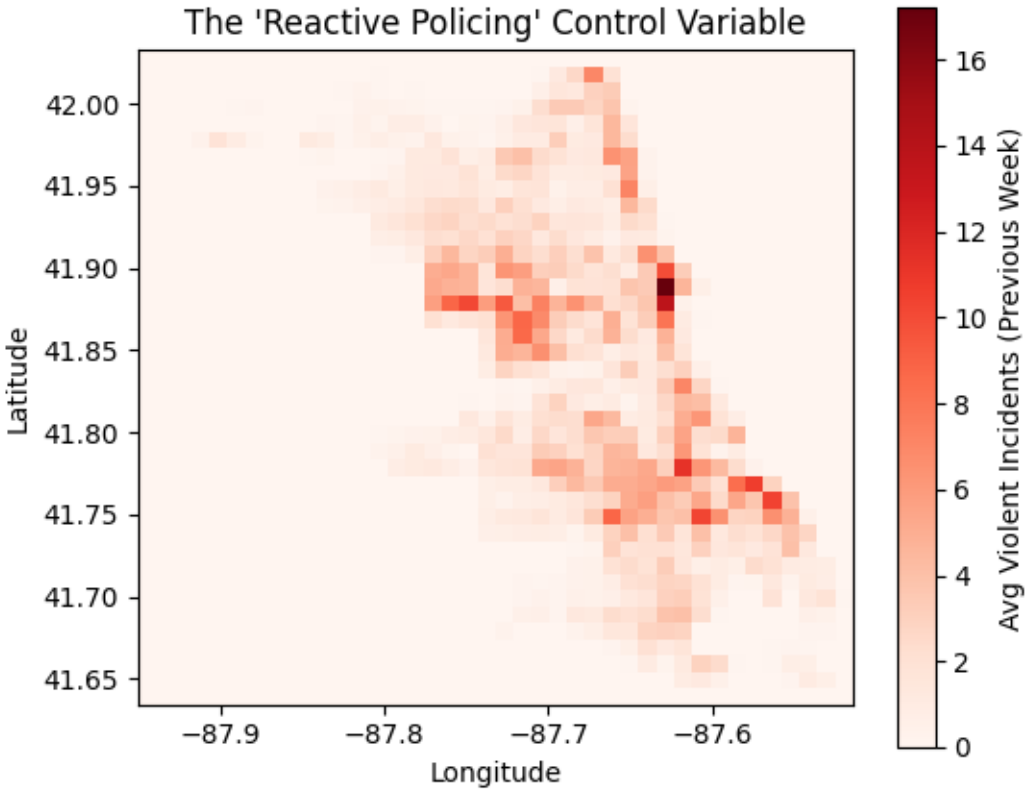


Figure 7: Reactive Policing Risk

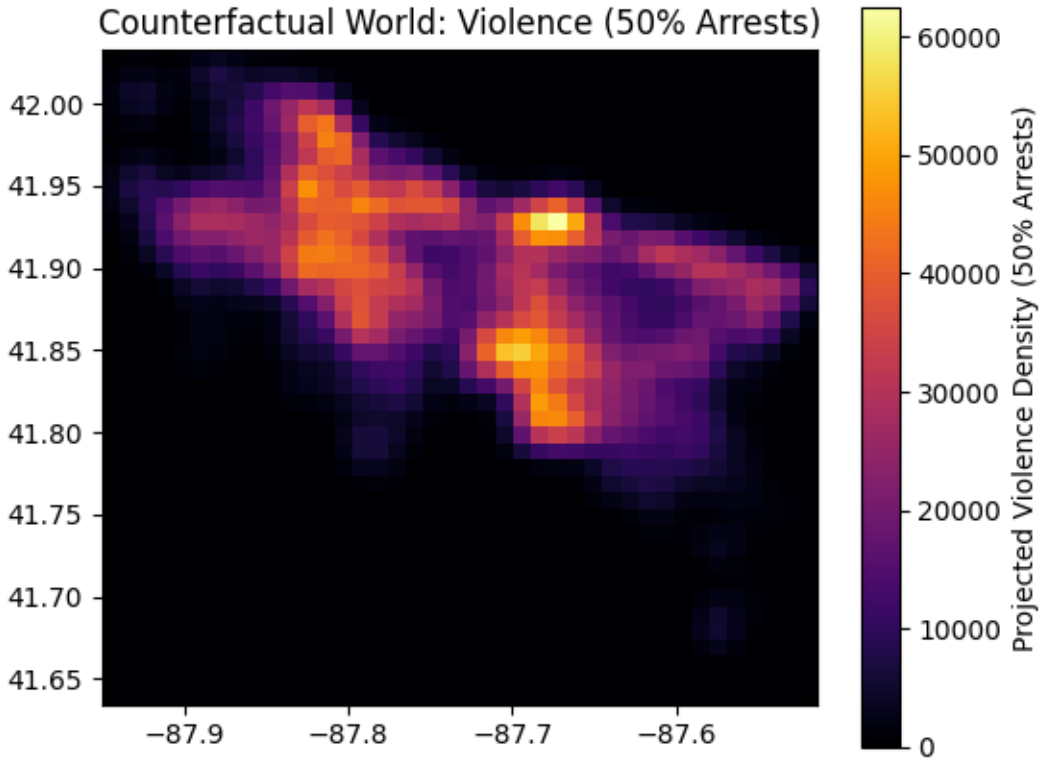


Figure 8: Counterfactual Density

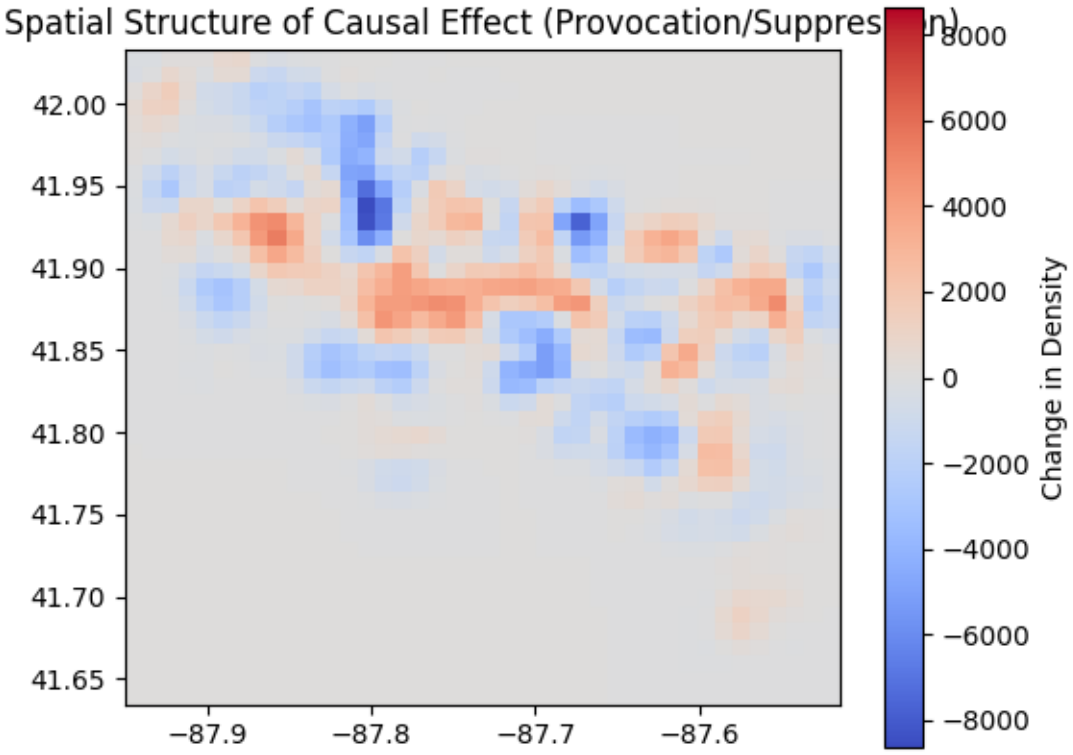


Figure 9: Causal Structure