Uncovering Heterogeneous Treatment Effects

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Introduction

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- Moderators can be unobserved, mismeasured, or unknown

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- Distribution of effects is estimated

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4. Collect more data and test new hypotheses

Overview of the Talk

1. Model and Intuition
2. Empirical Example
3. Simulation Study
4. Conclusion

Model for Treatment Heterogeneity

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$$\underbrace{Y_i}_{\text{Outcome}} = \underbrace{T_i}_{\text{Treatment}} \underbrace{\tau}_{\text{ATE}} + \underbrace{X_{1i}\gamma_1 + X_{2i}\gamma_2 + \dots}_{\text{Covariates predicting outcome}} + \epsilon_i$$

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$\rightsquigarrow$ Individual-specific effects:
Unidentifiable—fundamental problem of causal inference

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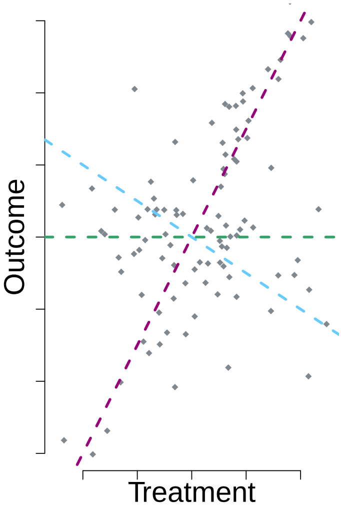
- Problem: Clustering membership is not observed
  1. Which individuals are in the same cluster?
  2. How many clusters?

Data-driven Clustering



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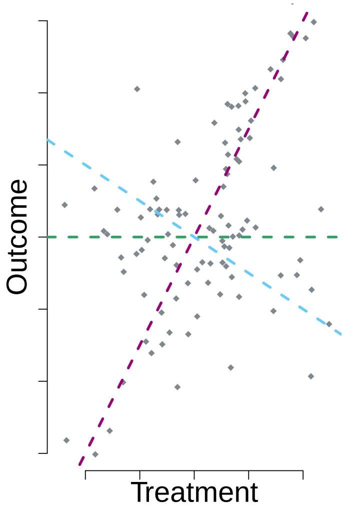

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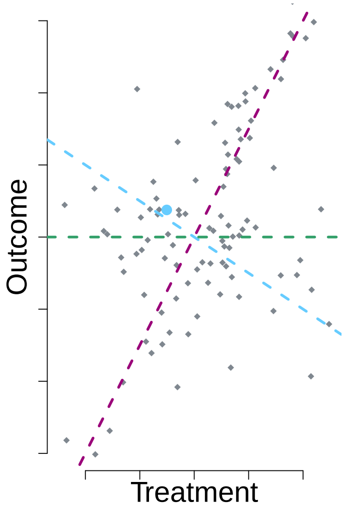

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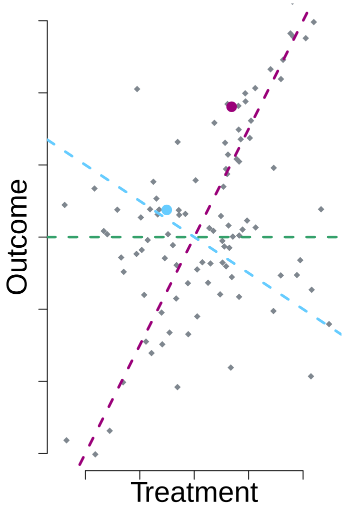

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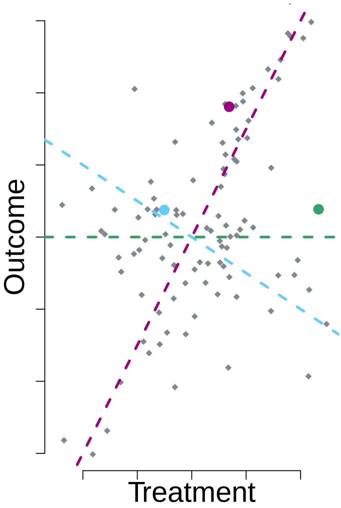

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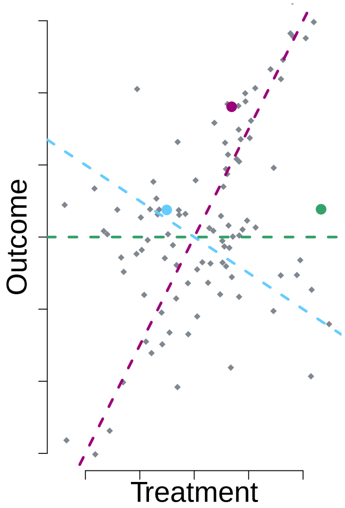

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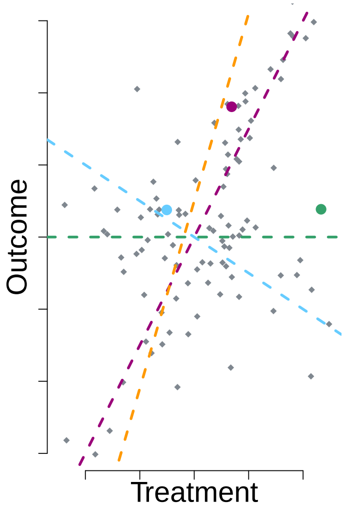

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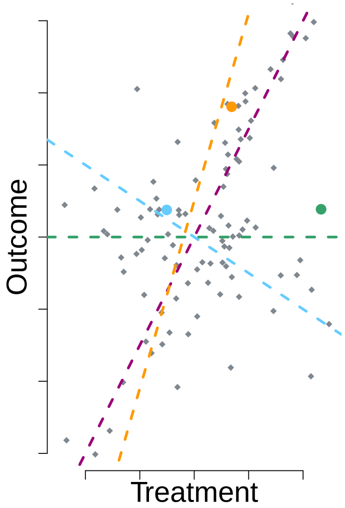

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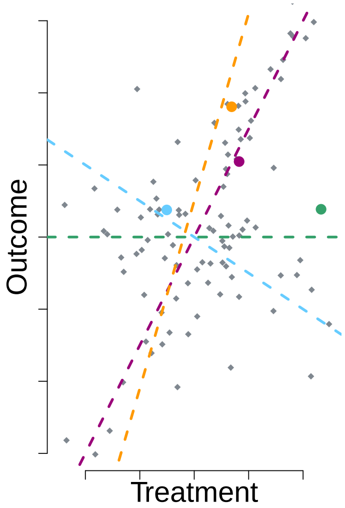

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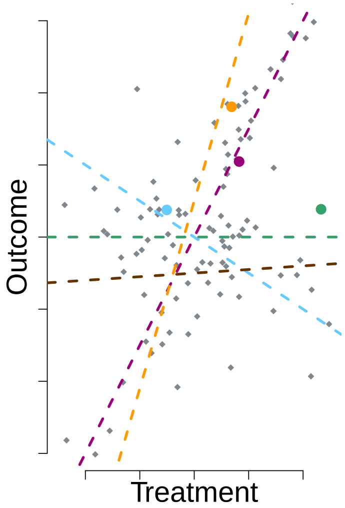

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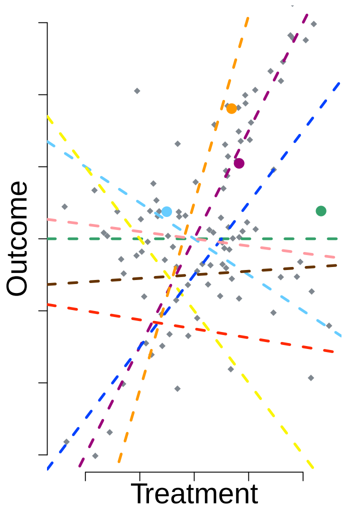

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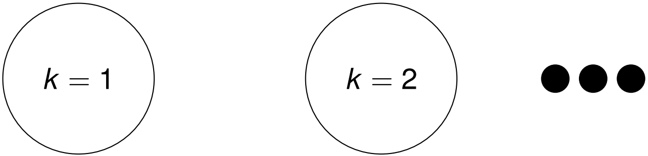
- Balance between likelihood and prior $\rightsquigarrow$ estimated clusters fewer than individuals

Prior Leading to Fewer Clusters

- Chinese restaurant process with tuning parameter α

Prior Leading to Fewer Clusters



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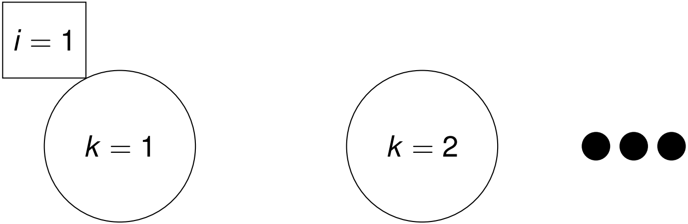

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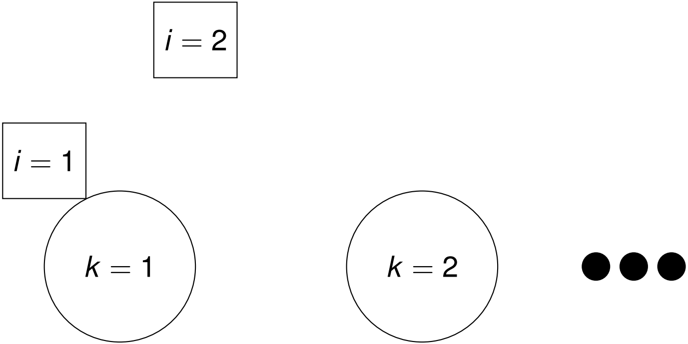

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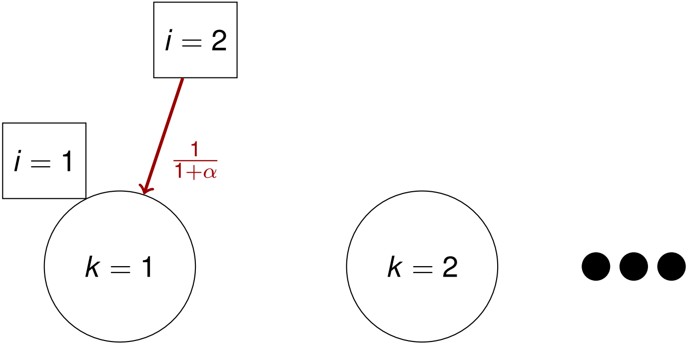

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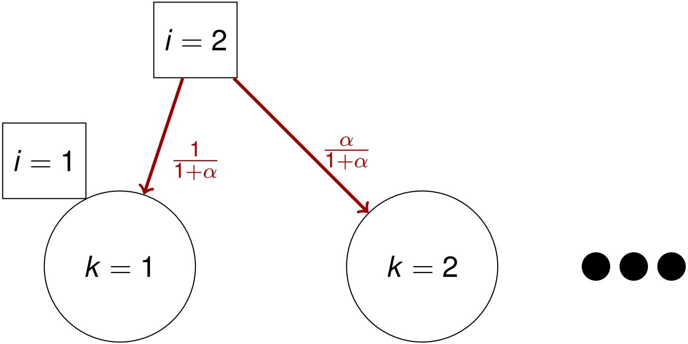

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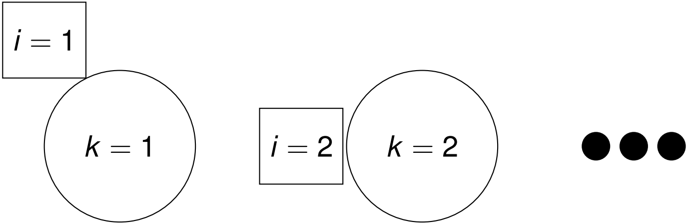

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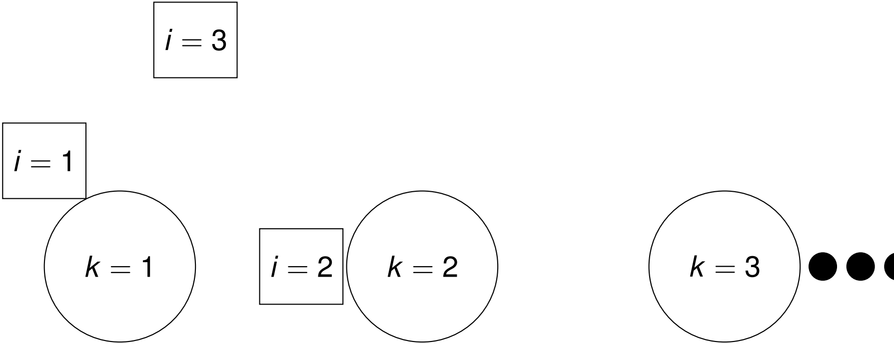

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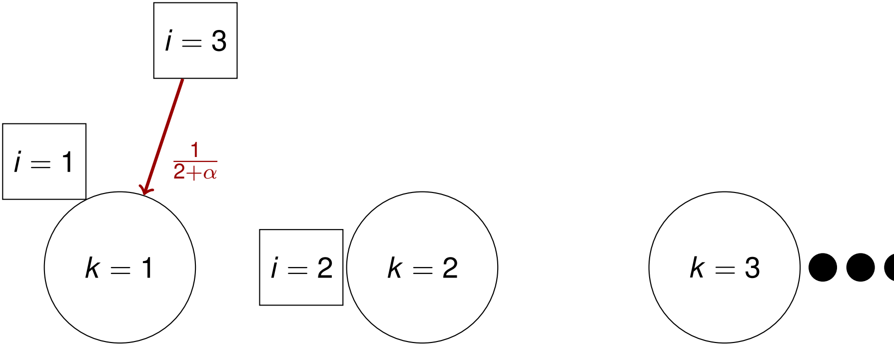

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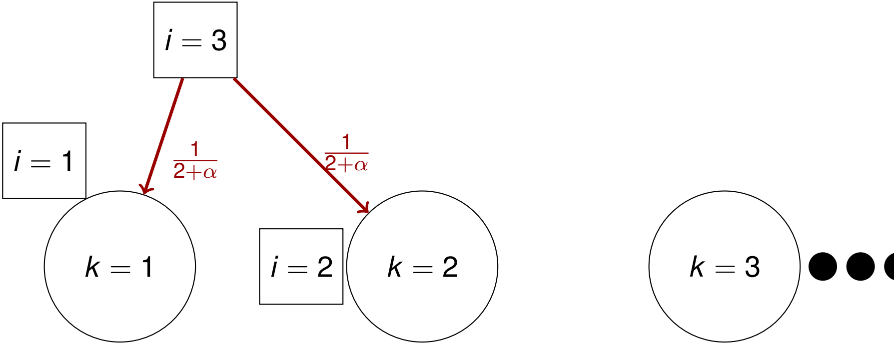

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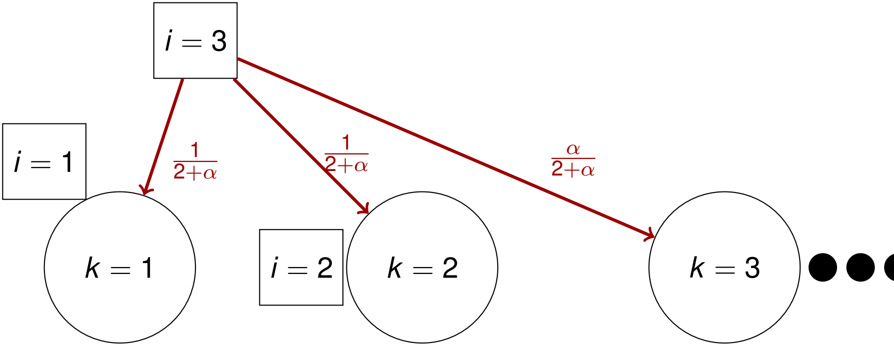

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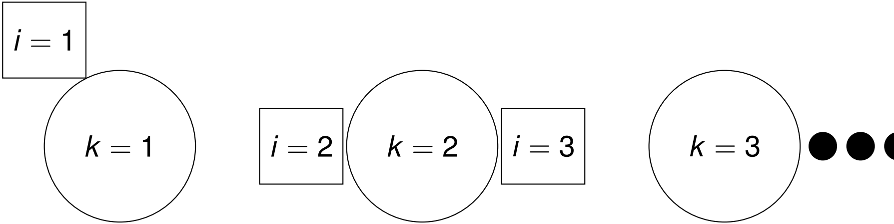

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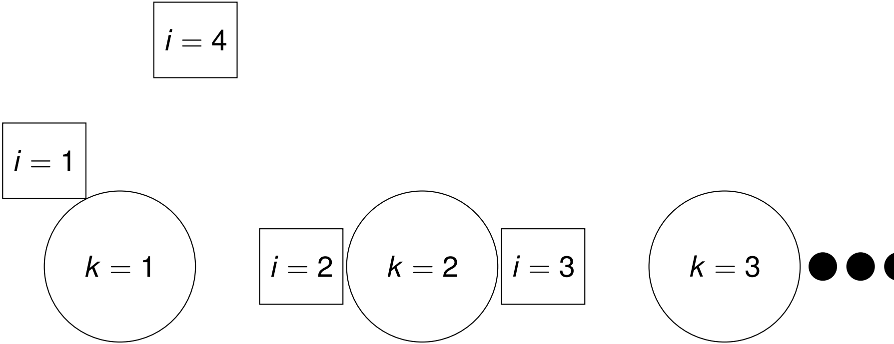

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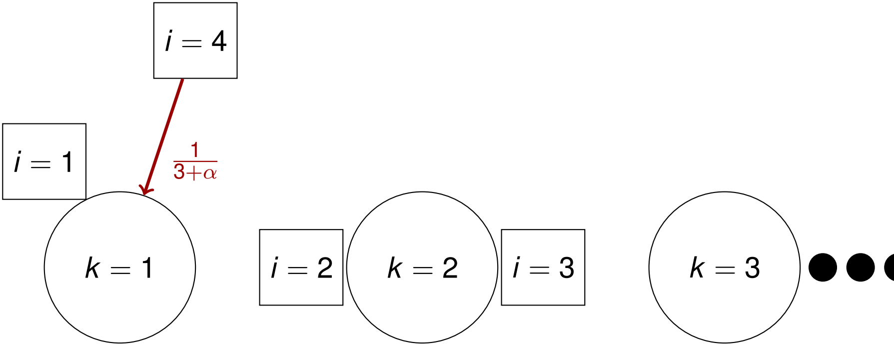

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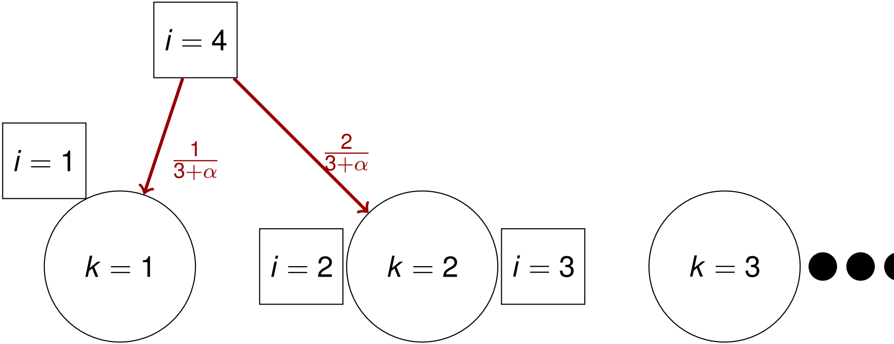

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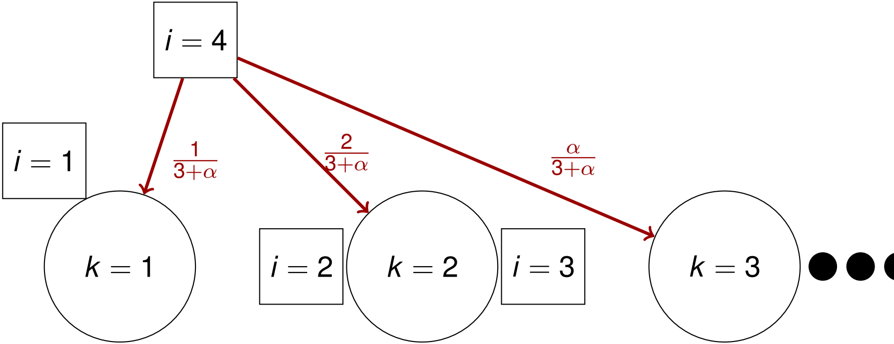

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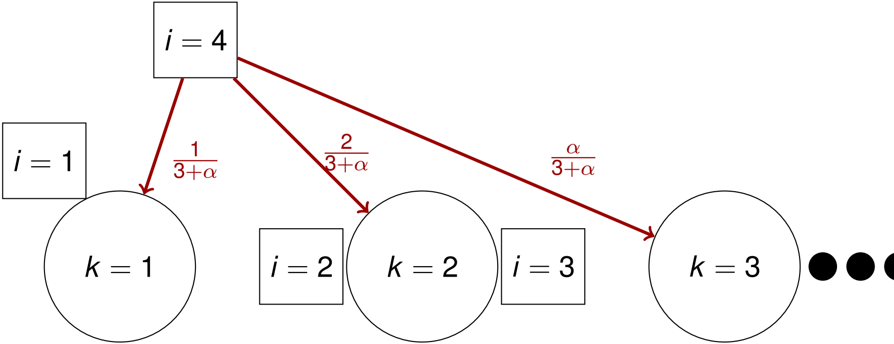

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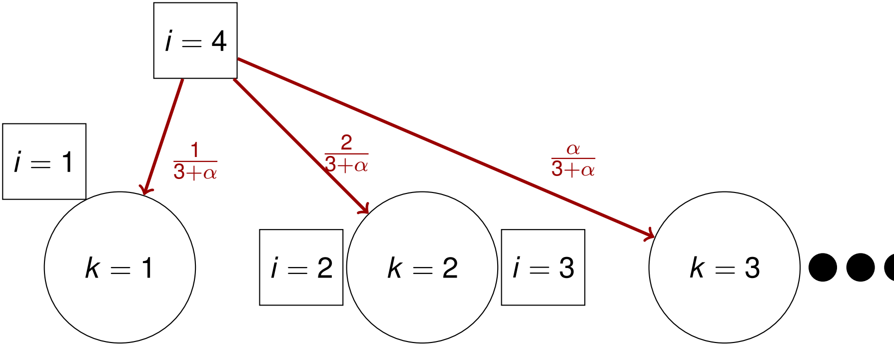

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- Encourages larger and fewer clusters

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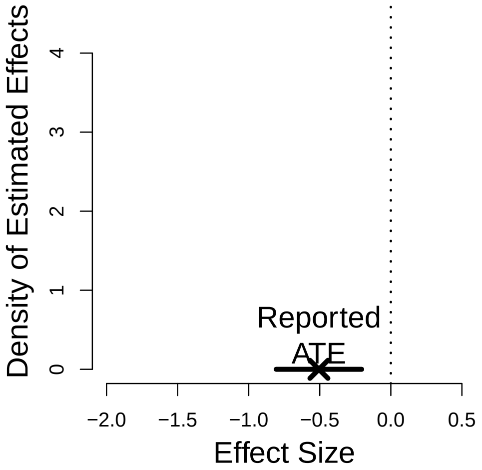
  - Treatment: Russian artillery attacks
  - Covariates: Village level variables used by Lyall (2009)

Heterogeneous Effect of Artillery Attacks



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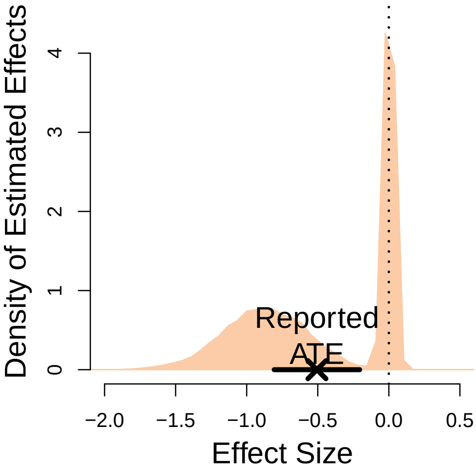

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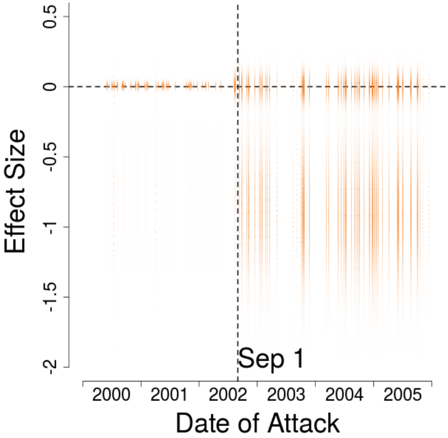

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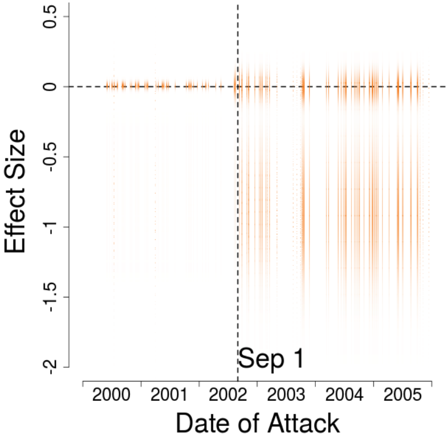

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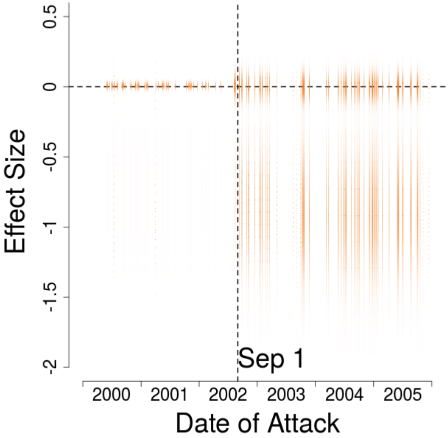
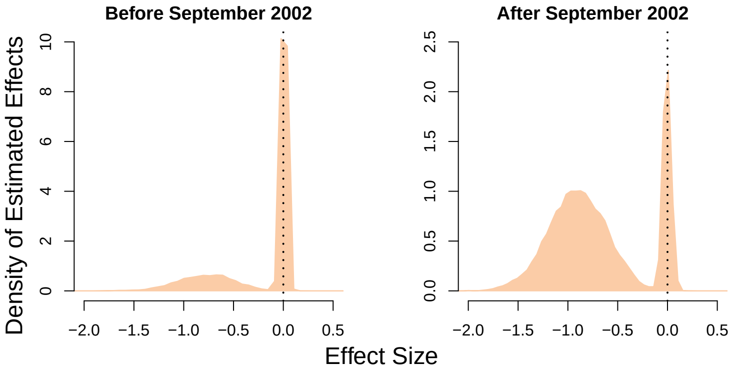


- Change in mid-2002
- What happened?

Possible Mechanism



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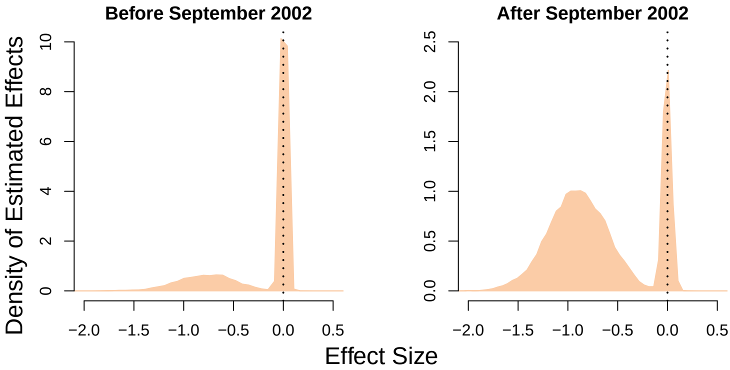

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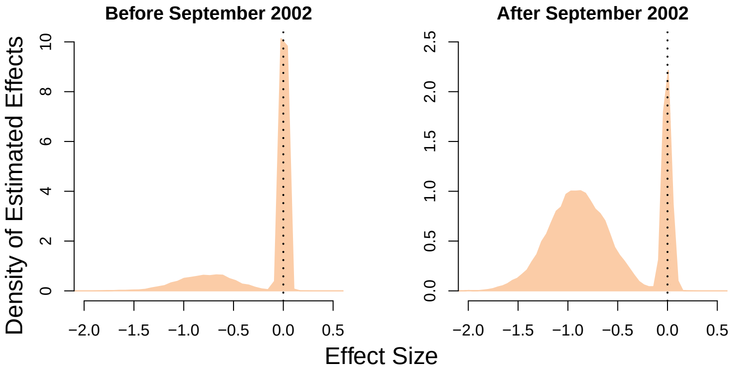

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- New hypothesis!

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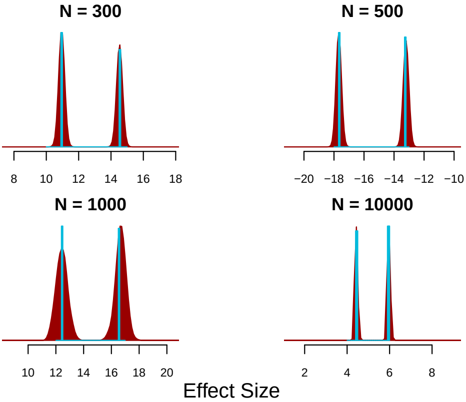
- Unobserved moderator
  1. Binary
  2. Continuous

Simulation Results: Binary Moderator

- Binary $U_i \overset{\text{i.i.d.}}{\sim} \text{Bernoulli}(.5)$

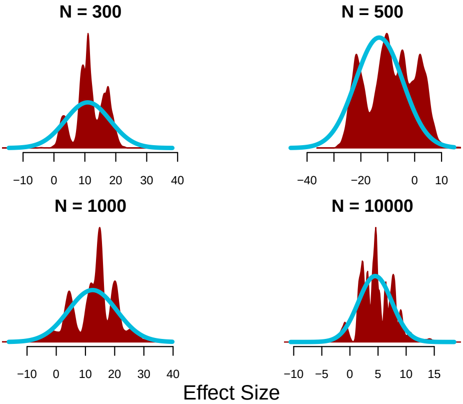
$$Y_i = \begin{cases} T_i\tau + X_{1i}\gamma_{1k} + \cdots + \epsilon_i \\ T_i(\tau + \nu) + X_{1i}(\gamma_1 + \delta_1) + \cdots + \epsilon_i \end{cases}$$



Simulation Results: Continuous Moderator

- Continuous $U_i \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, 4)$

$$Y_i = T_i(\tau + U_i\nu) + X_{1i}(\gamma_1 + U_i\delta_1) + \cdots + \epsilon_i$$



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- Misspecification:
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  - Distribution of error

No Moderation with Model Misspecification

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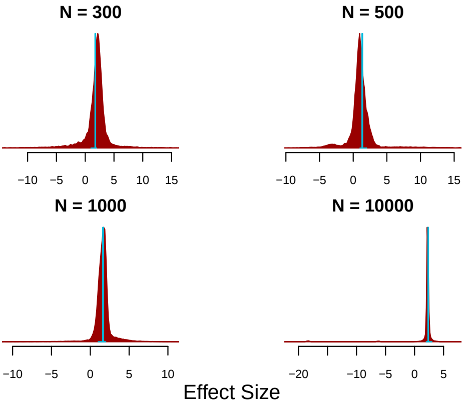
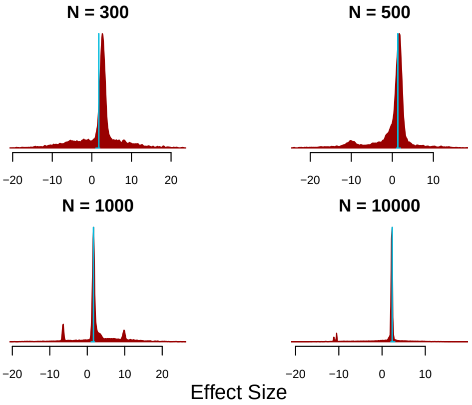


No Moderation with Model and Error Misspecification

- Model and Error Misspecification

$$Y_i = T_i\tau + (X_{1i}^3 - 3 \times X_{1i}^2)\gamma_{1k} + \cdots + \epsilon_i^2 - \epsilon_i^5,\ k = 1, \ldots, 5$$



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