

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

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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

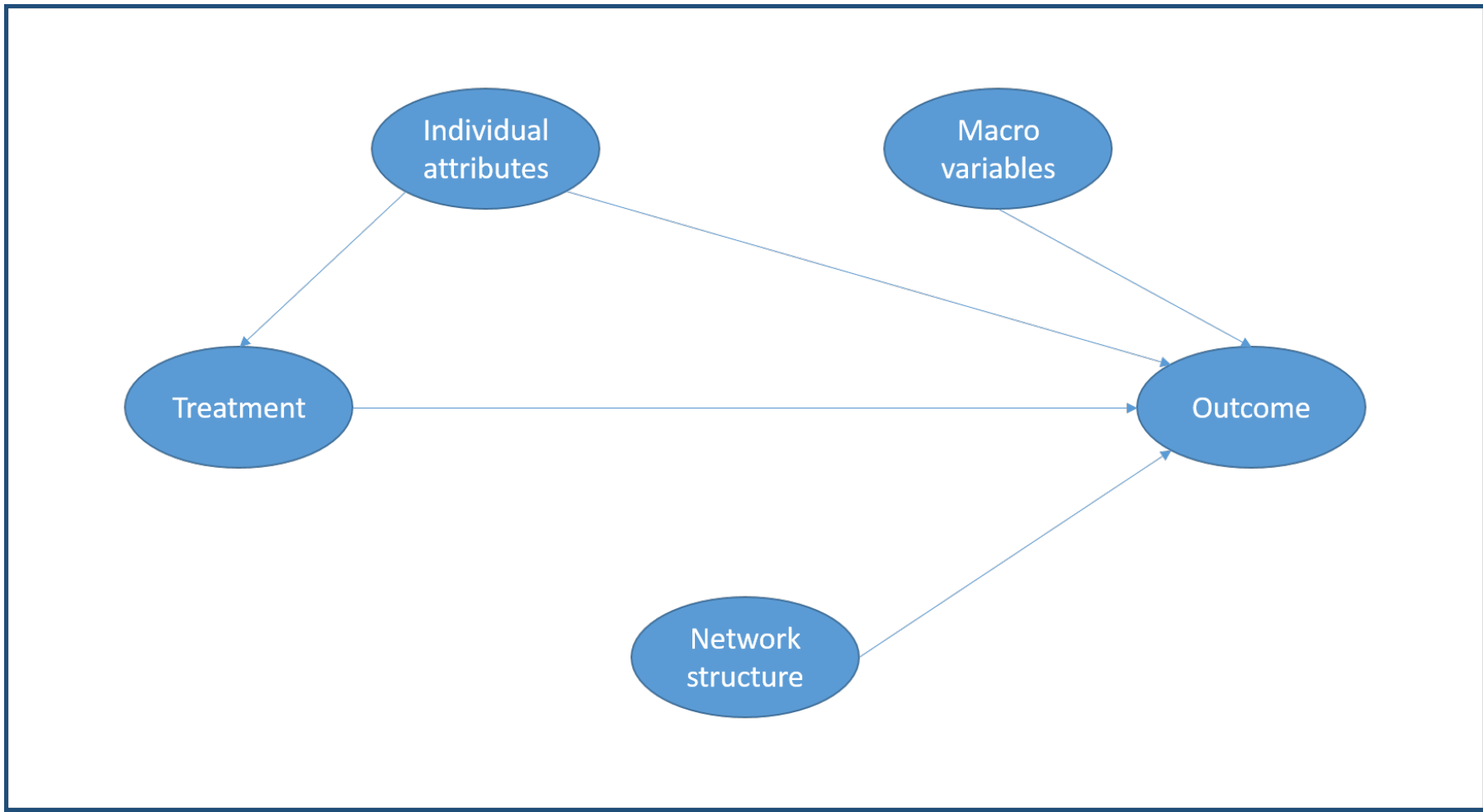
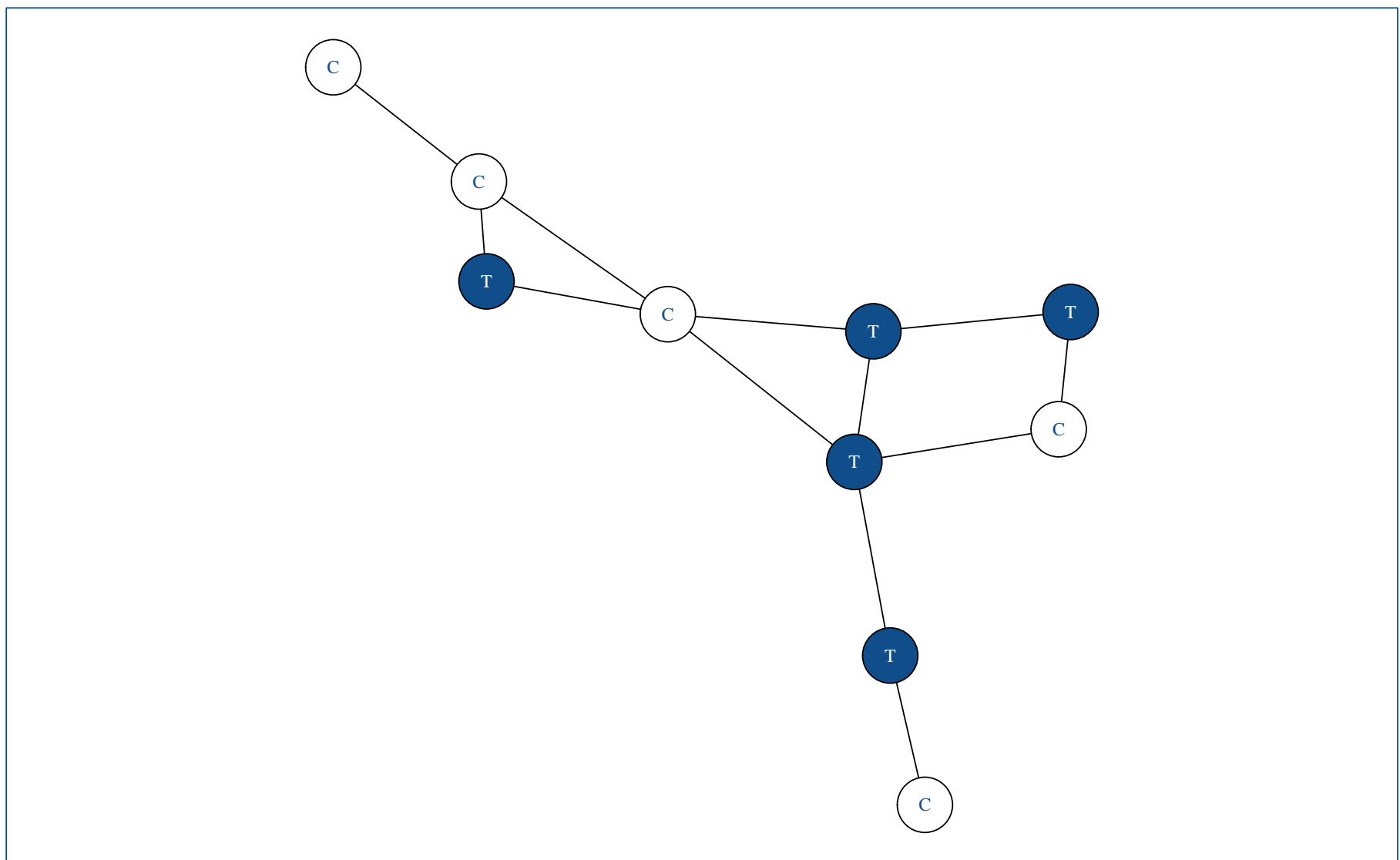


Figure: Network plot: This is a simple illustration showing how the treatment assignment in the neighborhood of each control unit can impact the spillover treatment effect it may receive. T indicates treated unit and C indicates control



Existing Approaches

Bowers et. al. method:

Bowers, Fredrickson and Panagopoulos 2012 proposed a method for modeling and testing for spillover effects in network setup.

- Assume the 'sharp null hypothesis of no effects' i.e. the treatment assignment has no effect on any unit
- Specify the causal model which describes the change in potential outcomes when treatment assignment changes from \mathbf{u} to \mathbf{w} ; $\mathcal{H}(y_{i,\mathbf{u}}, \mathbf{w}, \theta)$
- Potential outcomes from the causal model must be mapped to observed outcomes $\mathbf{y}_{\mathbf{z}}$. Treatment assignment in the experiment (\mathbf{z}) must be mapped to the uniformity trial ($\mathcal{H}(\mathbf{y}_{\mathbf{z}}, \mathbf{0}, \theta) = \mathbf{y}_0$) which is based on the baseline condition of no-treatment assignment i.e. every unit is a control unit
- Test statistic \mathcal{T} 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. We need a sensitive measure to account for similarity on not just the center but also higher-order moments of a distribution. Bowers et. al. recommend the Kolmogorov-Smirnov (KS) test statistic
- Assume that treatment only spreads through edges and the spillover effect only depends on the number of neighbours treated. Spillover effect modeled using a growth curve $\beta + (1 - \beta)e^{-\tau^2 \mathbf{z}^T \mathbf{S}}$
- Generate the distribution of test statistic under our hypothesis. The exact distribution is specified by computing $t_k = \mathcal{T}(\mathbf{y}_0, \mathbf{Z}_k)$ for each $\mathbf{Z}_k \in \Omega$. Alternatively, we can use sampling methods and limit theorems to estimate the distribution from data.
- p-value calculated using $\frac{\sum_{k=1}^{abs(\Omega)} I(x_i > t_k)}{abs(\Omega)}$

Coppock method

Coppock 2014 extends the Bowers method of inference using the New Mexico Legislator experiment conducted by Butler, Nickerson et al. 2011. Coppock uses ideological similarity scores in the adjacency matrix, and models the direct treatment effect and spillover occurring through the network.

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.)

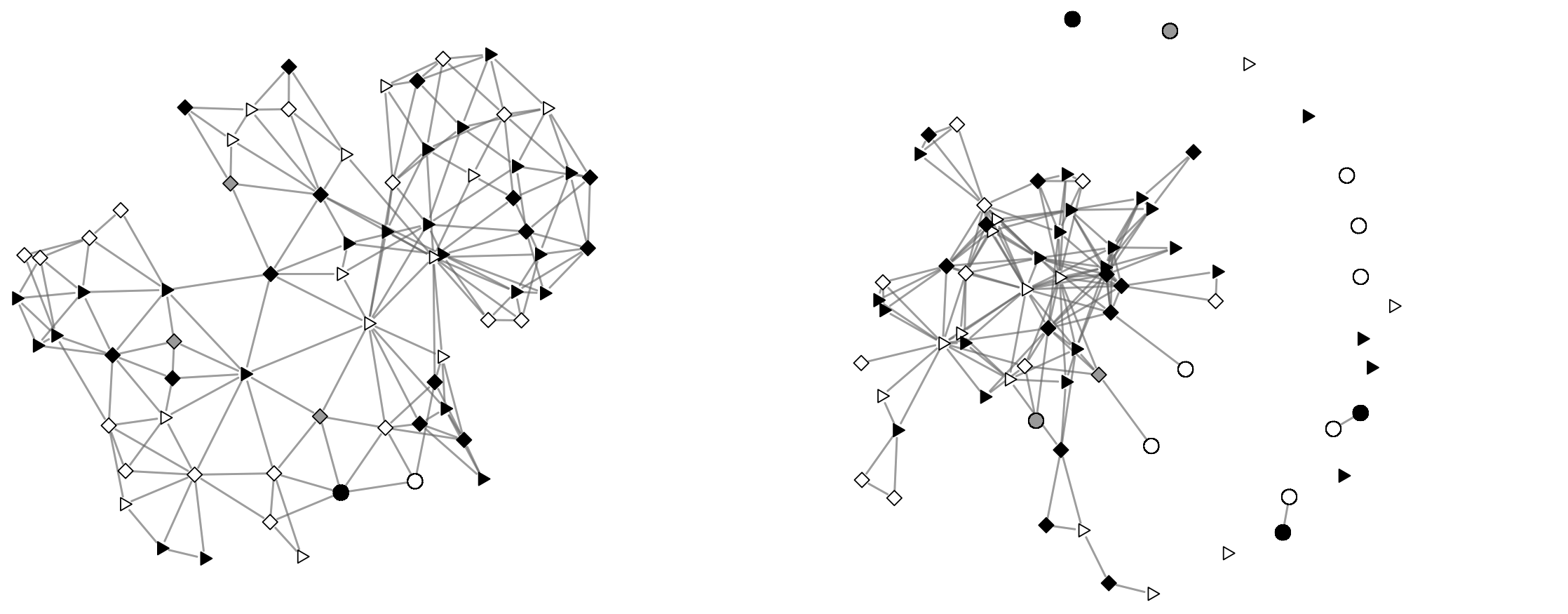
	Distance < 5		Distance > 5	
	Linear	Non-linear	Linear	Non-linear
Number of treated neighbors	1	2	5	6
Proportion of treated neighbors	3	4	7	8

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:

Geographic Network Committee Network (>1 in common)



Ideological Network (top 5%)

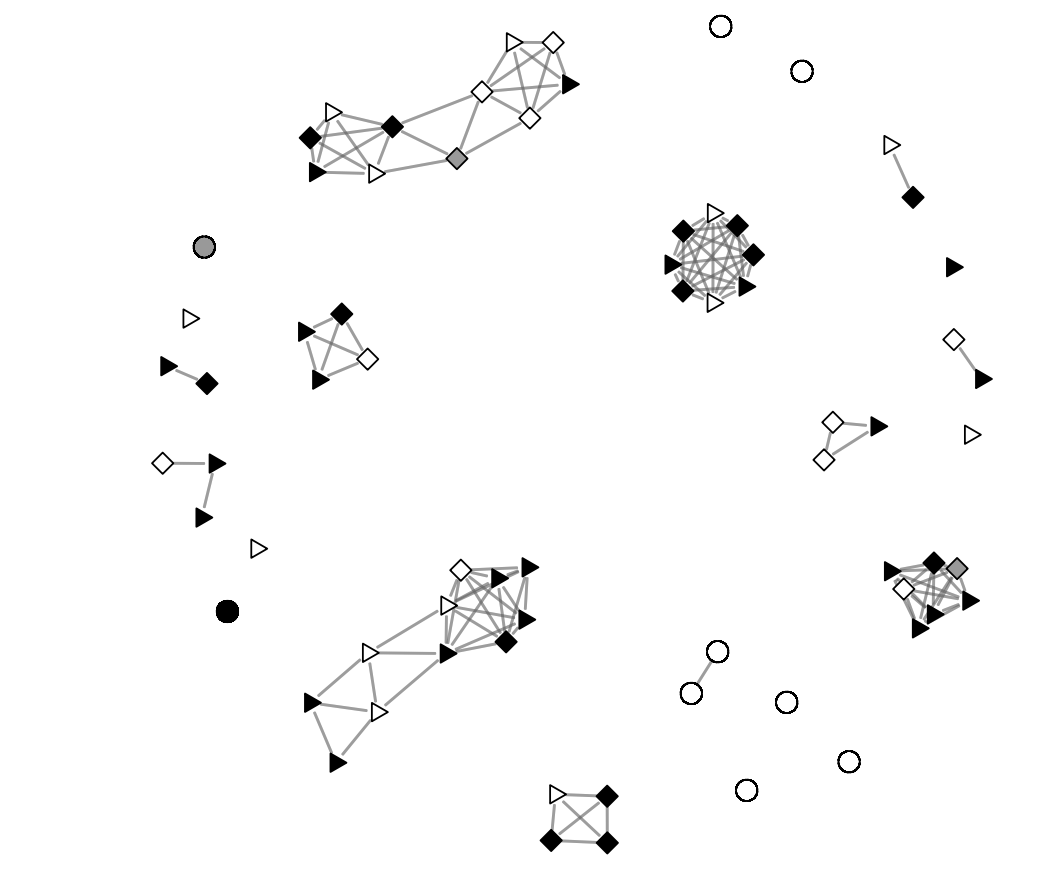


Figure: Different networks among New Mexico legislators. Colors denote outcome: black means voted with district, gray means abstained, white means voted against. Shape denotes treatment status. Triangles are treated. Squares are adjacent to treated. Circles are isolated from treatment

Replication

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.

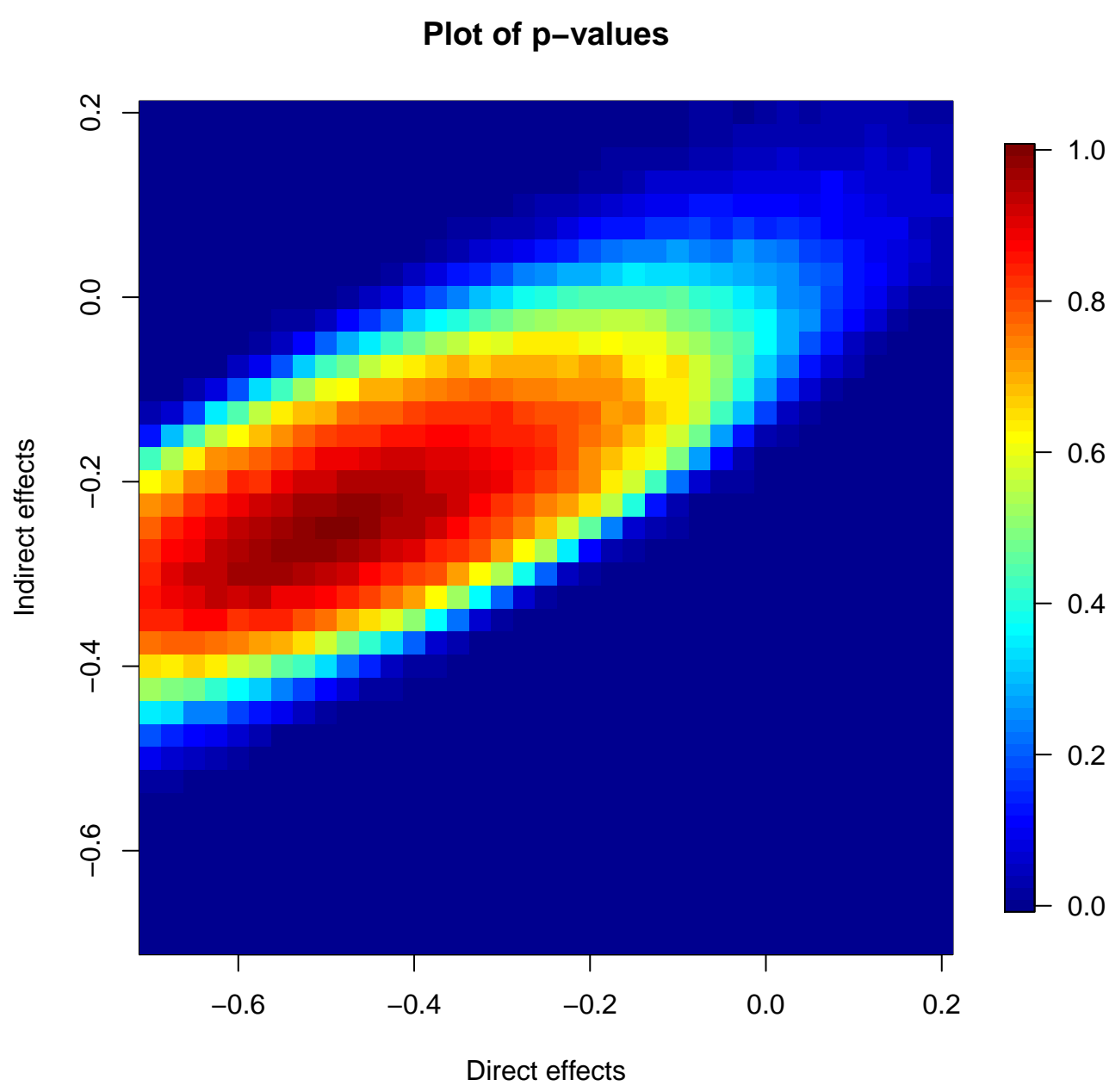


Figure: p-values using Coppock model

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.

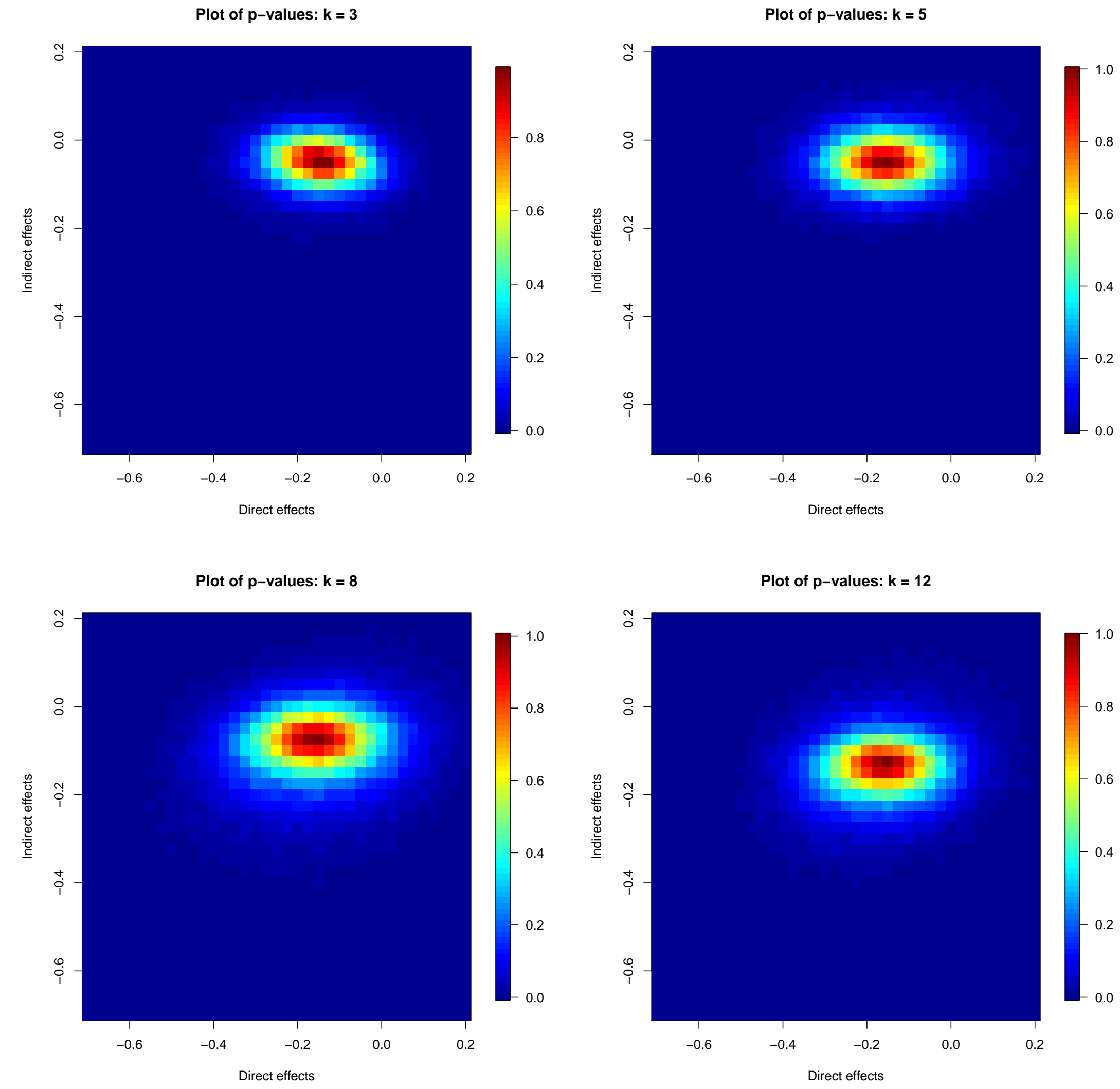


Figure: p-values using nearest ideological neighbors. k is the number of neighbors considered

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

- 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.

