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 approaches to causal inference rely on the Stable Unit Treatment Value Unit Assumption (SUTVA) i.e. they assume that the outcome of a unit is unaffected by the treatment statuses of other units
- Traditionally, individual-level micro attributes and context-dependent macro attributes used to estimate treatment effect
- However, most social processes involve complex interaction and dependence among units connected through a network
- Interpersonal interactions influence behavior leading to propagation of treatment effect through network to control units and, SUTVA breaks down
- Various factors impact how and how much the treatment effect spreads
- Must take the interference structure into account in order to correctly estimate the effect of the treatment effect
- In policy planning or marketing strategy, understanding the propagation of treatment itself can be of interest
- 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
- Therefore we look at methods suitable for identifying and estimating causal effect using field experiments

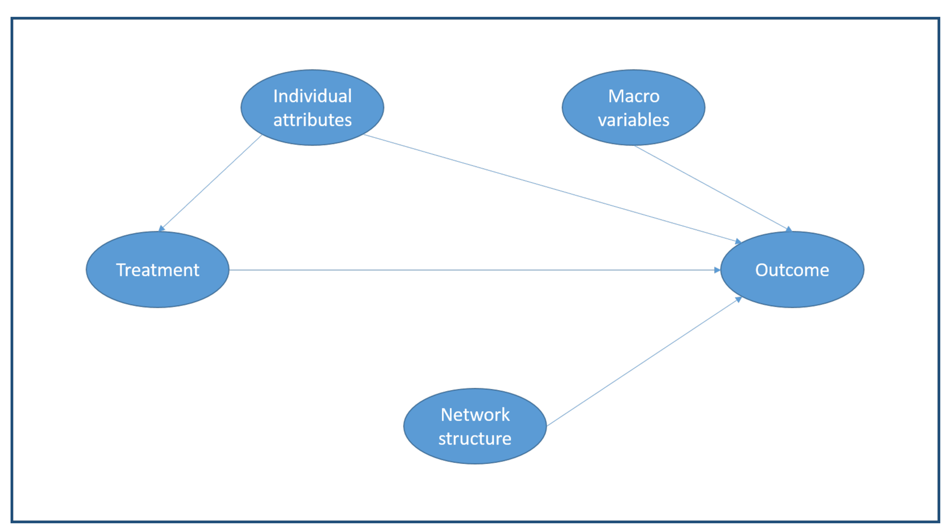

Figure: Individual causal diagram: In addition to the unit's treatment status, the network structure and treatment assignments within it are also important in determining its outcome

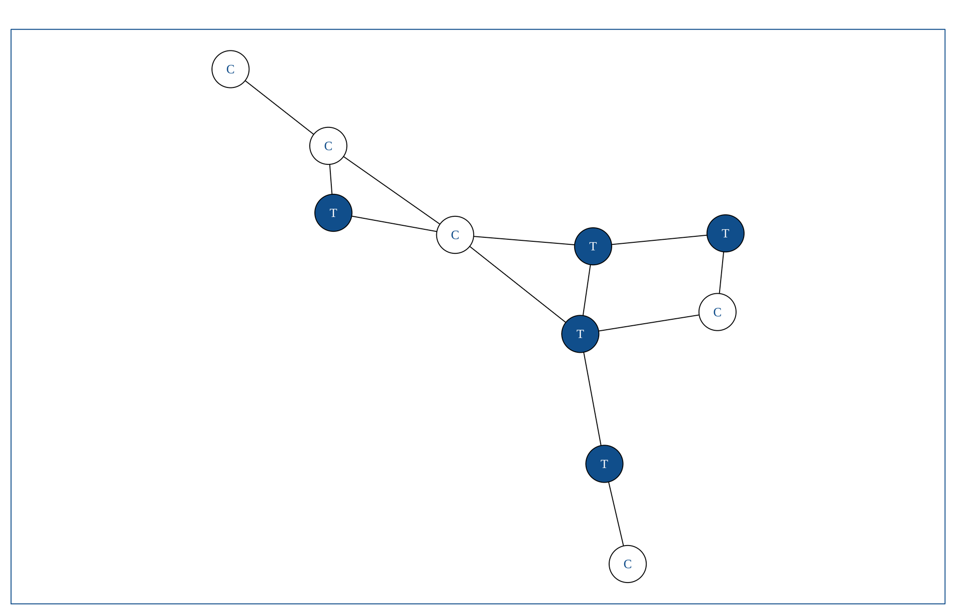

Figure: Network plot: This is a simple illustration showing how the treatment assignment in the neighborhood of each control unit can impact the spillover treatment effect it may receive. T indicates treated unit and C indicates control

Existing Approaches

Bowers et. al. method:

Bowers, Fredrickson and Panagopoulos 2012 proposed a method for modeling spillover effect as a nonlinear growth curve expression, and testing it using the Kolmogorov-Smirnov (KS) test statistic under Fisherian inference algorithm. The 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, which is then mapped to the uniformity trial i.e. the condition where every unit is a control unit
- 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
- Assume treatment only spreads through edges and spillover depends on the number of treated neighbours
- Generate the distribution of test statistic under our hypothesis
- Calculate the p-value calculated as the proportion of test statistic under permutation testing, lesser than the observed test statistic

Coppock method

Coppock 2014 extends the Bowers method of inference using the New Mexico Legislator experiment conducted by Butler, Nickerson et al. 2011. Bowers methodology is inadequate to handle categorical outcomes. Coppock uses ideological similarity scores in the adjacency matrix, and models the direct treatment effect and spillover using OLS regression.

Proposed extensions

We would like to extend this methodology along the following dimensions:

- Diffusion of treatment effect along a network will depend on the neighborhood of control units. We will consider various models that consider the following aspects: (tabulated below)
  - Distance from the nearest treated node
  - Number/proportion of treated neighbors
  - Form of spread (linear or non-linear)
- Consider other legislator networks depending on geographical proximity and co-sponsorship
- Consider additional test statistics such as the Anderson-Darling test and other tests mentioned in (**?**) (Mann-Whitney U test, Control Median test etc.)

	Distance < 5		Distance > 5	
	Linear	Non-linear	Linear	Non-linear
Number of treated neighbors	1	2	5	6
Proportion of treated neighbors	3	4	7	8

Table: Possible models

Data

The Senate Bill 24 was proposed in the New Mexico state legislature during a special session in 2008. Bill proposed to return a projected budget surplus to taxpayers in form of a rebate. 35 out of the 70 legislators received estimates of support within their constituencies, using matched pair randomization (treatment). Their final vote choice was noted (outcome). Below we see the three possible network structures connecting the legislators:

Replication

The figure below contains p-values for a model using ideological similarity scores to explain the spillover of treatment effect. Direct effects are on the X-axis and indirect effects on Y-axis. A p-value here indicates the proportion of simulated test statistic lesser than the observed test statistic. Therefore, a higher p-value indicates support for evidence of spillover effect. Direct and indirect effect values are linear.

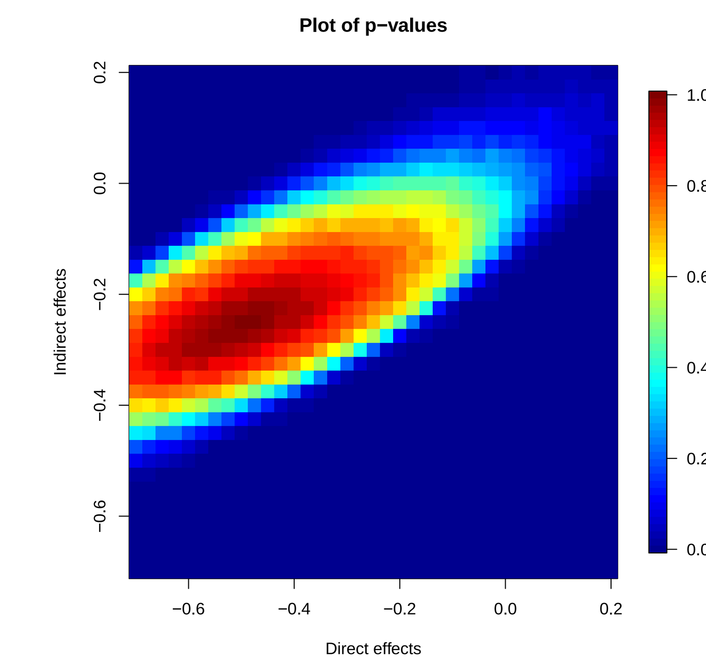

Figure: p-values using Coppock model

Extension

We extend the Coppock model using a separate network structure. We use ideological scores and create an adjacency matrix based on whether a particular legislator is one of the k nearest neighbors. We consider values 3, 5, 8 and 12 for k.

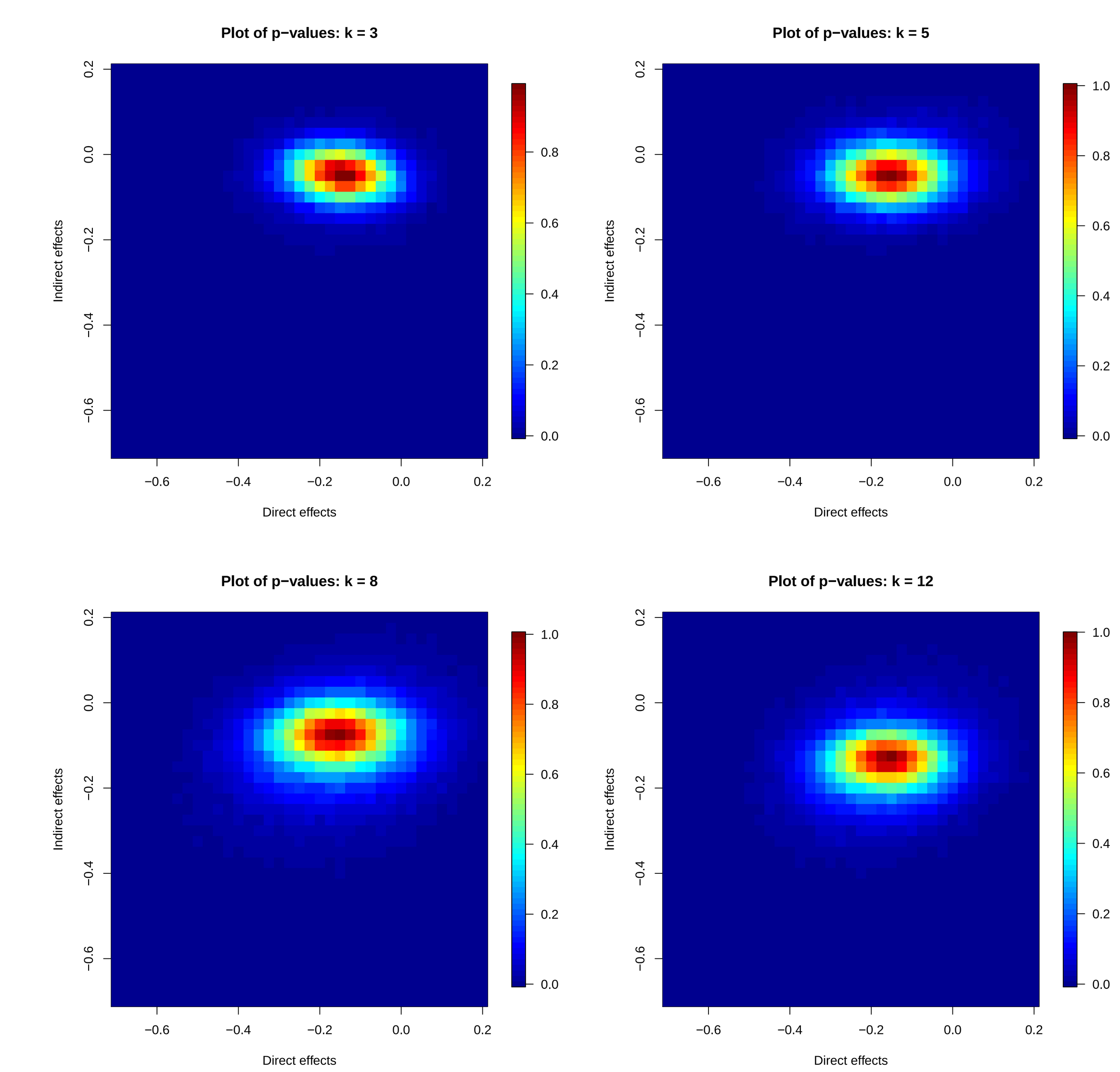

Figure: p-values using nearest ideological neighbors. k is the number of neighbors considered

Under the new specification, the highest p-value moves closer to zero, for both direct and indirect effects. In the original setup, it is -0.45 for direct effects and -0.25 for indirect effects.

References:

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