Difference-in-Differences with Spatial Spillovers

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Spatial Spillovers

Researchers aim to estimate the **average treatment effect on the treated**:

$$\tau \equiv \mathbb{E}\left[Y_{i1}(1) - Y_{i1}(0) \mid D_i = 1\right]$$

Estimation is complicated by **Spillover Effects**

Spillover effects occur when the effect of treatment extends over the treatment boundaries (states, counties, etc.). Example: Amazon Shipping Center

- A shipping center opening in county *c* has positive employment effects on **nearby control counties**
- Having nearby counties with shipping centers raises employment and therefore reduces the effect of **treated counties** through general equilibrium effects

This Paper

In this paper, I...

- Present a potential outcomes framework to formalize spillover effects and evaluate ad-hoc adjustments commonly found in the literature
- Propose an estimation strategy that improves on current practices by being more robust to spillovers
- Apply this framework to improve estimation of the local effect of place-based policies in Urban Economics

Bias from Spatial Spillovers

The canonical difference-in-differences estimate is:

$$\hat{\tau} = \underbrace{\hat{\mathbb{E}}\left[Y_{i1} - Y_{i0} \mid D_i = 1\right]}_{\text{Counterfactual Trend } + \tau} - \underbrace{\hat{\mathbb{E}}\left[Y_{i1} - Y_{i0} \mid D_i = 0\right]}_{\text{Counterfactual Trend}}$$

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Two problems occur in the presence of spillover effects:

- **Spillover onto Control Units:**
  Nearby "control" units fail to estimate counterfactual trends because they are affected by treatment
- **Spillover onto other Treated Units:**
  Treated units are also affected by nearby units and therefore combine "direct" effects

Remove Bias

$$y_{it} = \mu_t + \mu_i + \tau D_{it} + \varepsilon_{it}$$

$$\mathbb{E}[\hat{\tau}] = \tau + \text{Spillover on Control} + \text{Spillover on Treated}$$

Remove Bias

$$y_{it} = \mu_t + \mu_i + \tau D_{it} + \tau_{\text{spill,control}} \text{Within}_{it} * (1 - D_{it}) + \tau_{\text{spill,treat}} \text{Within}_{it} * D_{it} + +\varepsilon_{it}$$

$$\mathbb{E}[\hat{\tau}] = \tau,$$

so long as Within_{it} contains all the units with spillovers.

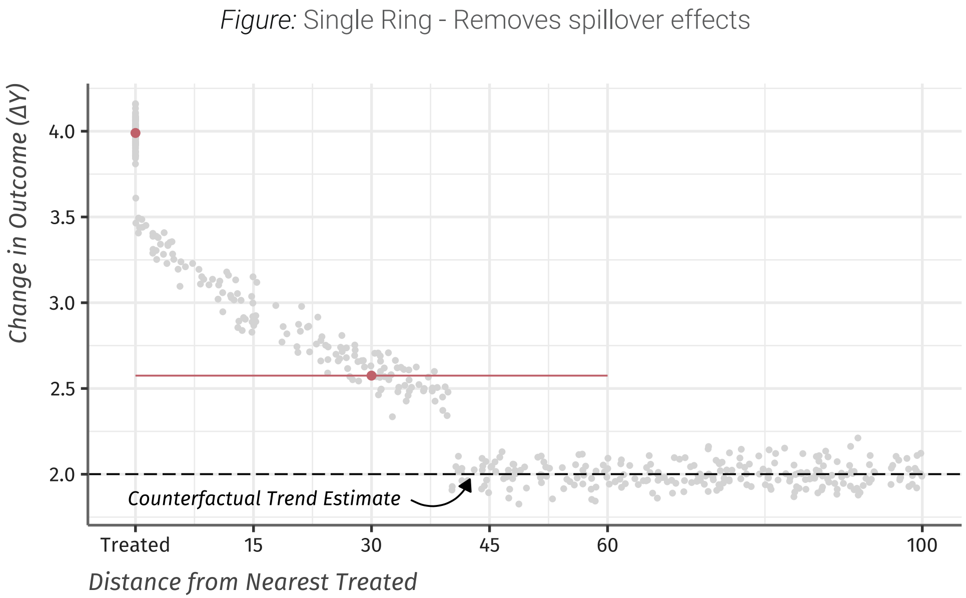
Figure: Single Ring - Removes spillover effects
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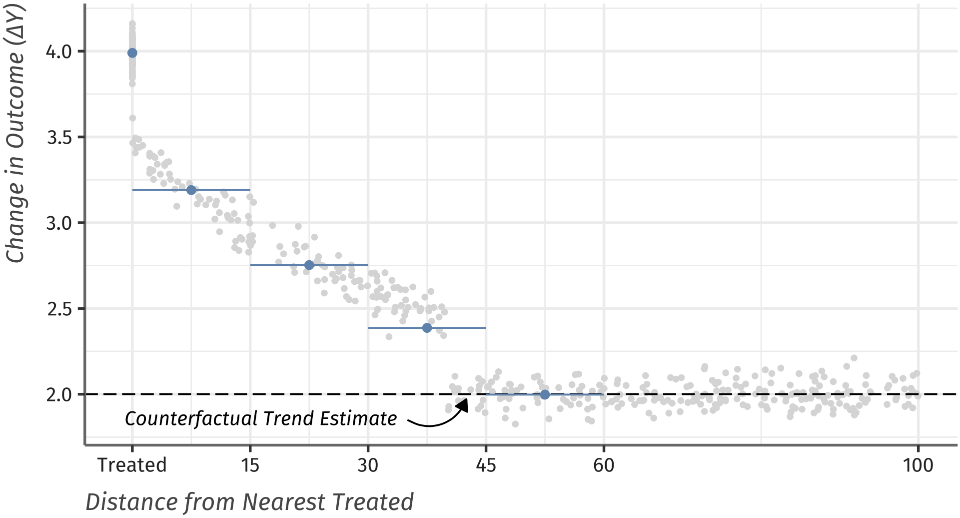
Figure: Multiple Rings - Improves estimation of spillover effects



Outline

1– Formalize spillovers into a potential outcomes framework:

[Clarke (2017), Berg and Streitz (2019), and Verbitsky-Savitz and Raudenbush (2012)]

- I decompose the difference-in-differences estimator into three parts: Direct Effect of Treatment, Spillover onto Treated Units, Spillover onto Control Units
- Show that an indicator for being close to treated units remove *all bias* so long as the indicator contains all units affected by spillovers
- 'Rings' are able to estimate spillover effects while still removing all bias

Outline

2– Apply framework to Urban Economics

- Revisit Kline and Moretti (2014a) analysis of the Tennessee Valley Authority
  - The local effect estimate is contaminated by spillover effects to neighboring counties (Kline and Moretti, 2014b)
  - Large scale manufacturing investment creates an 'urban shadow' (Cuberes, Desmet, and Rappaport, 2021; Fujita, Krugman, and Venables, 2001)
- Discuss how framework can reconcile conflicting findings on effect of federal Empowerment Zones (Busso, Gregory, and Kline, 2013; Neumark and Kolko, 2010)
- Event Study estimates of Community Health Centers find highly localized efffects (Bailey and Goodman-Bacon, 2015)

Outline

Theory

Estimation of Spillovers

Application in Urban Economics

Event Study

Conclusion

Potential Outcomes Framework

For exposition, I will label units as counties. Assume all treatment occurs at the same time (2-periods or pre-post averages).[1]

- $Y_{it}(D_i, h(\vec{D}, i))$ is the potential outcome of county $i \in \{1, \dots, N\}$ at time t with treatment status $D_i \in \{0, 1\}$.
- $\vec{D} \in \{0, 1\}^N$ is the vector of all units treatments.
- The function $h(\vec{D}, i)$ maps the entire treatment vector into an 'exposure mapping' which can be a scalar or a vector.
- No exposure is when $h(\vec{D}, i) = \vec{0}$.

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Examples of $h_i(\vec{D})$

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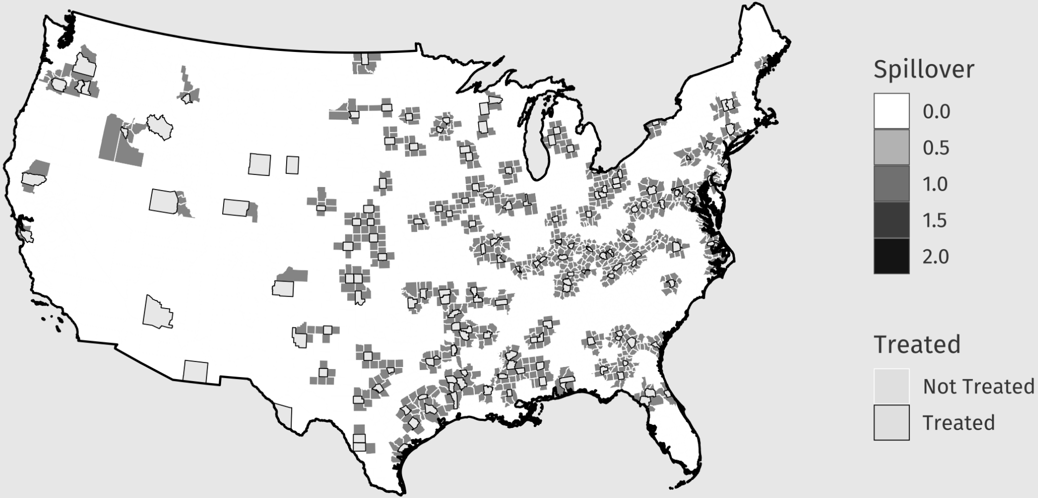
- **Treatment within x miles:**

  $h(\vec{D}, i) = max_j \, 1\left(d(i,j) \leq x\right)$ where $d(i,j)$ is the distance between counties i and j.

  - e.g. library access where x is the maximum distance people will travel
  - Spillovers are non-additive, i.e. spillover effects do not depend on number of nearby treated areas

Within 40mi.



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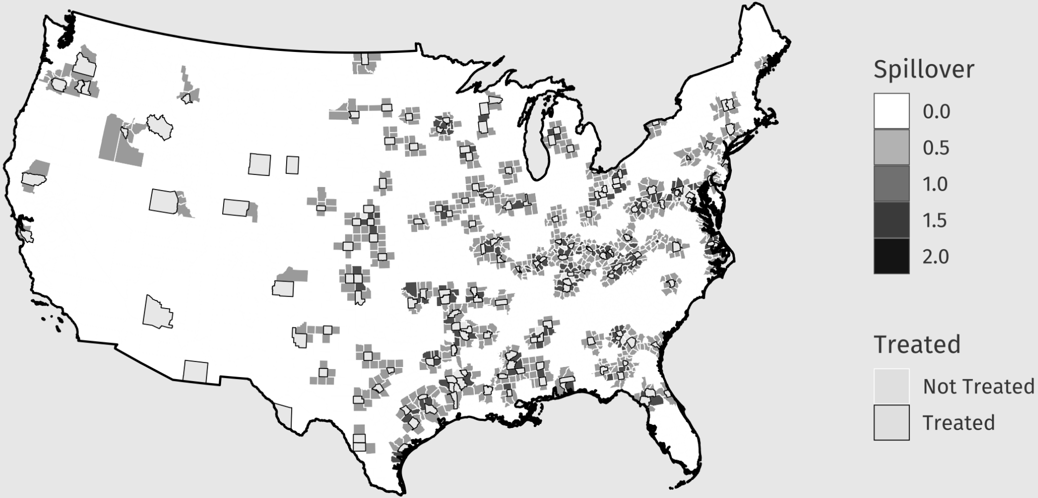
- **Number of Treated within x miles:**

  $h(\vec{D}, i) = \sum_{j=1}^{k} 1(d(i,j) \leq x)$.

  - e.g. Amazon shipping center
  - Agglomeration economies suggest spillovers are additive

Within 40mi. (Additive)



Estimand of Interest

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$$\tau_{\text{direct}} \equiv \mathbb{E}\left[Y_{i,1}(1,0) - Y_{i,1}(0,0) \mid D_i = 1\right]$$

Spillover Effects:

$$\tau_{\text{spillover, treated}} \equiv \mathbb{E}\left[Y_{i1}(1, h_i(\vec{D})) - Y_{i1}(1,0) \mid D_i = 1\right]$$

$$\tau_{\text{spillover, control}} \equiv \mathbb{E}\left[Y_{i1}(0, h_i(\vec{D})) - Y_{i1}(0,0) \mid D_i = 0\right]$$

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Parallel Trends

I assume a modified version of the parallel counterfactual trends assumption:

Assumption: *Parallel Counterfactual Trends*

$$\mathbb{E}\big[\underbrace{Y_{i,1}(0,\vec{0}) - Y_{i,0}(0,\vec{0})}_{\text{Counterfactual Trend}} \mid D_i = 1\big] = \mathbb{E}\big[\underbrace{Y_{i,1}(0,\vec{0}) - Y_{i,0}(0,\vec{0})}_{\text{Counterfactual Trend}} \mid D_i = 0\big]$$

In the *complete absence of treatment* (not just the absence of individual i's treatment): Changes in outcomes do not depend on treatment status

What does Difference-in-Differences identify?

With the parallel trends assumption and random assignment of D_i, I decompose the difference-in-differences estimate as follows:

$$\mathbb{E}\left[\hat{\tau}\right] = \underbrace{\mathbb{E}\left[Y_{i1} - Y_{i0} \mid D_i = 1\right] - \mathbb{E}\left[Y_{i1} - Y_{i0} \mid D_i = 0\right]}_{\text{Difference-in-Differences}}$$

$$= \mathbb{E}\left[Y_{i1}(1,0) - Y_{i1}(0,0) \mid D_i = 1\right]$$

$$+ \quad \mathbb{E}\left[Y_{i1}(1, h_i(\vec{D})) - Y_{i1}(1,0) \mid D_i = 1\right]$$

$$- \quad \mathbb{E}\left[Y_{i1}(0, h_i(\vec{D})) - Y_{i1}(0,0) \mid D_i = 0\right]$$

$$= \tau_{\text{direct}} + \tau_{\text{spillover, treated}} - \tau_{\text{spillover, control}}$$

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$$\begin{aligned} &= \mathbb{E}[Y_{i1}(1,0) - Y_{i1}(0,0) \mid D_i = 1] \\ &\quad + \quad \mathbb{E}\left[Y_{i1}(1, h_i(\vec{D})) - Y_{i1}(1,0) \mid D_i = 1\right] \\ &\quad - \quad \mathbb{E}\left[Y_{i1}(0, h_i(\vec{D})) - Y_{i1}(0,0) \mid D_i = 0\right] \end{aligned}$$

$$= \tau_{\text{direct}} + \tau_{\text{spillover, treated}} - \tau_{\text{spillover, control}}$$

Removing Bias

Assumption: *Spillovers are Local*

Let $d(i, j)$ be the distance between units i and j. There exists a distance $\bar{d}$ such that

(i) For all units i,

$$\min_{j:D_j=1} d(i, j) > \bar{d} \implies h(\vec{D}, i) = \vec{0}.$$

(ii) There are treated and control units such that $\min_{j:\ D_j=1} d(i, j) > \bar{d}$.

Removing Bias

With assumption that spillovers are local, define S_it to be an indicator equal to one in the post period for all units with $h(\vec{D}, i) \neq \vec{0}$ (and potentially some units with $= \vec{0}$).

Estimation of the following equation:

$$y_{it} = \mu_t + \mu_i + \tau D_{it} + \tau_{\text{spill,treat}} S_{it} * D_{it} + \tau_{\text{spill,control}} S_{it} * (1 - D_{it}) + \varepsilon_{it}$$

- $\hat{\tau}$ is consistent for τ_{direct}
- $\hat{\tau}_{\text{spill}}$'s are not consistent for average spillover effects (hence the need for rings).

Aside – Removing “contaminated” controls

A common solution to the problem of spillover is to re-estimate on a subsample with neighboring control units removed.

This is not recommended for two reasons:

- Removing control units from the sample decreases precision of the estimates
- Spillover effects on treated units will still remain in the estimand.

Outline

- Theory
- Estimation of Spillovers
- Application in Urban Economics
- Event Study
- Conclusion

Robustness to Misspecification

Generate data using the following data-generating process with different exposure mappings:

$$y = \mu_t + \mu_i + 2D_{it} + \beta_{\text{spill,control}} * (1 - D_{it}) h(\vec{D}, i) + \varepsilon_{it}$$

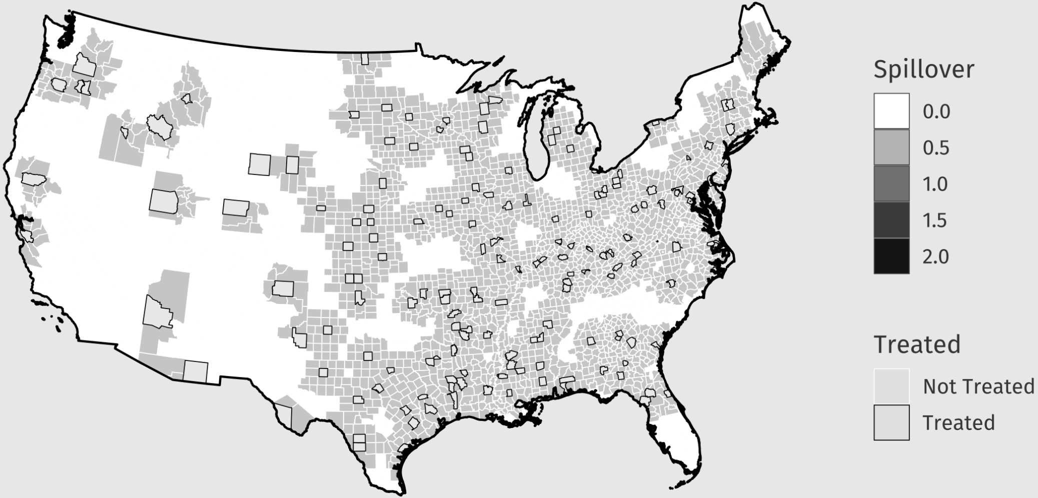
- Observation i is a U.S. county, year $t \in \{2000, \ldots, 2019\}$, treatment D_{it} turns on in 2010 and is assigned randomly.
- Details in the paper, but μ_t is normally distributed on a linear time trend, μ_i are normally distributed

Then, I estimate each data-generating process using (potentially) misspecified $\tilde{h}(\vec{D}, i)$ and report the average estimate bias.

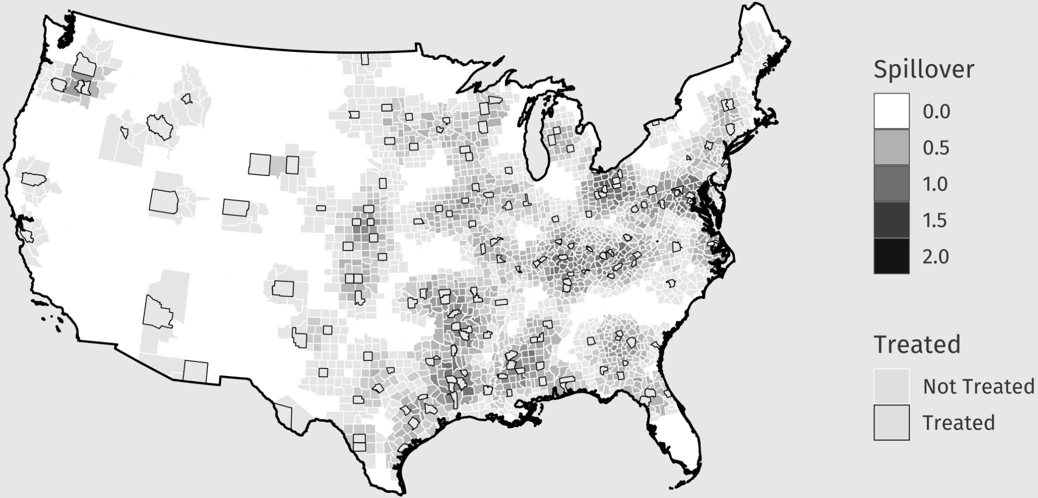
Specifications of $h(\vec{D}, i)$

- *Within* $40/80$*mi.*:
  - Indicator for nearest treated unit being within $40/80$ miles.
- *Within* $40/80$*mi. (Additive)*:
  - Number of treated units being within $40/80$ miles.

Within 80mi.



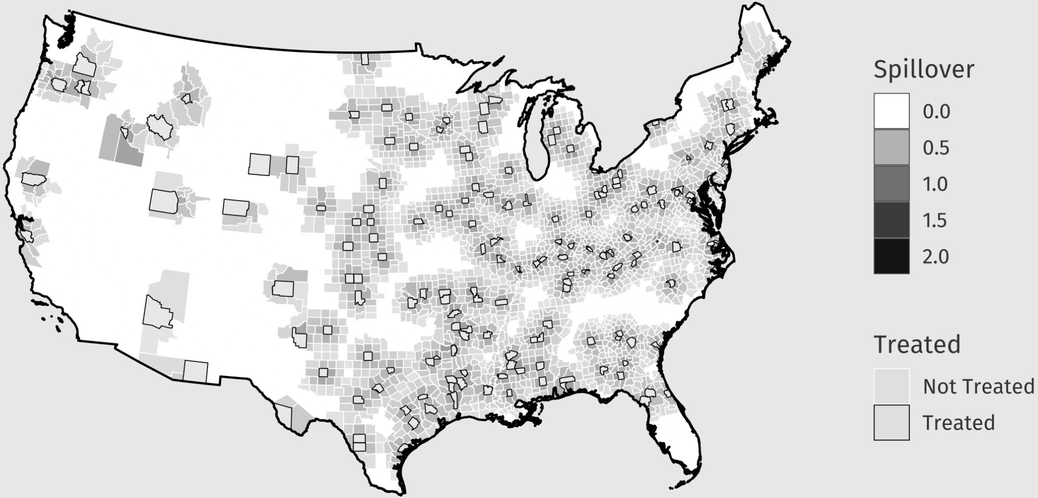
Within 80mi. (Additive)



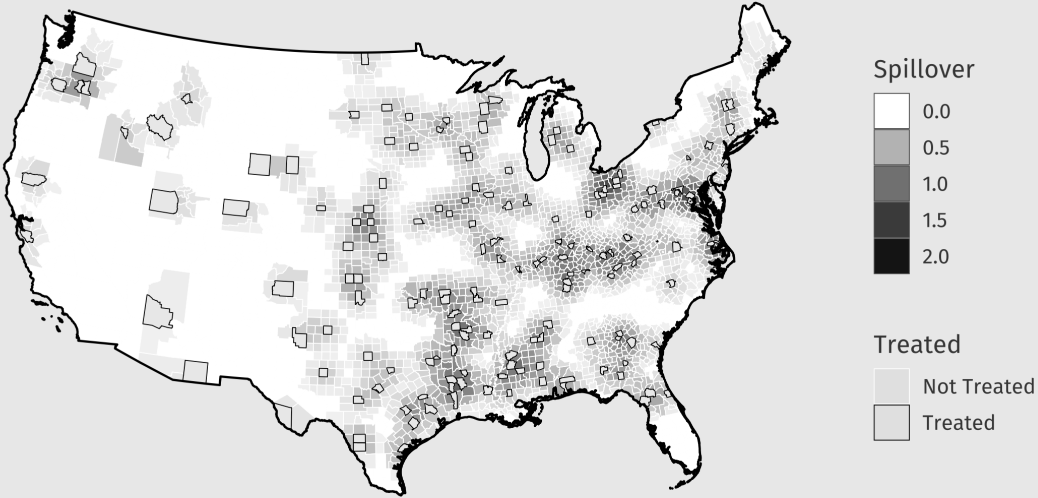
Specifications of $h(\vec{D}, i)$

- *Decay*:
  - $\max_j D_j * e^{-0.02d(i,j)} * 1(d(i,j) < 80)$
- *Decay (Additive)*:
  - $\sum_j D_j * e^{-0.02d(i,j)} * 1(d(i,j) < 80)$

Decay



Decay (Additive)



Specifications of $h(\vec{D}, i)$

- *Rings*:
  - Set of concentric rings. For each ring, indicator for nearest treated unit being within that distance bin
- *Rings (Additive)*:
  - Set of concentric rings. For each ring, number of treated units being within that distance bin

Rings (0-20, 20-30, 30-40, 40-60, 60-80)

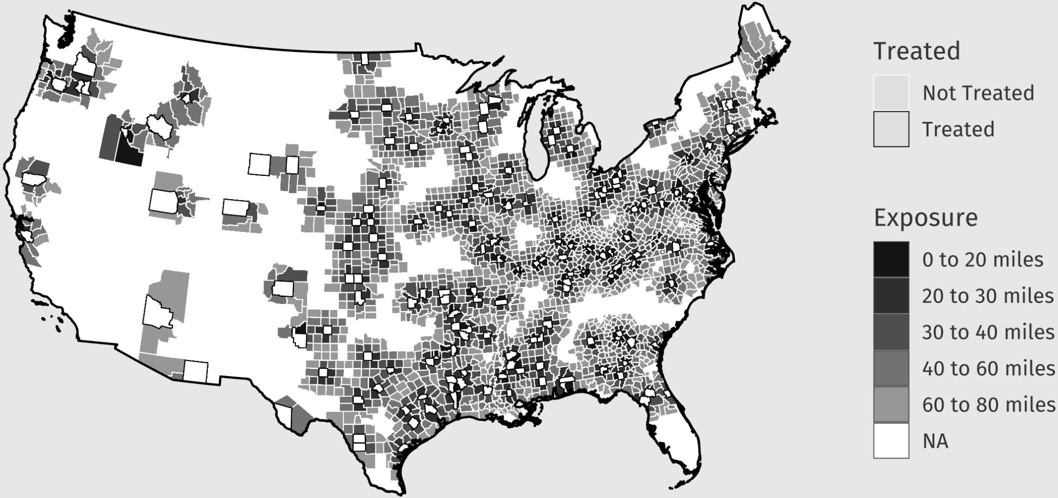


Table: Bias from Misspecification of Spillovers

	Data-Generating Process					
Specification	**Within 40mi.**	**Within 80mi.**	**Within 40mi. (Additive)**	**Within 80mi. (Additive)**	**Decay 80mi.**	**Decay 80mi. (Additive)**
TWFE (No Spillovers)	0.258	0.258	0.258	0.258	0.258	0.258
Within 40mi.	−0.005	0.213	−0.005	0.176	0.159	0.143
Within 80mi.	−0.009	−0.009	−0.009	−0.009	−0.009	−0.009
Within 40mi. (Additive)	0.043	0.221	−0.006	0.177	0.174	0.143
Within 80mi. (Additive)	0.034	0.134	−0.012	−0.009	0.099	−0.010
Decay 80mi.	−0.159	0.070	−0.174	0.014	−0.009	−0.033
Decay 80mi. (Additive)	−0.023	0.148	−0.084	0.019	0.088	−0.008
Rings (0-20, 20-30, 30-40)	−0.005	0.213	−0.005	0.176	0.159	0.143
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Rings (0-20, 20-30, 30-40, 40-60, 60-80) (Additive)	0.036	0.134	−0.008	−0.008	0.100	−0.009

Indicator (or set of rings) that captures *all* affected unit removes all bias

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Spillovers as Estimand of Interest

Until now, we assumed our estimand of interest is τ_{direct}.

However, the two other spillover effects are of interest as well:

- $\tau_{\text{spillover, control}}$: Do the benefits of a treated county come at a cost to neighbor counties?
- $\tau_{\text{spillover, treated}}$: Does the estimated effect change based on treatment of neighbors?

To estimate the spillover effects, we have to parameterize $h(\vec{D}, i)$ function and the potential outcomes function $Y_i(D_i, h(\vec{D}, i))$.

Estimation of Spillover Effects

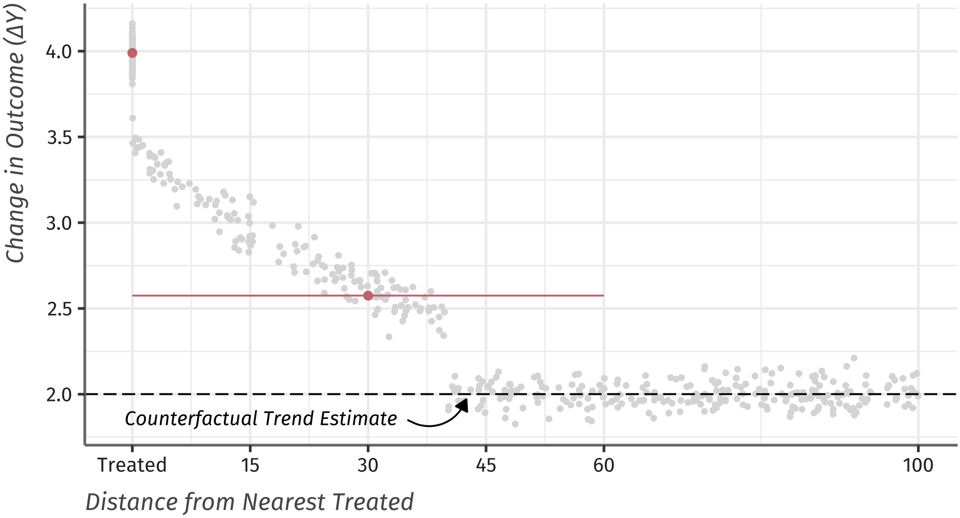
To see which specifications can predict spillover effects well, I estimate the spillover effects for each control unit, $\hat{\beta}_{\text{spill, control}} * \tilde{h}(\vec{D}, i)$.

Then calculate

$$1 - \frac{\overbrace{\sum_{i:D_i=0} (\beta_{\text{spill, control}} h(\vec{D}, i) - \hat{\beta}_{\text{spill, control}} \tilde{h}(\vec{D}, i))^2}^{\text{Mean Square Prediction Error}}}{\underbrace{\sum_{i:D_i=0} (\beta_{\text{spill, control}} h(\vec{D}, i))^2}_{\text{Normalization}}}$$

This gives the proportion of spillovers explained by $\tilde{h}(\vec{D}, i)$

Figure: Single Ring - Removes spillover effects



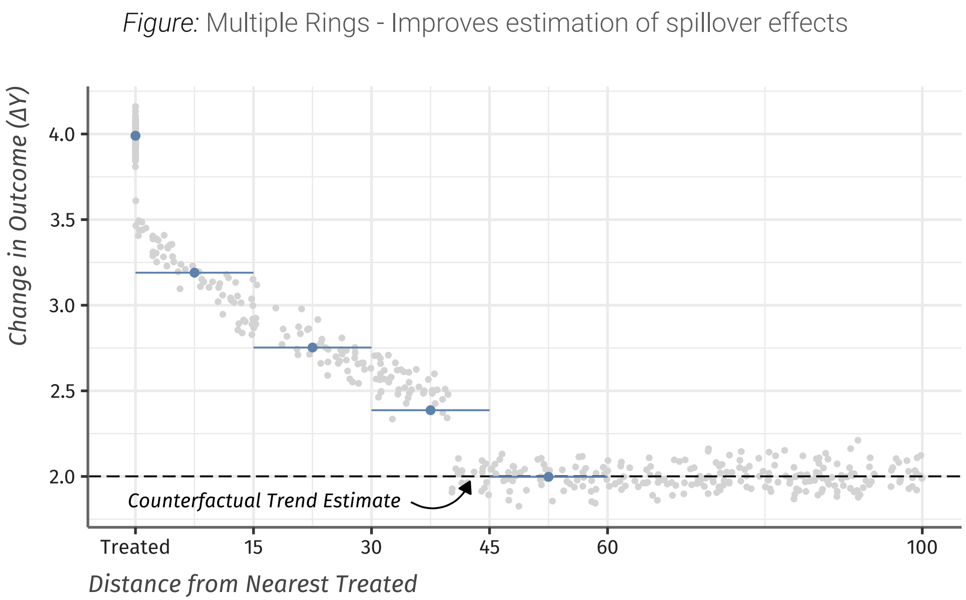


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Table: Percent of Spillovers Predicted by Specification

Specification	Within 40mi.	Within 80mi.	Within 40mi. (Additive)	Within 80mi. (Additive)	Decay 80mi.	Decay 80mi. (Additive)
	Data-Generating Process					
TWFE (No Spillovers)	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Within 40mi.	99.4%	25.9%	85.6%	38.8%	59.5%	56.1%
Within 80mi.	39.8%	96.2%	34.3%	71.7%	85.6%	68.0%
Within 40mi. (Additive)	85.3%	21.2%	99.5%	40.6%	52.0%	60.7%
Within 80mi. (Additive)	45.8%	61.8%	47.2%	98.4%	71.0%	93.6%
Decay 80mi.	60.1%	82.5%	52.7%	75.8%	97.5%	82.2%
Decay 80mi. (Additive)	60.7%	56.9%	63.8%	93.5%	79.0%	98.7%
Rings (0-20, 20-30, 30-40)	98.4%	23.7%	85.9%	37.5%	58.9%	56.2%
Rings (0-20, 20-30, 30-40, 40-60, 60-80)	96.6%	91.7%	84.2%	72.7%	91.9%	78.4%
Rings (0-20, 20-30, 30-40, 40-60, 60-80) (Additive)	83.5%	57.4%	97.6%	95.0%	73.5%	94.9%

Donuts perform best at estimating spillover effects.

It is important to get Additive vs. Non-Additive correct.

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Within 80mi.	39.8%	96.2%	34.3%	71.7%	85.6%	68.0%
Within 40mi. (Additive)	85.3%	21.2%	99.5%	40.6%	52.0%	60.7%
Within 80mi. (Additive)	45.8%	61.8%	47.2%	98.4%	71.0%	93.6%
Decay 80mi.	60.1%	82.5%	52.7%	75.8%	97.5%	82.2%
Decay 80mi. (Additive)	60.7%	56.9%	63.8%	93.5%	79.0%	98.7%
Rings (0-20, 20-30, 30-40)	98.4%	23.7%	85.9%	37.5%	58.9%	56.2%
Rings (0-20, 20-30, 30-40, 40-60, 60-80)	96.6%	91.7%	84.2%	72.7%	91.9%	78.4%
Rings (0-20, 20-30, 30-40, 40-60, 60-80) (Additive)	83.5%	57.4%	97.6%	95.0%	73.5%	94.9%

Donuts perform best at estimating spillover effects.

It is important to get Additive vs. Non-Additive correct.

Table: Percent of Spillovers Predicted by Specification

Specification	Within 40mi.	Within 80mi.	Within 40mi. (Additive)	Within 80mi. (Additive)	Decay 80mi.	Decay 80mi. (Additive)
	Data-Generating Process					
TWFE (No Spillovers)	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Within 40mi.	99.4%	25.9%	85.6%	38.8%	59.5%	56.1%
Within 80mi.	39.8%	96.2%	34.3%	71.7%	85.6%	68.0%
Within 40mi. (Additive)	85.3%	21.2%	99.5%	40.6%	52.0%	60.7%
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Tennessee Valley Authority

Kline and Moretti (2014a) look at the long-run impacts of the Tennessee Valley Authority (TVA).

- The TVA was a large-scale federal investment started in 1934 that focused on improving manufacturing economy. (Hundreds of dollars spent anually per person)
- The program focused on large-scale dam construction that brought cheap wholesale electricity to the region

Research Questions:

- What are the local effects of TVA on manufacturing and agricultural economies?
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Identification

Kline and Moretti (2014a) run the county-level difference-in-differences specification:

$$y_{c,2000} - y_{c,1940} = \alpha + \text{TVA}_c \tau + X_{c,1940}\beta + (\varepsilon_{c,2000} - \varepsilon_{c,1940}) \quad (1)$$

- y are outcomes for agricultural employment and manufacturing employment.
- TVA_c is the treatment variable
- $X_{c,1940}$ allow for different long-term trends based on covariates in 1940.

They trim the sample using a logit regression to predict treatment using $X_{c,1940}$ and then keep control units in the top 75% of predicted probability.

Spillovers in the TVA Context

In our context, there is reason to believe spillovers can occur to nearby counties

- **Agriculture:**
  - Employees might be drawn to hire wages for new manufacturing jobs in Tennessee Valley (negative spillover on control units)
- **Manufacturing:**
  - Cheap electricity might be available to nearby counties (positive spillover on control units)
  - Manufacturing jobs that would have been created in the control units in the absence of treatment might move to the Tennessee Valley (negative spillover on control units)

Specification including spillovers

$$\Delta y_c = \alpha + \text{TVA}_i \tau + \sum_{d \in \text{Dist}} \text{Ring}(d)\delta_d + X_{i,1940}\beta + \Delta\varepsilon_c \quad (2)$$

- Ring(d) is a set of indicators for being in the following distance bins (in miles) from the Tennessee Valley Authority:

$$d \in \{(0,50], (50,100], (100,150](150,200]\}$$

Effective Sample and Spillover Variables

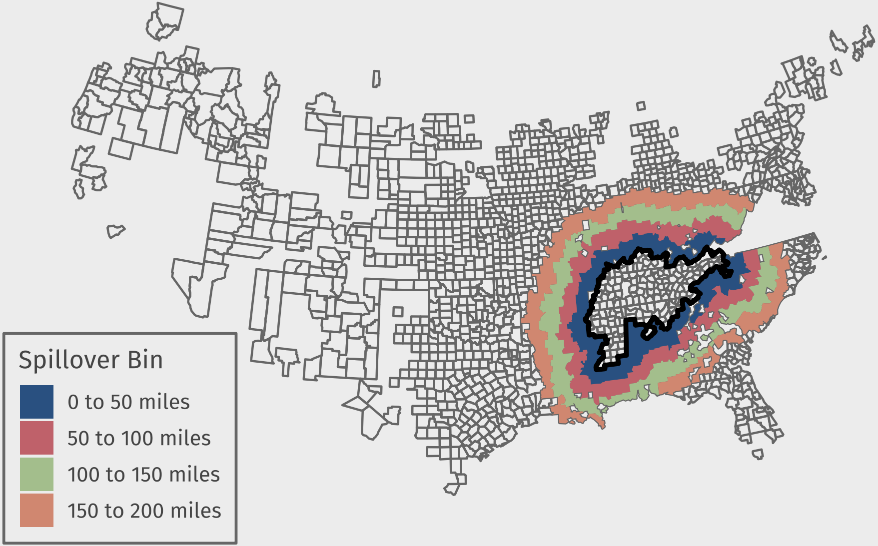

Table: Effects of Tennessee Valley Authority on Decadel Growth, 1940-2000

	Diff-in-Diff	**Diff-in-Diff with Spillovers**				
	TVA	TVA	TVA between 0-50 mi.	TVA between 50-100 mi.	TVA between 100-150 mi.	TVA between 150-200 mi.
Dependent Var.	(1)	(2)	(3)	(4)	(5)	(6)
Agricultural employment	-0.0514^{***}	-0.0739^{***}	-0.0371^{***}	-0.0164	-0.0298^{***}	-0.0157^{*}
	(0.0114)	(0.0142)	(0.0002)	(0.0114)	(0.0096)	(0.0088)
Manufacturing employment	0.0560^{***}	0.0350	-0.0203^{***}	-0.0245	-0.0331^{*}	-0.0296^{**}
	(0.0161)	(0.0218)	(0.0006)	(0.0282)	(0.0189)	(0.0142)

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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Identification Strategies and Place-Based Policies

The literature on federal Enterprise Zones, place-based policy that gives tax breaks to businesses that locate within the boundary, has found conflicting results, suggesting positive or near-zero effects of the program (Neumark and Young, 2019).

Identification Strategies and Place-Based Policies

- Busso, Gregory, and Kline (2013) compare census tracts in Empowerment Zones to census tracts that qualified and were rejected from the program. They find significant large reduction of poverty.
- Neumark and Kolko (2010) compare census tracts in Empowerment Zones to census tracts within 1,000 feet of the Zone. They find near-zero effects on poverty.

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Gardner (2021) Overview

$$y_{it} = \mu_i + \mu_t + \tau D_{it} + \varepsilon_{it}$$

The problem with estimating this by OLS is that the treatment variable becomes residualized $\tilde{D}_{it}$ and this leads to all sorts of problems... (see new diff-in-diff literature)

Gardner (2021) recommends a two-step approach:

1. Estimate μ_i and μ_t using never-treated/not-year-treated observations (D_{it} = 0). Then subtract off $\hat{\mu}_i$ and $\hat{\mu}_t$.
2. Then, regress $y_{it} - \hat{\mu}_i - \hat{\mu}_t \equiv \tilde{y}_{it}$ on τD_{it} (or event study leads/lags). This estimate is unbiased because D_{it} is non-residualized (standard errors require adjusting).

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Controlling for Spillovers in Staggered Treatment Timing

$$y_{it} = \mu_i + \mu_t + \tau D_{it} + \tau_{\text{spill,control}} \text{Within}_{it} * (1 - D_{it}) + \tau_{\text{spill,treat}} \text{Within}_{it} * D_{it} + \varepsilon_{it}$$

Adjust two-step approach:

1. Estimate μ_i and μ_t using observations that aren't yet treated/affected by spillovers ($D_{it} = 0$ and $Within_{it} = 0$). Then subtract off $\hat{\mu}_i$ and $\hat{\mu}_t$.

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Community Health Centers

Bailey and Goodman-Bacon (2015) study the creation of federal community health centers between 1965 and 1974

Research Question: Do low-/no-cost health services lower the mortality rate of the treated counties? *New Question:* Do these effects spread to neighboring counties?

Figure: Effects of Establishment of Community Health Centers

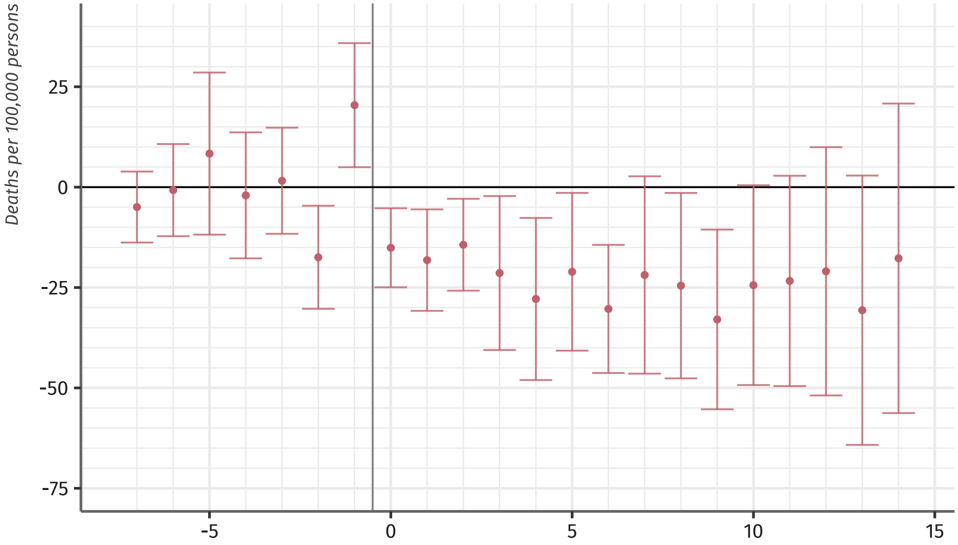
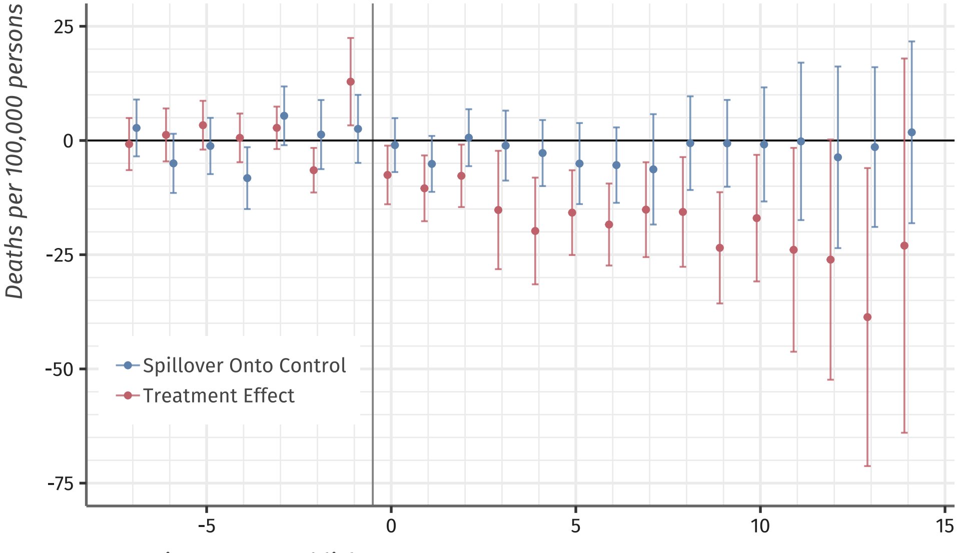


Figure: Direct and Spillover Effects of Community Health Centers



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- I decomposed the TWFE estimate into the direct effect and two spillover terms
- I showed that a set of concentric rings allows for estimation of the direct effect of treatment and they are able to model spillovers well
- For place-based policies, I show the importance of considering spatial spillovers when estimating treatment effects
- More generally, identification strategies that use very close control units in order to minimize differences in unobservables should consider the problems with treatment effect spillovers.