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**, when the effect of treatment extends over the treatment boundaries (states, counties, etc.).

Example: Amazon Shipping Center on employment

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

This Paper

In this paper, I...

- Present a potential outcomes framework to formalize treatment and spillover effects and discuss potential estimands of interest
- Discuss estimation of effects in the presence of 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:

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

Use the control units to estimate what the treated units' trends would have been without treatment

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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

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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
- **Spillover onto other Treated Units:** Treated units are also affected by nearby units and therefore combine “direct” effects with spillover effects

Outline

1– Formalize spillovers into a potential outcomes framework:

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

→ I focus on non-parametric identification conditions

→ Discuss estimands of interest and classify identification for each

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)

Roadmap

Theory

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 $i \in \{1, \ldots, N\}$ 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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- **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.

  $\rightarrow$ e.g. library access where x is the maximum distance people will travel

  $\rightarrow$ Spillovers are non-additive, i.e. spillover effects do not depend on number of nearby treated areas

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  $\rightarrow$ Spillovers are non-additive

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

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

  $\rightarrow$ e.g. Amazon shipping center

  $\rightarrow$ Agglomeration economies suggest spillovers are additive

Estimands

Treatment Effect without Spillovers

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

- The average effect of switching on unit i's treatment

Estimands

Switching Effect

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

- Keep everyone's treatment constant and toggle unit i's treatment effect. Average across all units with exposure h.
- This is policy relevant: what will happen if my county turns on treatment.
- This requires knowledge of $h_i(\vec{D})$ in order to find control units to estimate $Y_{i1}(0, h_i(\vec{D}))$.

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Estimands

Switching Effect

$$\tau_{\text{switch}}(h) = \mathbb{E}\left[Y_{i1}(1, h_i(\vec{D})) - Y_{i0}(0, \vec{0}) \mid D_i = 1, h_i(\vec{D}) = h\right]$$
$$- \mathbb{E}\left[Y_{i1}(0, h_i(\vec{D})) - Y_{i0}(0, \vec{0}) \mid D_i = 1, h_i(\vec{D}) = h\right]$$

Identification requires two things:

1. Knowledge of $h_i(\vec{D})$ in order to estimate the second term with control units.
2. Spillover effect homogeneity (so second term would be the same for treated units).

Estimands

Total Effect

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

- Toggle entire vector of treatment effects. Average across all treated units.
- This is helpful for post-hoc policy analysis: what was the average effect on treated units of implementing $\vec{D}$.

Estimands

Total Effect

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Identification much simpler:

- Need to identify control units without spillover effects

Estimands

Direct Effect

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

- Toggle treatment effect for individuals with no exposure.
- This is the switching effect with $h = 0$.
- Identified under mild assumptions.

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Identification much simpler:

- Need to identify treated/control units without spillover effects

Estimands

Spillover Effects

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

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

What does Difference-in-Differences identify?

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?

Decomposition

With the parallel trends assumption, I decompose the difference-in-differences estimate as follows:

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

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

$$= \tau_{\text{total}} - \tau_{\text{spillover, control}}$$

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Identification of Direct/Total Effects

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 $\min_{j:\, D_j=1} d(i, j) > \bar{d}$.

Identification of Total Effect

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:

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

- $\hat{\tau}$ is consistent for τ_{total}
- $\hat{\tau}_{\text{spill, control}}$ is not consistent for average spillover effects.

Identification of Direct Effect

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.

Roadmap

Theory

Application in Urban Economics

Event Study

Conclusion

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 is the total effect of TVA investments on manufacturing and agricultural employment?
- Do these effects come at the cost of other counties?

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Identification

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

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

- 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

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

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

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

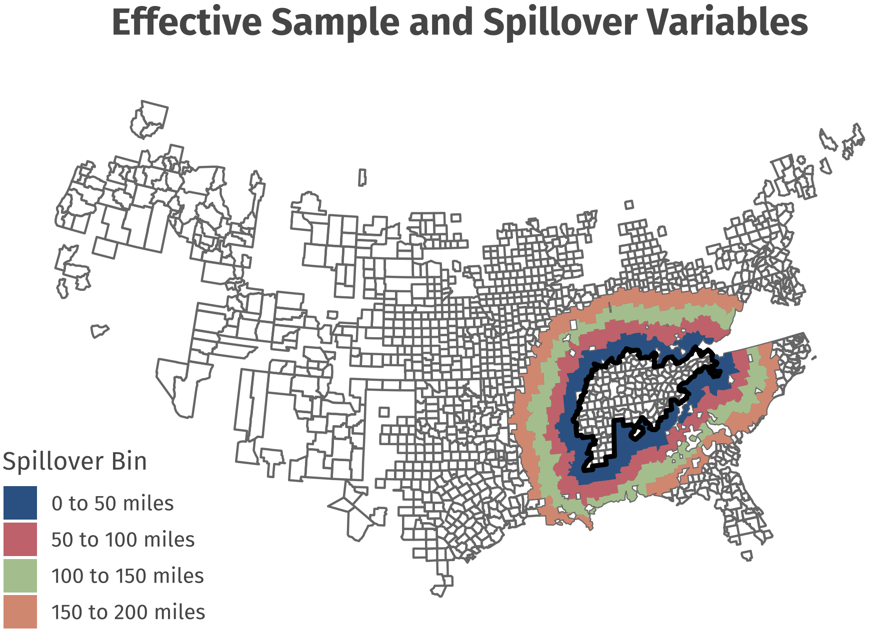
Effective Sample and Spillover Variables
Spillover Bin
0 to 50 miles
50 to 100 miles
100 to 150 miles
150 to 200 miles

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.

My framework can explain both of these results. If census tracts just outside the Empowerment Zones also benefit from the policy, then the estimates of Neumark and Kolko (2010) are attenuated towards zero

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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

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

Adjust two-step approach:

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

2. Then, regress $\tilde{y}_{it}$ on $\tau D_{it} + \tau_{\text{spill,control}} S_{it} * (1 - D_{it}) + \tau_{\text{spill,treat}} S_{it} * D_{it}$ (or interacted event study leads/lags). This estimate is unbiased because D_{it} is non-residualized (standard errors require adjusting).

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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

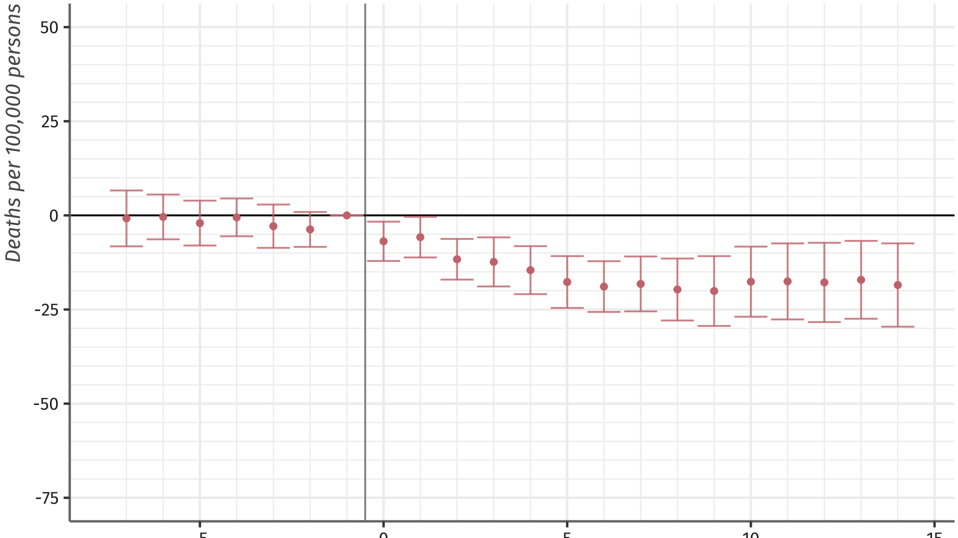
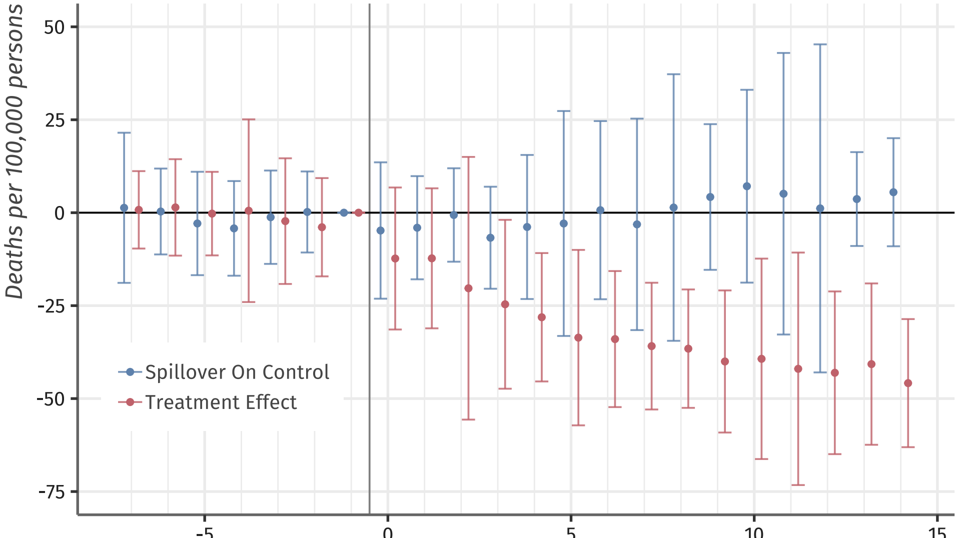


Figure: Direct and Spillover Effects of Community Health Centers



Roadmap

- Theory
- Application in Urban Economics
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Conclusion

- 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.