Testing for Network Effects in Field Experiments: Examples from Legislative Studies

Sayali Phadke[†1], Bruce A. Desmarais[†2]

[†]Pennsylvania State University; | [1]sayalip@psu.edu; [3]bdesmarais@psu.edu

Research Objectives

- Model spillover of treatment effect via network structures.
- Examine how different types of networks interact with various specifications of treatment spillover.
- Evaluate the models using data from field experiments on US State legislatures.

Motivation

- Conventional causal inference methods rely on SUTVA (Stable Unit Treatment Value Unit Assumption)
- Use individual-level micro attributes & context-dependent macro attributes to estimate treatment effect
- However, most social processes involve complex interaction and dependence among networked units
- Interpersonal interactions propagate treatment effect to control units and
- Various factors impact how and how much the treatment effect spreads
- Must account for the interference structure to correctly estimate the treatment effect
- Understanding the propagation of treatment itself of interest in policy planning or marketing strategy
- Generally not possible to identify the causal effects that map onto the process of social influence in observational data (Shalizi and Thomas, 2011), and randomized experiments not always feasible
- Look at methods suitable for identifying and estimating causal effect using field experiments

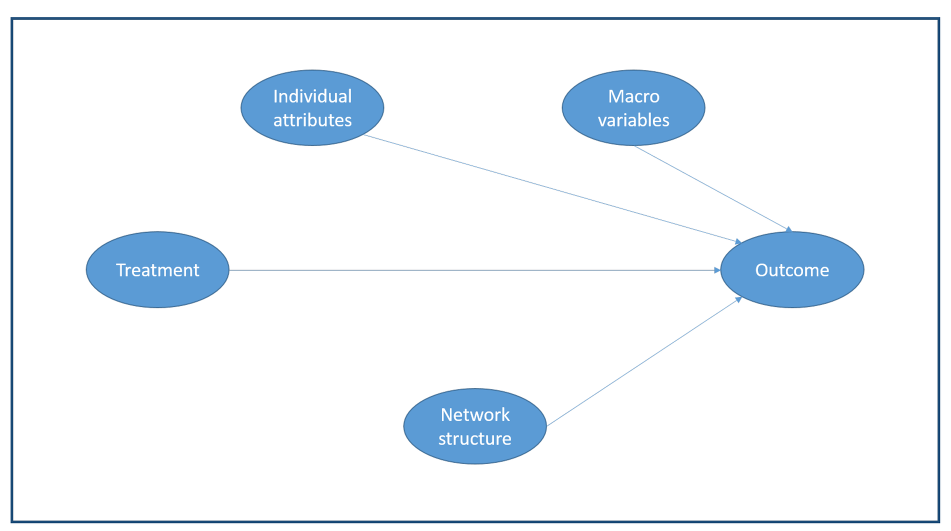

Figure: Individual causal diagram: In addition to the unit's treatment status, the network structure and treatment assignments within it are also important in determining its outcome

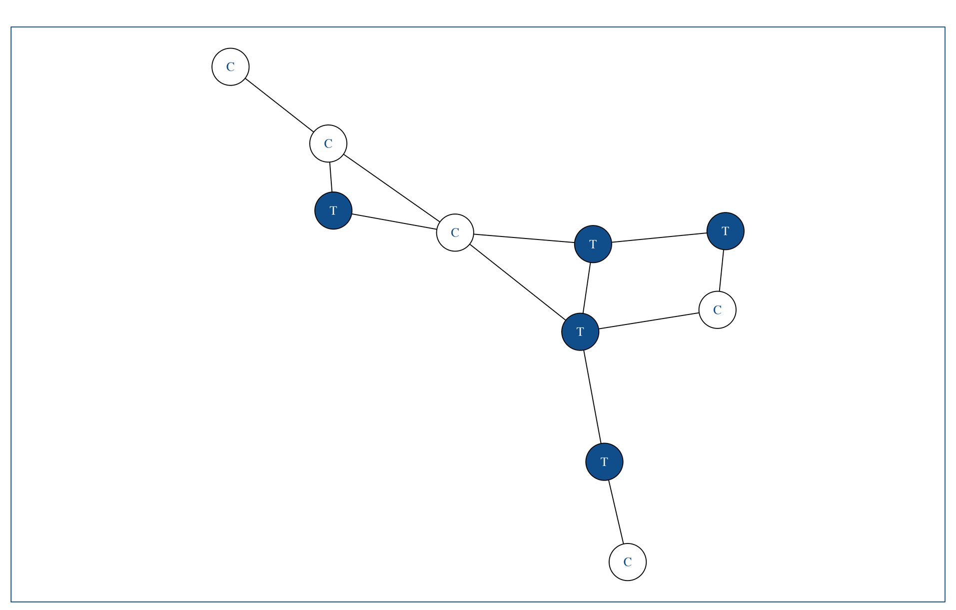

Figure: Network plot: How would we expect the treatment to affect untreated units? Simple illustration showing possible neighborhoods of control units. **T: treated unit and C: control**

Existing Approaches

Bowers et. al. method:

Bowers, Fredrickson and Panagopoulos 2012 proposed a non-parametric testing method for interference effects. Overall idea of this method is as follows:

- Assume the 'sharp null hypothesis of no effects' i.e. treatment assignment has no effect on any unit
- Specify causal model describing the change in potential outcomes when treatment assignment changes
- Map potential outcomes from the causal model to observed outcomes
- Assume treatment only spreads along edges and spillover depends on the number of treated neighbors
- Test statistic should be a small value when distribution of treated and control outcomes in the adjusted data are similar, and a large value when distributions are dissimilar
- p-value is the proportion of permutation tests whose test statistic is lesser than the observed test statistic

Coppock application

Coppock 2014 implements Bowers method to analyze the New Mexico Legislator experiment conducted by Butler, Nickerson et al. 2011. Uses ideological network with a different choice of diffusion model and test statistic. Bowers methodology is inadequate to handle categorical outcomes.

Proposed extensions along various dimensions

- **Neighborhood specification:**
  - Effect from all units
  - Effect from k-nearest neighbors
- **Diffusion model specification:** Consider models varying along following dimensions:
  - Distance from the nearest treated node
  - Number/proportion of treated neighbors
  - Form of spread (linear or non-linear)
- **Network selection:**
  - Ideological network
  - Committee network
  - Co-sponsorship network
  - Geographical network network
- **Test statistic selection:**
  - Kolmogorov-Smirnov test
  - Anderson-Darling test
  - Mann-Whitney U test
  - Control Median test

Data

Bill to return a projected budget surplus in form of a rebate proposed in the New Mexico state legislature during a special session in 2008. 35 out of the 70 legislators (matched pairs) received estimates of support within their constituencies. Below are three possible network structures connecting the legislators:

Ideological Network (top 5%) | Geographic Network | Committee Network (>1 common)

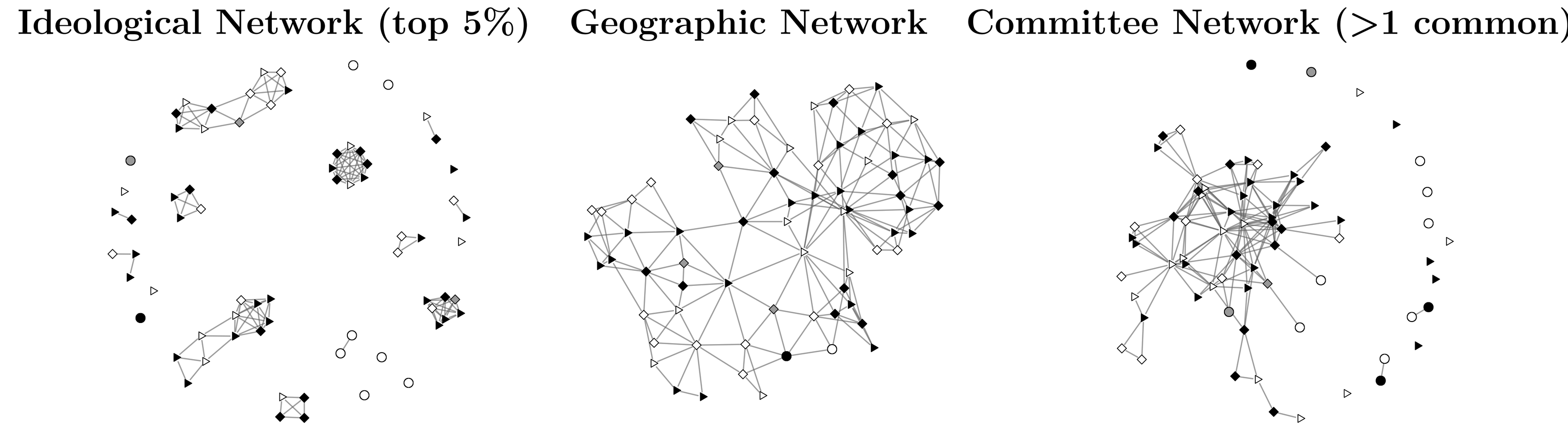

Figure: Different networks among New Mexico legislators. Colors denote outcome: black means voted with district, gray means abstained, white means voted against. Shape denotes treatment status. Triangles are treated. Squares are adjacent to treated. Circles are isolated from treatment

Replication of Coppock analysis

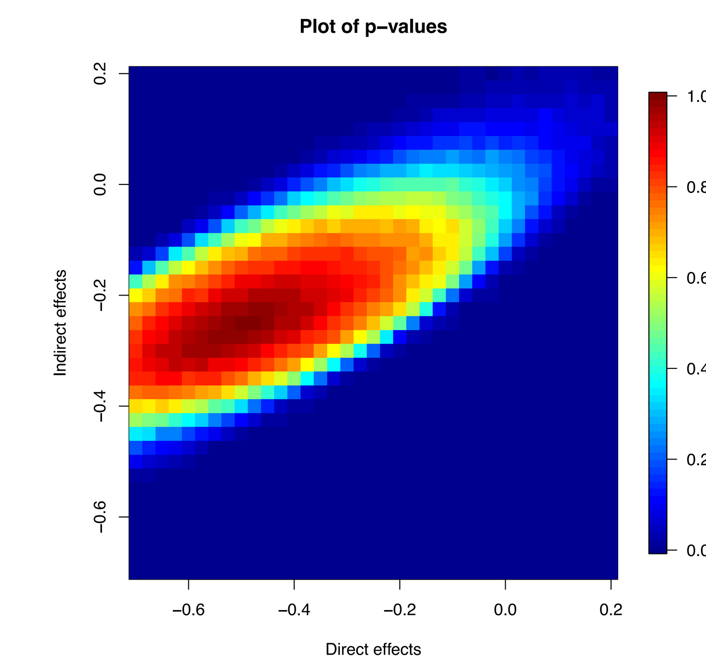

Figure: Higher values provide evidence for spillover effect

Extension

Extend the Coppock analysis using a different neighborhood specification. We use ideological scores and create an adjacency matrix based on whether a particular legislator is one of the k nearest neighbors

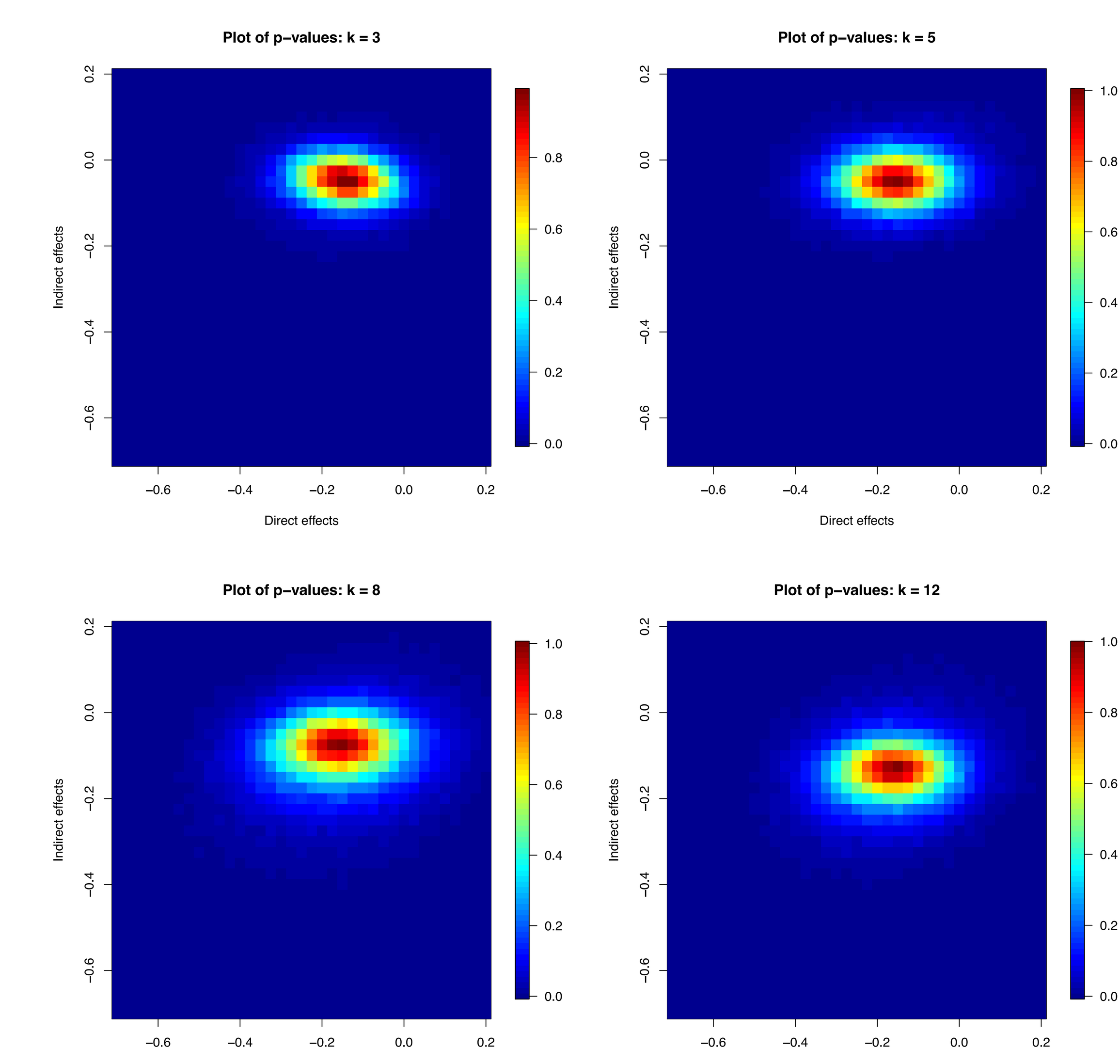

Figure: p-values: highest values move closer to zero value for both effects

Future direction

- Consider another example of a field experiment on New Hampshire state legislature
- Evaluate models specified by various dimensions under the extensions

References:

Bowers, Jake, Mark M Fredrickson and Costas Panagopoulos. 2012. "Reasoning about interference between units: A general framework." *Political Analysis* p. mps038.

Butler, Daniel M, David W Nickerson et al. 2011. "Can learning constituency opinion affect how legislators vote? Results from a field experiment." *Quarterly Journal of Political Science* 6(1):55–83.

Coppock, Alexander. 2014. "Information spillovers: Another look at experimental estimates of legislator responsiveness." *Journal of Experimental Political Science* 1(02):159–169.

Shalizi, Cosma Rohilla and Andrew C Thomas. 2011. "Homophily and contagion are generically confounded in observational social network studies." *Sociological methods & research* 40(2):211–239.

This material is based on work supported by the National Science Foundation under IGERT Grant DGE-1144860, Big Data Social Science.