Treatment Effect Estimation with Geocoded Microdata

Kyle Butts

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Motivation

Treatment often isn't assigned to groups of individuals (e.g. counties), but rather to specific locations

- Environmental: Local pollutants (Marcus, 2021; Currie et al., 2015) , shale gas discovery (Muehlenbachs, Spiller, and Timmins, 2015)
- Urban: foreclosures (Gerardi et al., 2015; Campbell, Giglio, and Pathak, 2011) , abandon lot cleanups (South et al., 2018) , apartment construction (Asquith, Mast, and Reed, 2021)

Identification of Treatment Effects

Difference-in-differences is often used to estimate treatment effects. How do you choose a control group?

1. Find alternative treatment locations to serve as a control group. For example propensity score match census blocks and use observations in blocks likely to receive treatment but did not.
   - Problem if areas actually treated are targeted due to contemporaneous shocks to trends.
2. Compare observations very near to treatment, "the treated", to observations just slightly further away, "the control".
   - Identification allows treatment to be targeted due to 'neighborhood' trends but not targeted for differential trends 'within' the neighborhood.

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   - Identification allows treatment to be targeted due to ‘neighborhood‘ trends but not targeted for differential trends ‘within‘ the neighborhood.

Examples of Identification Discussion

Linden and Rockoff (2008) look at the arrival of sexual offenders on neighborhood prices.They compare home sales **within 0.1 mile (about 2 city blocks) to home sales between 0.1 - 0.3 miles**.

> *"This framework would be compromised only if sex offenders consistently moved into properties near which a localized disamenity was likely to emerge."*

Examples of Identification Discussion

Marcus (2021) considers leaking underground petroleum storage tanks that affect hyper-local drinking water. Look at long-run outcomes of children exposed to petroleum pollution

> *"I find that low-SES mothers are more likely to live near pollution sites. ... The remaining threat to identification is time-varying un-observable characteristics (e.g. local economic conditions) that vary systematically with the observed leak timing. To address this concern, I compare mothers* ***within two small radii of the leaking site, 300 and 600 meters.****"*

Problem

The central problem is how do you chose the radii of the two rings?

- Does treatment effects stop at 0.1 miles? 0.2 miles? 0.3 miles?
- How far constitutes the ”neighborhood” that control units can be in?

Contribution

1. I formalize the identification strategy in an econometric framework.
2. Define what assumptions are needed to identify estimands: ‘parallel trends’ within control ring and correct treatment effect cutoff distance.
3. I propose a new estimator that relaxes the correct treatment effect cutoff assumption using new work on non-parametric series estimators Cattaneo, Crump, et al. (2019) and Cattaneo, Farrell, and Feng (2019) .

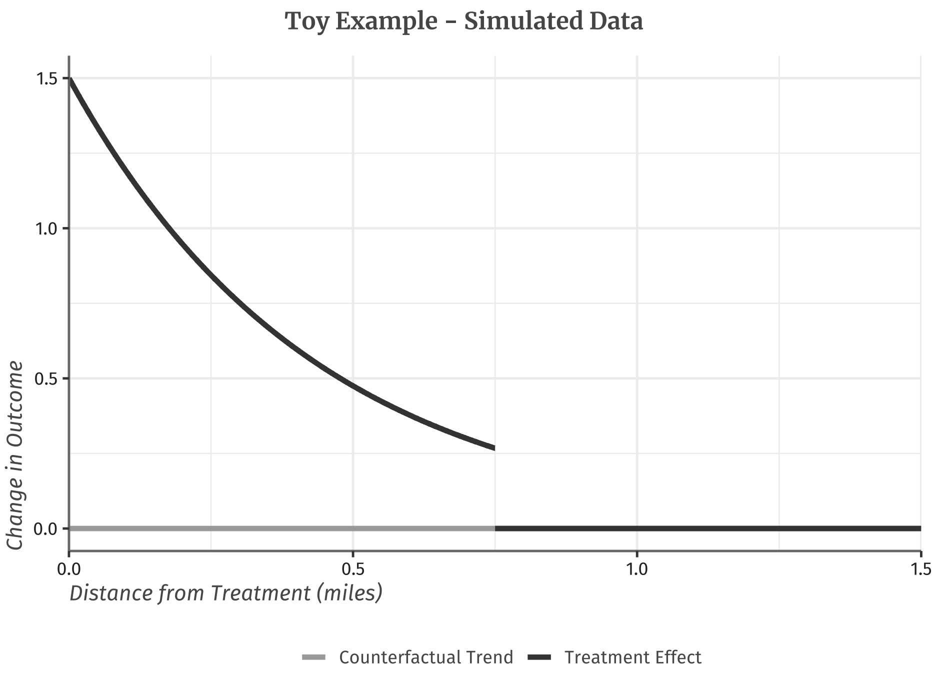
Outline

Example of Problems

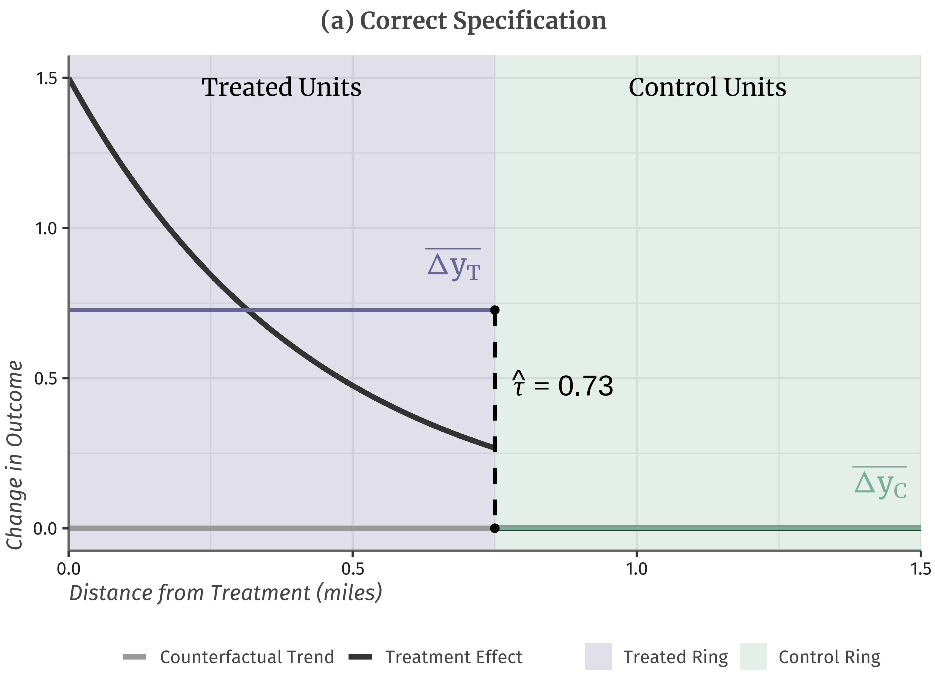
Theory

Improved Estimator

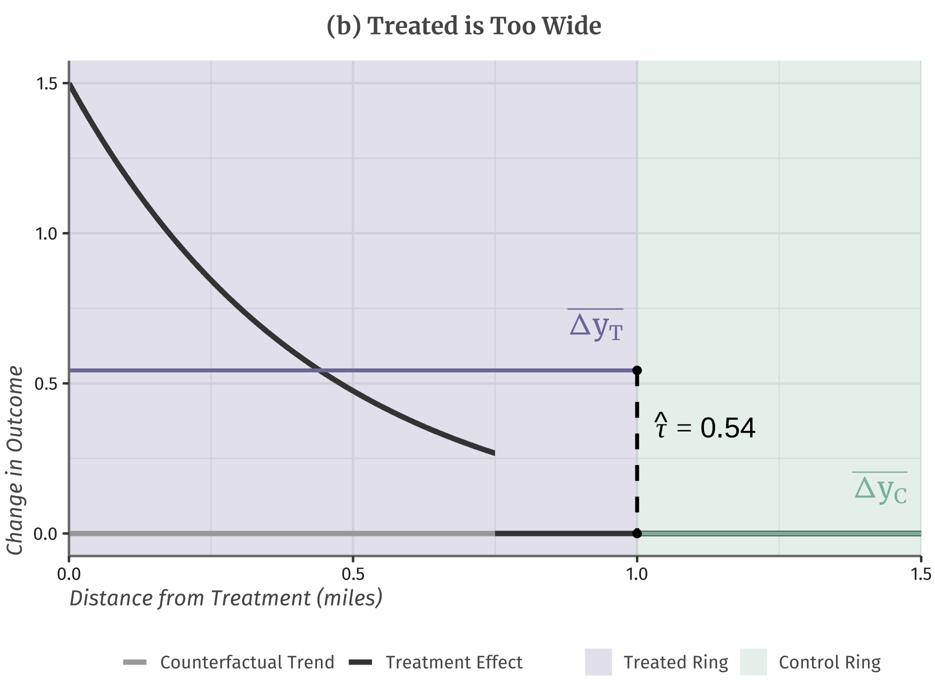
Application



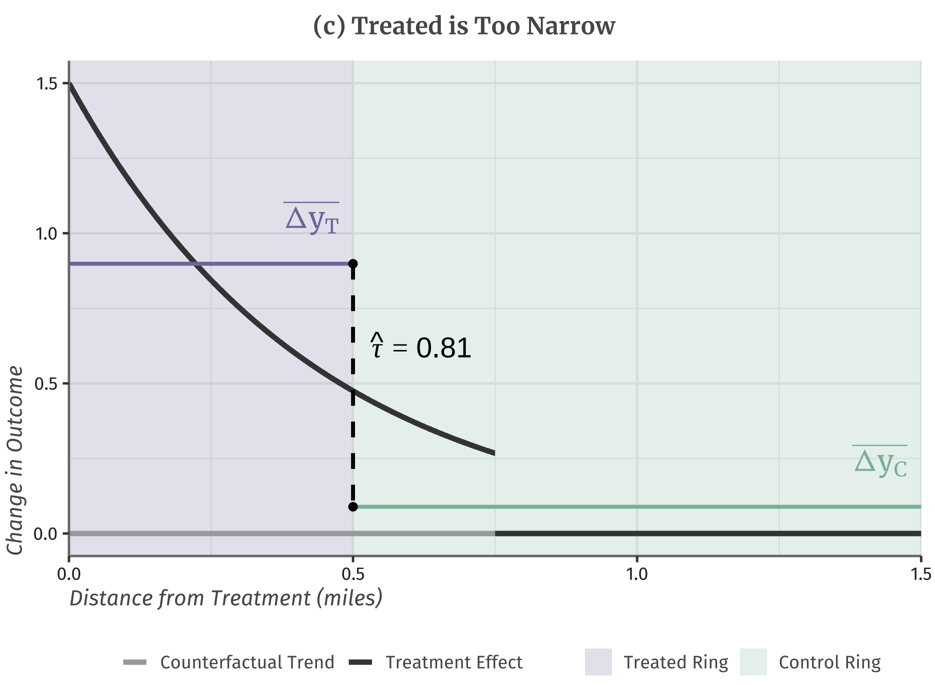
Toy Example - Simulated Data
1.5
1.0
0.5
0.0
Change in Outcome
0.0
0.5
1.0
1.5
Distance from Treatment (miles)
Counterfactual Trend
Treatment Effect

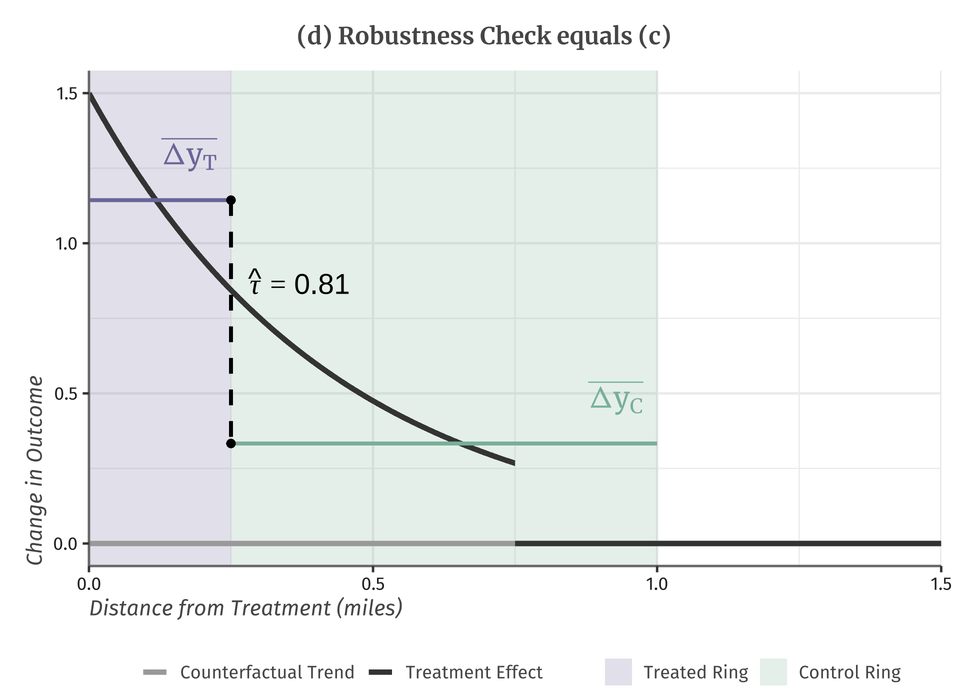


(a) Correct Specification
Treated Units
Control Units
$\overline{\Delta y_T}$
$\hat{\tau}$ = 0.73
$\overline{\Delta y_C}$
1.5
1.0
0.5
0.0
Change in Outcome
0.0
0.5
1.0
1.5
Distance from Treatment (miles)
Counterfactual Trend
Treatment Effect
Treated Ring
Control Ring



(b) Treated is Too Wide
$\overline{\Delta y_T}$
$\hat{\tau}$ = 0.54
$\overline{\Delta y_C}$
1.5
1.0
0.5
0.0
Change in Outcome
0.0
0.5
1.0
1.5
Distance from Treatment (miles)
Counterfactual Trend
Treatment Effect
Treated Ring
Control Ring


(c) Treated is Too Narrow
$\overline{\Delta y_T}$
$\hat{\tau}$ = 0.81
$\overline{\Delta y_C}$
1.5
1.0
0.5
0.0
Change in Outcome
0.0
0.5
1.0
1.5
Distance from Treatment (miles)
Counterfactual Trend
Treatment Effect
Treated Ring
Control Ring



(d) Robustness Check equals (c)
$\overline{\Delta y_T}$
$\hat{\tau}$ = 0.81
$\overline{\Delta y_C}$
1.5
1.0
0.5
0.0
Change in Outcome
0.0
0.5
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1.5
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Model for Outcomes

Setup

Units i have locations (x_i, y_i). Treatment turns on between the two periods $t = 0, 1$ at point $(\bar{x}, \bar{y})$. Therefore units vary in Dist_i, their distance to treatment. We have an iid panel sample.

Outcomes are given by:

$$Y_{it} = \underbrace{\tau(\text{Dist}_i)\mathbf{1}_{t=1}}_{\text{Treatment Effect Curve}} + \mu_i + \underbrace{\lambda(\text{Dist}_i)\mathbf{1}_{t=1}}_{\text{Counterfactual Trend}} + \varepsilon_{it},$$

where we assume $\varepsilon_{it} \perp \text{Dist}_i$.

Model

Estimand

Estimand of interest:

$$\bar{\tau} = \mathbb{E}\left[\tau(\text{Dist}_i) \mid \tau(\text{Dist}_i) > 0\right]$$

This is just the average treatment effect on those affected by treatment.

Model

First-Differences

Taking first differences, we have:

$$\Delta Y_{it} = \tau(\text{Dist}_i) + \lambda(\text{Dist}_i) + \Delta\varepsilon_{it}$$

With no additional assumptions, the treatment effect curve and the counterfactual trend are not seperately identifiable.

Model

Assumptions

Assumption: Local Parallel Trends

For a distance d_c, local parallel trends hold if λ is constant for $0 < d < d_c$.

Assumption: Average Parallel Trends

For a distance d_c and d_t, average parallel trends hold if

$$\mathbb{E}\left[\lambda_d \mid 0 \leq d \leq d_t\right] = \mathbb{E}\left[\lambda_d \mid d_t < d \leq d_c\right]$$

- Average Parallel Trends is a milder assumption, but usually researchers justify the method by Local Parallel Trends.

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Model

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Assumption: Correct Treatment Effect Cutoff

A distance d_t satisfies this assumption if for all $d \leq d_t$, $\tau(d) > 0$ and for all $d > d_t$, $\tau(d) = 0$.

- This is difficult to know!!!
- Later on, I show how to relax this assumption under Local Parallel Trends

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Estimator

For a given d_t and d_c, we define the treated and control groups as:

$$\mathcal{D}_t = \{i \ : \ \text{Dist}_i \leq d_t\}; \quad \mathcal{D}_c = \{i \ : \ d_t < \text{Dist}_i \leq d_c\}$$

On the sample $\mathcal{D}_t \cup \mathcal{D}_c$, the following regression is run:

$$\Delta Y_{it} = \beta_0 + \beta_1 \mathbf{1}_{i \in D_t} + u_{it}$$

$\hat{\beta}_1$ is the difference-in-differences estimate

Identification

Decomposition of Ring Method

(i) The estimate of β_1 has the following expectation:

$$\mathbb{E}\left[\hat{\beta}_1\right] = \underbrace{\mathbb{E}\left[\tau(\text{Dist}) \mid \mathcal{D}_t\right] - \mathbb{E}\left[\tau(\text{Dist}) \mid \mathcal{D}_c\right]}_{\text{Difference in Treatment Effects}} + \underbrace{\mathbb{E}\left[\lambda(\text{Dist}) \mid \mathcal{D}_t\right] - \mathbb{E}\left[\lambda(\text{Dist}) \mid \mathcal{D}_c\right]}_{\text{Difference in Trends}}.$$

Identification

Decomposition of Ring Method

(ii) More, if d_c satisfies Local Parallel Trends (or Average Parallel Trends), then

$$\mathbb{E}\left[\hat{\beta}_1\right] = \underbrace{\mathbb{E}\left[\tau(\text{Dist}) \mid \mathcal{D}_t\right] - \mathbb{E}\left[\tau(\text{Dist}) \mid \mathcal{D}_c\right]}_{\text{Difference in Treatment Effects}}.$$

Identification

Decomposition of Ring Method

(iii) If d_c satisfies Local Parallel Trends(or Average Parallel Trends) and d_t is the correct distance cutoff, then

$$\mathbb{E}\left[\hat{\beta}_1\right] = \bar{\tau}.$$

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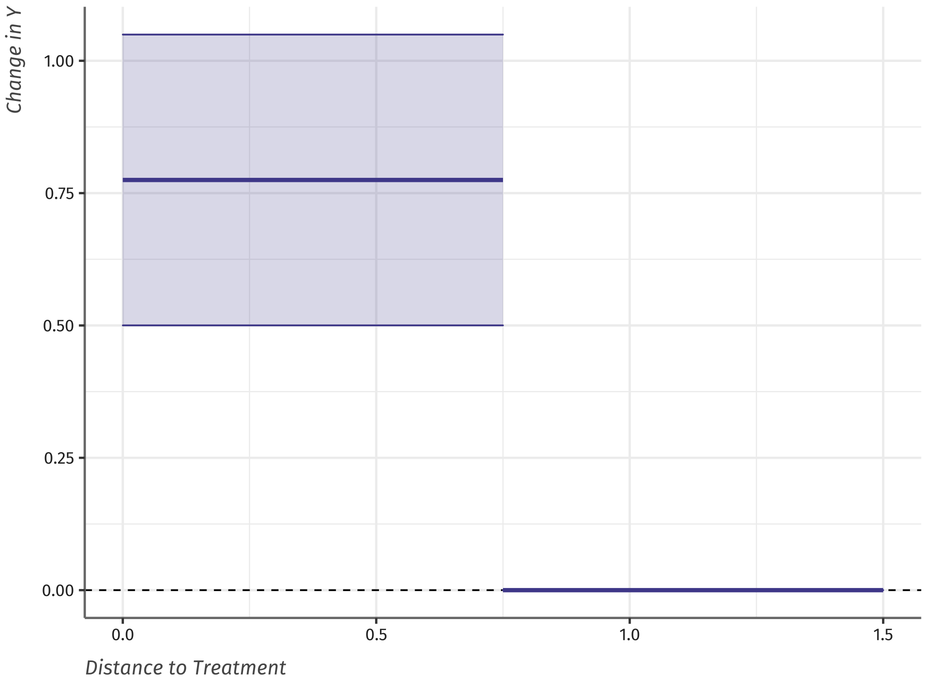
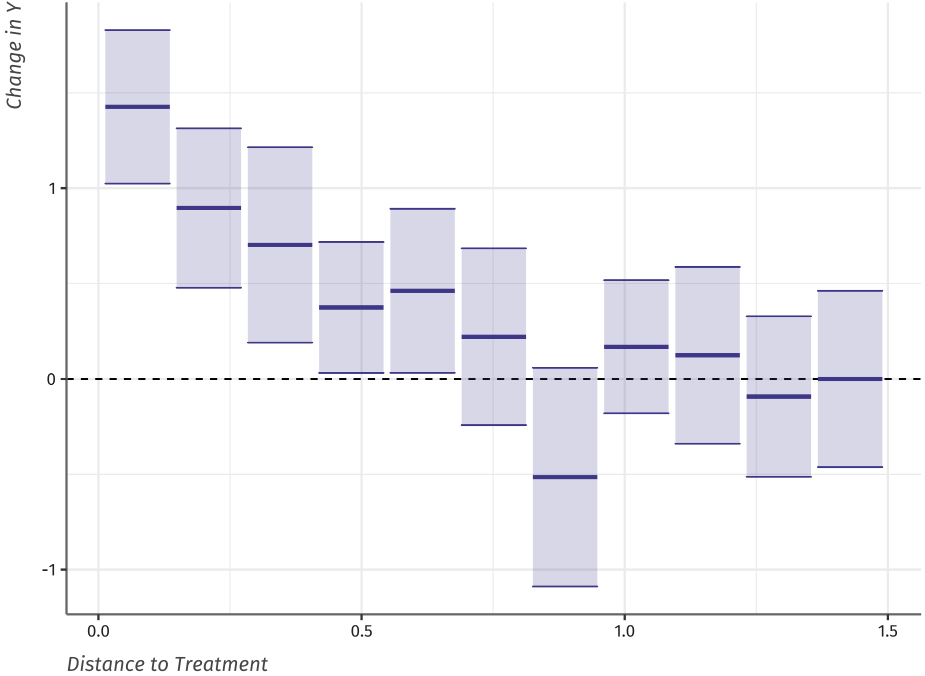
Difficulties with Assumptions

In most cases, it is hard for a researcher to know ad-hoc what the correct d_t is to satisfy the correct cutoff assumption.

There is a *data-driven* way to estimate treatment effect curve, $\tau(\text{Dist})$ without specifying d_t.

- The method uses a non-parametric partition-based estimator proposed by Cattaneo, Farrell, and Feng (2019) .


Change in Y
1.00
0.75
0.50
0.25
0.00
0.0
0.5
1.0
1.5
Distance to Treatment


Change in Y
1
0
-1
0.0
0.5
1.0
1.5
Distance to Treatment

Improved Estimator

Advantages

1. Estimates a treatment effect curve rather than an average effect
   - E.g. bus stop is built. Negative effects very close, positive effects slightly further away. Average effect ≈ 0.
2. Gives an informal visual test of Local Parallel Trends
   - Curve should level off around zero

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   - Curve should level off around zero

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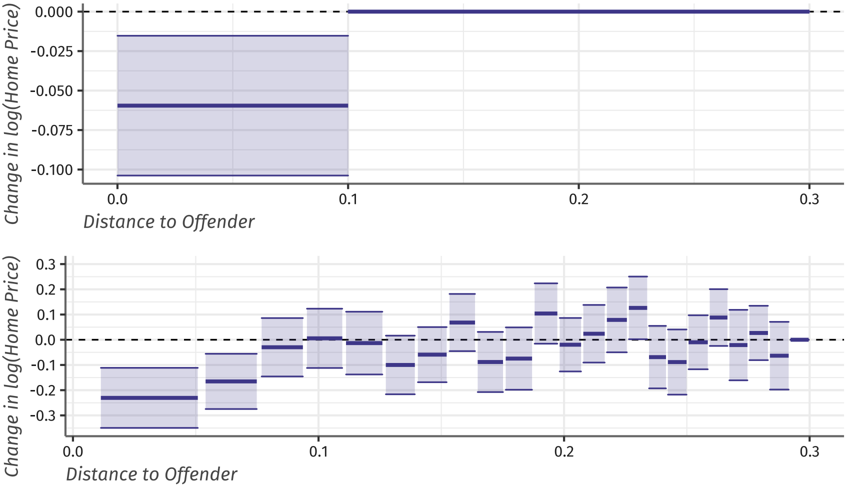
Application

Linden and Rockoff (2008)

Linden and Rockoff (2008) look at the local effects on home prices of a registered sex offender moving into the neighborhood.

- They compare homes within 0.1 miles of the offender's home to control units between 0.1 mile and 0.3 miles.
  Is 0.1 mile the correct cutoff?
- They assume that treatment effect is constant for being on the same block and being a few blocks away.
  Is this a assumption correct?

Figure: Effects of Offender Arrival on Home Prices (Linden and Rockoff, 2008)



Conclusion

The standard “indicator” version of the rings method requires knowledge of the treatment effect cutoff.

I proposed an estimator that:

1. Relaxes this assumption
2. Allows estimation of the treatment effect curve instead of average effect

Thank you!

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