# Treatment Effect Estimation with Geocoded Microdata

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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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# 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 unobservable 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) .

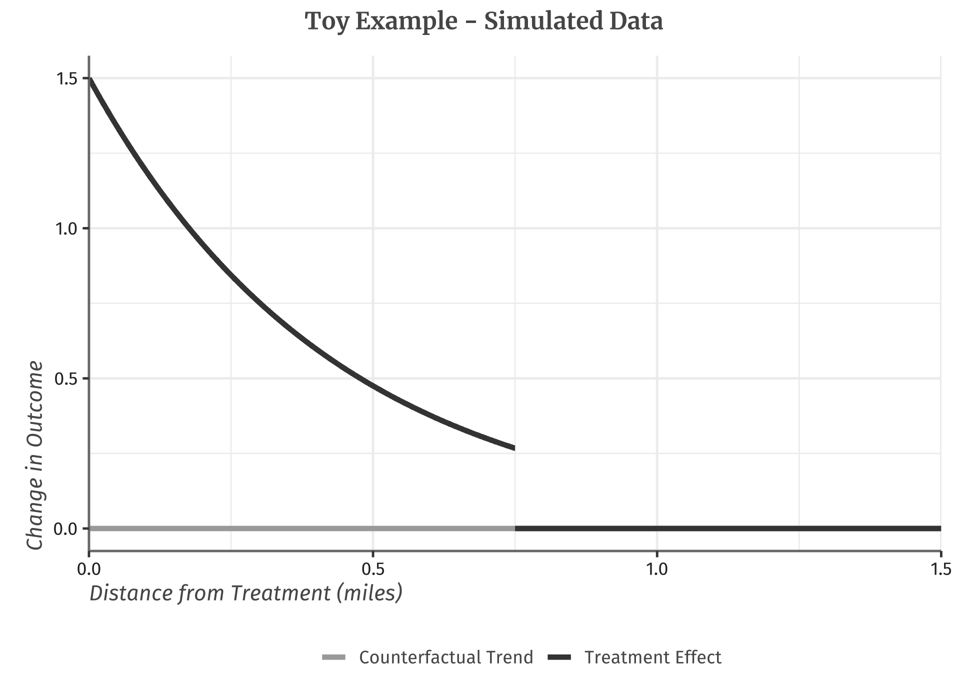
# Outline

Example of Problems

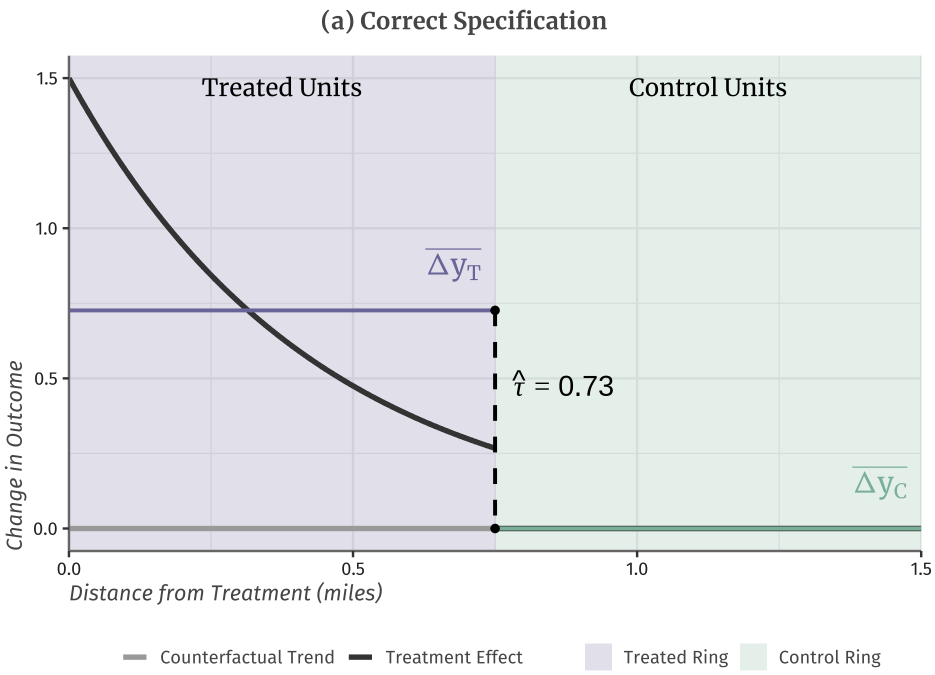
Theory

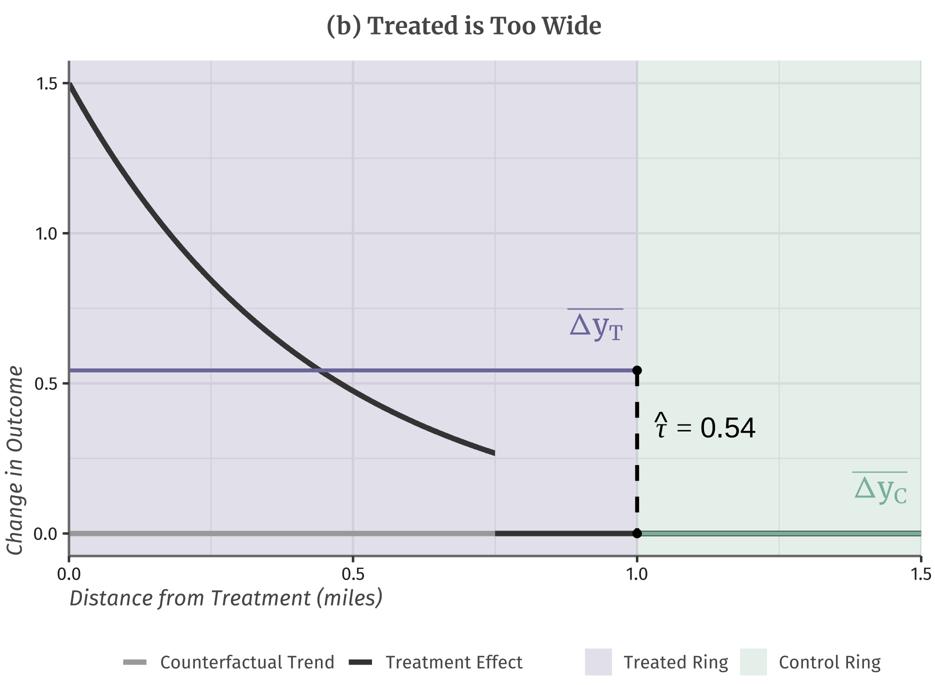
Improved Estimator

Application

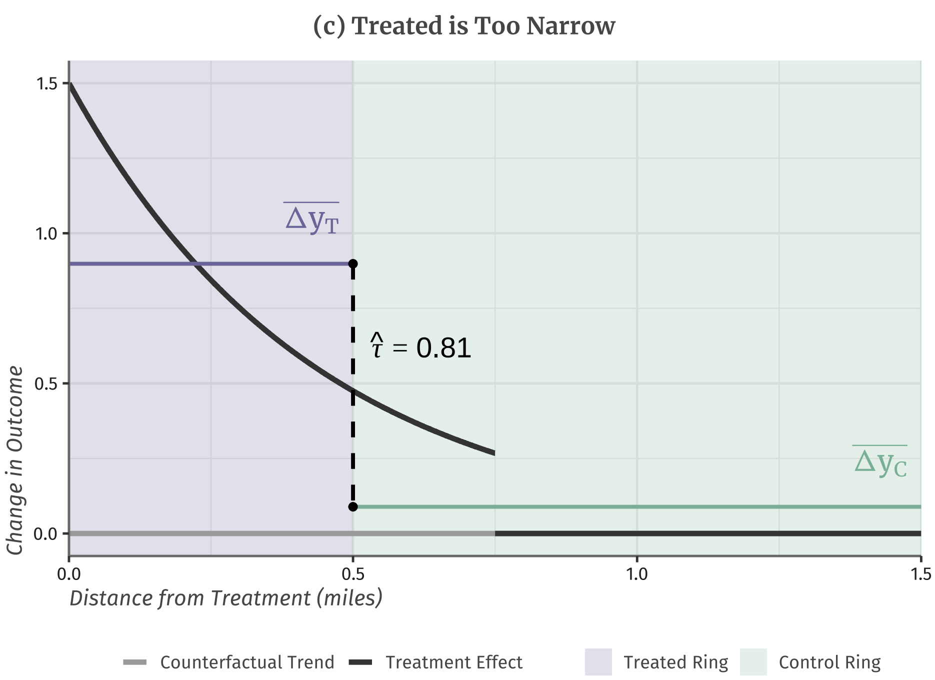


Toy Example - Simulated Data
Change in Outcome
1.5
1.0
0.5
0.0
0.0
0.5
1.0
1.5
Distance from Treatment (miles)
Counterfactual Trend
Treatment Effect

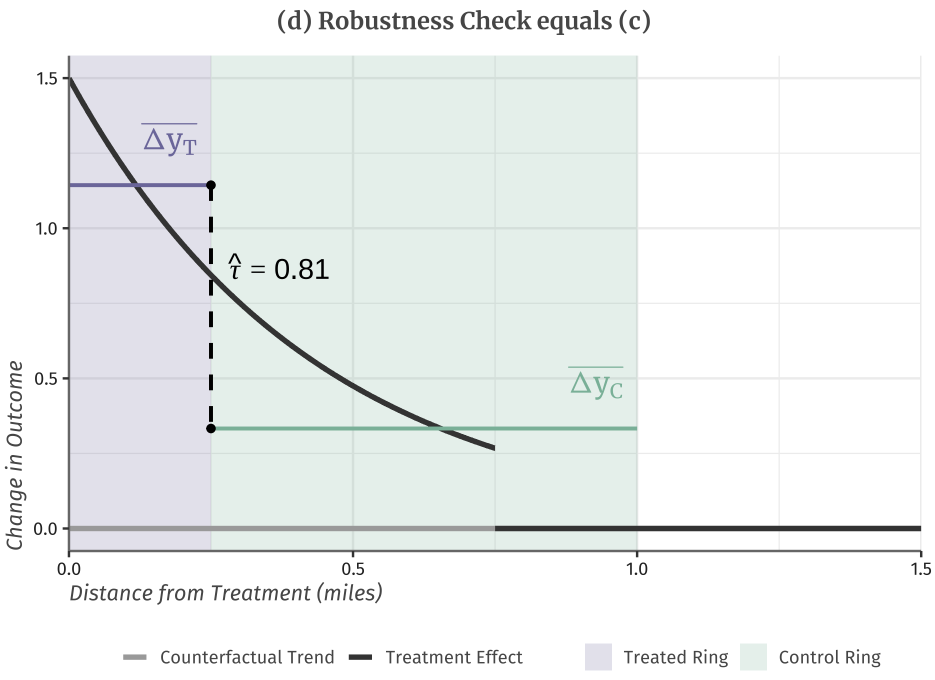

(a) Correct Specification
Treated Units
Control Units
$\overline{\Delta y_T}$
$\hat{\tau}$ = 0.73
$\overline{\Delta y_C}$
1.5
1.0
0.5
0.0
Change in Outcome
0.0
0.5
1.0
1.5
Distance from Treatment (miles)
Counterfactual Trend
Treatment Effect
Treated Ring
Control Ring



(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
1.0
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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 $\text{Dist}_i$, 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 $\lambda$ 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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**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 $d > d_t$, $\tau(d) = 0$.

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- 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 $\beta_1$ 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

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

# Outline

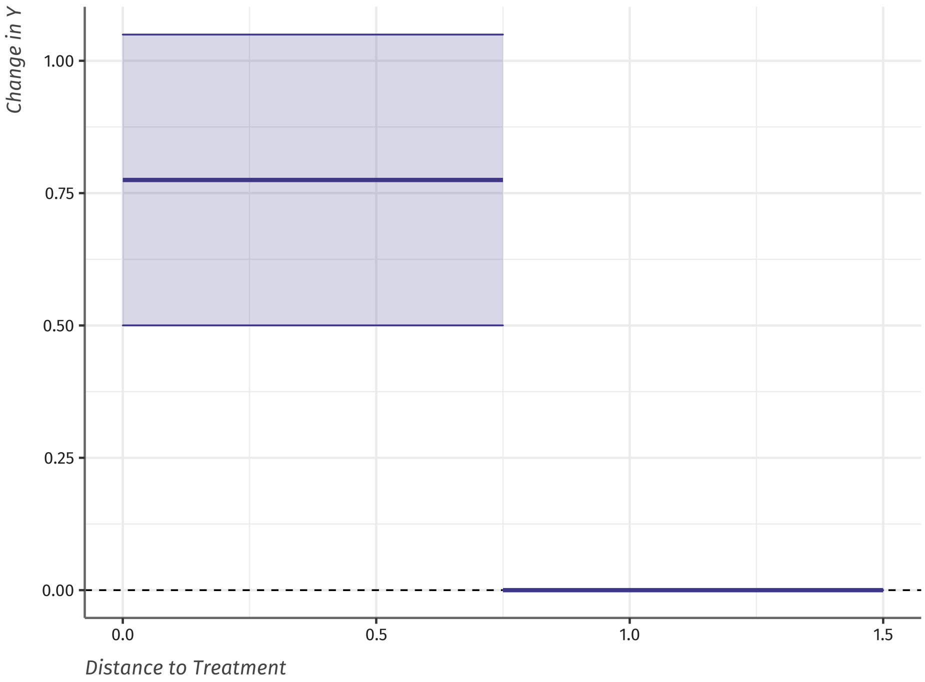
# Improved Estimator

*Difficulties with Assumptions*

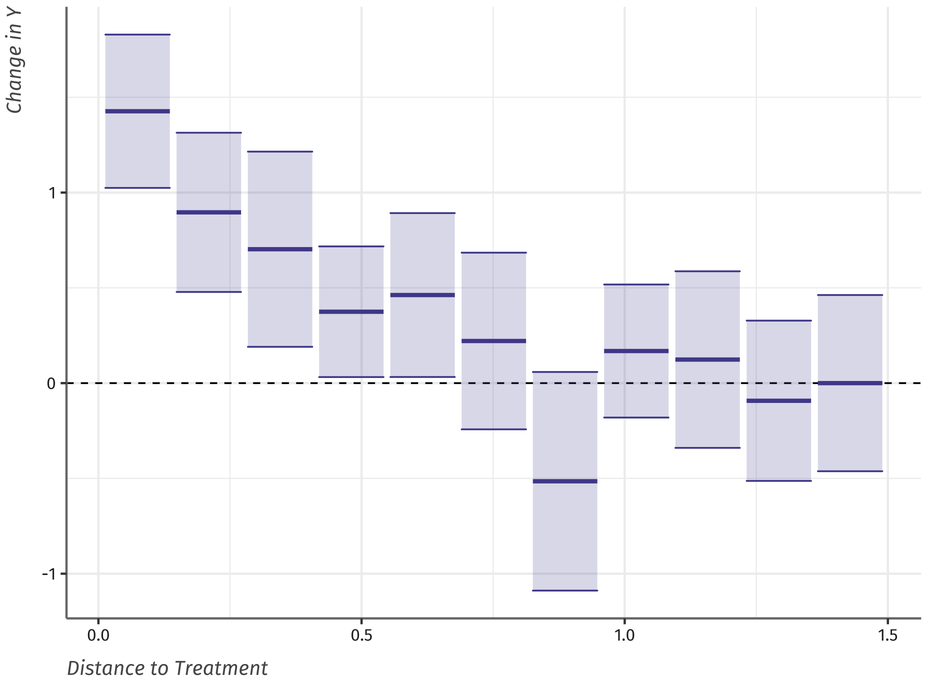
In most cases, it is hard for a researcher to know ad-hoc what the correct $d_t$ is to satisfy the correct cutoff assumption.

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 $\approx 0$.
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

# Outline

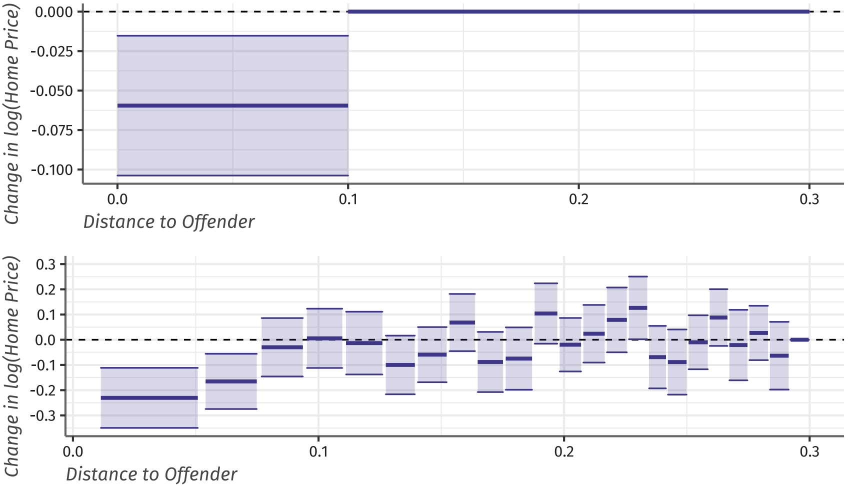
# Application

*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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