Information Spillovers: Another Look at Experimental Estimates of Legislator Responsiveness
Online Appendix

Alexander Coppock

January 12, 2015

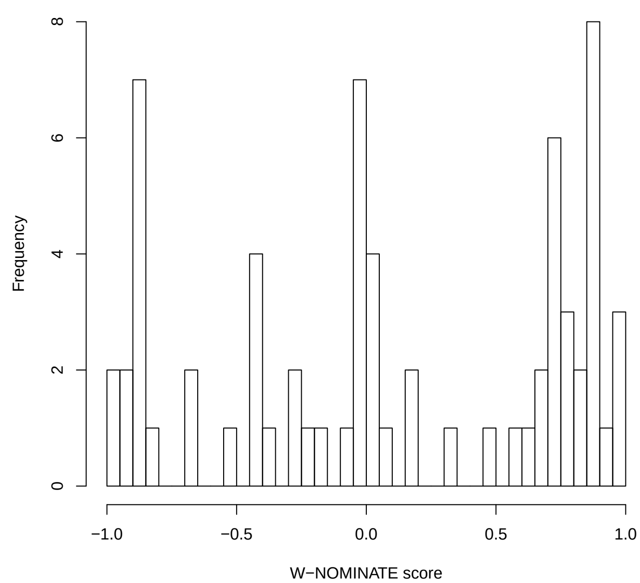
This appendix accompanies "Information Spillovers: Another Look at Experimental Estimates of Legislator Responsiveness." It contains four sections: 1) Alternative specification of similarity, 2) Treatment effect heterogeneity 3) Reference table for all specifications, and 4) Guide to the replication archive.

1 Alternative Specifications of Similarity

As noted in the main analysis, the specification of a spillover model requires the analyst to make theoretically-motivated assumptions about the pathways over which spillovers may occur. The theoretical basis of the ideological similarity model straightforward: to the extent that information represents an advantage, legislators who want to see their own ideologies promoted will share that advantage with ideologically proximate colleagues.

The distribution of ideal points is shown in the figure below.

Figure 1: Distribution of Estimated Ideal Points



In the main analysis, ideological similarity was calculated using the following formula:

$$\text{Similarity}_{i,j} = \frac{2 - |Ideo_i - Ideo_j|}{2} \tag{1}$$

This specification is useful because it generates a similarity score between zero and 1 for all legislator pairs (i,j). There are, of course, many functions that would take a pair of ideal points and return a score between zero and one. In this section, I show the robustness of the findings to alternative specifications of ideological similarity.

1.1 W-NOMINATE Ranks

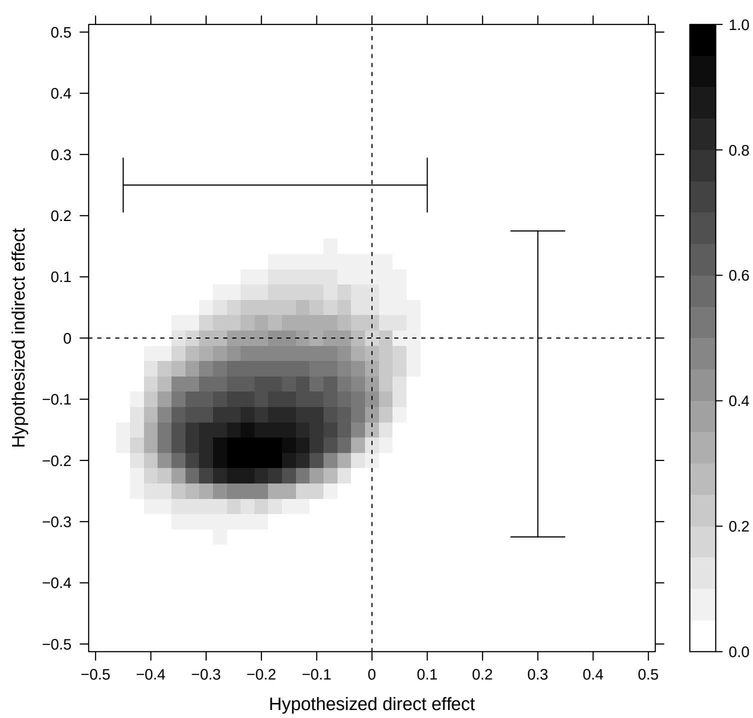
Instead of considering the absolute distance between any two ideal points, we can instead calculate the distance between the ranks of ideal points. Using the ranks "flattens" the distribution of ideal points – members of tight ideological blocks are assigned lower similarity scores and members of opposing ideological camps are given higher similarity scores.

The formula used to calculate similarity according to ranks is given in Equation 2:

$$\text{Similarity}_{i,j} = \frac{67 - |Rank(Ideo_i) - Rank(Ideo_j)|}{67} \tag{2}$$

The p-value map using this model is shown in Figure 2. The substantive findings when using this measure are similar to those reported in the main analysis: both direct and indirect exposure to information appear to decrease the probability of voting for SB24.

Figure 2: p-value map of ranked ideological similarity spillover model



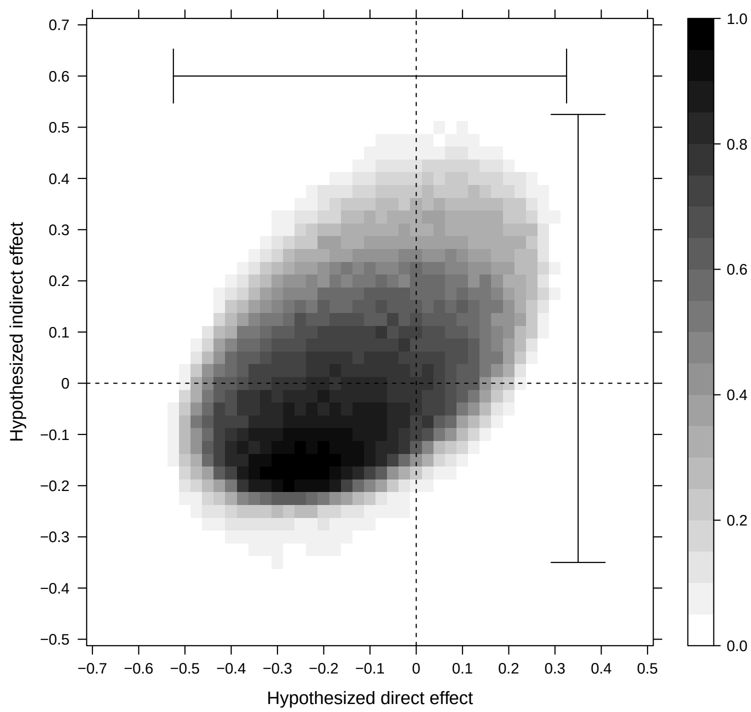
1.2 W-NOMINATE Absolute Squared Distance

Alternatively, one could parameterize the ideological similarity between any two legislators as a function of the squared distance between any two legislators. The function is given in Equation 3. Note that for any pair of ideal points i and j, Equation 3 returns a higher value than Equation 1. This parameterization reflects an assumption of a tighter information network in the New Mexico legislature.

$$\text{Similarity}_{i,j} = \frac{4 - (Ideo_i - Ideo_j)^2}{4} \tag{3}$$

The best guess of direct and indirect effects according to this model have the same sign and similar magnitude to the results reported in the main analysis, but these results are more uncertain. According to this model, the data support many hypotheses, including the hypothesis that the direct and indirect effects are both equal to zero.

Figure 3: p-value map of ideological similarity spillover model

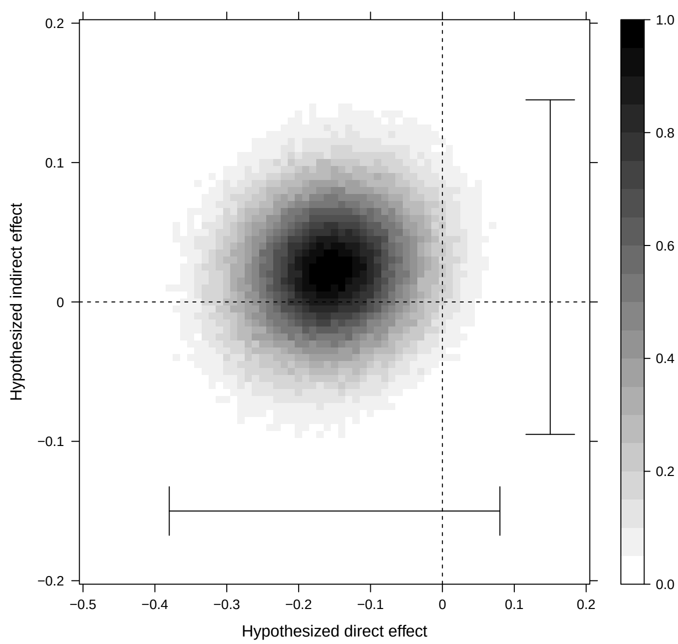


1.3 Placebo: Geographic contiguity

The theoretical justification for the spillover model considered in the previous section was that ideologically proximate legislators may share information in order to advance ideologically similar goals. As a demonstration that not all network models would generate evidence of indirect effects, consider a model of spillovers based on the geographic contiguity of legislative districts. Each legislator receives a “unit” of spillover for each directly treated legislator from a neighboring district. Cogent theoretical explanations for why the geographic adjacency of districts would be an pathway over which spillovers could occur are hard to find: perhaps contiguous districts have similar demographics and perhaps the representatives from places with similar constituents share legislative goals.

Allowing for the possibility that spillovers do occur over the geographic network yields the results presented in Figure 4. This model recovers suggestive evidence of direct effects, though the 95% confidence region does cross zero. The evidence in support of spillovers across the geographic network is quite weak: many hypotheses in which the indirect effects are presumed to be equal to zero are given large p-values. An information network based on geographic contiguity functions as a placebo – the theoretical motivation for such a model is thin, and we would be skeptical if the analysis produced statistically significant indirect effect estimates.

Figure 4: p-value map of contiguous district spillover model



2 Treatment Effect Heterogeneity

The subgroup analysis presented in Figure 3 of the article was estimated by subsetting the dataset into high and low support districts and comparing the observed SSR statistics from separate regressions to simulated SSR statistics. This mode of analysis did not allow for any dependence between the proposed direct and indirect parameters across high and low support districts.

Instead of estimating direct and indirect effects separately by high and low support, a four-parameter generalization of the causal model can be estimated. The causal model to be estimated is given in Equation 1. β_1 and β_2 are the direct and indirect effects of treatment among low support districts (for whom $x_i = 1$). β_3 and β_4, are the direct and indirect effects of treatment among high support districts (for whom $x_i = 0$. The function $g(\cdot)$ translates assignment $\mathbf{z}$ and the information network $\mathbf{\Gamma}$ into the level of indirect exposure experienced by each unit.

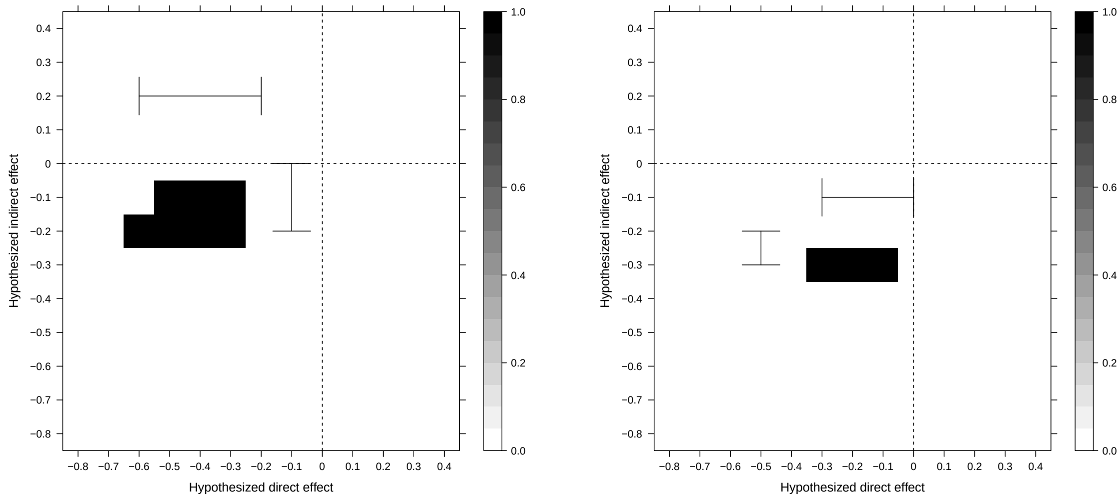
$$y_{i,\mathbf{0}} = y_{i,\mathbf{z}} - \beta_1 z_i x_i - \beta_2 g(\mathbf{\Gamma z}) x_i - \beta_3 z_i (1 - x_i) - \beta_4 g(\mathbf{\Gamma z}) * (1 - x_i) \quad (4)$$

The parameter space of this model is vast, so the results presented below are coarser than those presented in the main analysis. Nevertheless, as can been seen by a comparison of Figure 5 below and Figure 3 in the main paper, the substantive results are the same.

Figure 5: p-value maps by level of support: 4-parameter model

(a) Among low-support districts

(b) Among high-support districts



3 Summary Tables for All Models

Table 1: Summary of Constant Effects Models

	No Spillover	Absolute Distance	Rank Distance	Squared Distance	Geographic Contiguity
Direct Effect	-0.16	-0.3	-0.225	-0.25	-0.15
	[-0.34,0.02]	[-0.5,-0.075]	[-0.45,0.1]	[-0.525,0.325]	[-0.38,0.08]
Indirect Effect		-0.225	-0.2	-0.175	-0.025
		[-0.3,-0.1]	[-0.325,0.175]	[-0.35,0.525]	[-0.095,0.145]
Corresponding Figure	1a	2	A2	A3	A4

Table 2: Summary of Heterogeneous Effects Models

	No Spillover	Absolute Distance
Direct Effect – High Support	0.05	-0.175
	[-0.225,0.35]	[-0.45,0.075]
Indirect Effect – High Support		-0.3
		[-0.425,-0.175]
Direct Effect – Low Support	-0.375	-0.55
	[-0.675,-0.05]	[-0.825,-0.125]
Indirect Effect – Low Support		-0.125
		[-0.325,0]
Corresponding Figure	1b	3

4 Replication Materials

Replication materials for all results are available at `dx.doi.org/10.1017/xps.2014.9`.

1. CoppockJEPS_10000Randomizations.R
   - This file generates 10,000 matched pair randomizations for use in simulations. It must be run first.
   - Inputs: nm.replication.dta
   - Outputs: CoppockJEPS_10000randomizations.rdata
2. CoppockJEPS_datapreparation.R
   - This file prepares the data for analysis. Similarity matrices based on ideology and geography are created as well. It also creates a histogram of estimated ideal points. It must be run second. All subsequent files can be run in any order.
   - Inputs: nm.replication.dta, CoppockJEPS_10000Randomizations.rdata, CoppockJEPS_rollcalldata.csv, CoppockJEPS_shapefile (this directory must stay intact)
   - Outputs: CoppockJEPS.rdata, CoppockJEPS_appendixfigure1.pdf
3. CoppockJEPS_figure1acode.R
   - Inputs: CoppockJEPS.rdata
   - Outputs: CoppockJEPS_figure1a.pdf, fig1a.rdata
4. CoppockJEPS_figure1bcode.R
   - Inputs: CoppockJEPS.rdata
   - Outputs: CoppockJEPS_figure1a.pdf, fig1b.rdata
5. CoppockJEPS_figure2code.R
   - Inputs: CoppockJEPS.rdata
   - Outputs: CoppockJEPS_figure2.pdf, fig2.rdata
6. CoppockJEPS_figure3code.R
   - Inputs: CoppockJEPS.rdata
   - Outputs: CoppockJEPS_figure3a.pdf, CoppockJEPS_figure3b.pdf, fig3.rdata
7. CoppockJEPS_appendixfigure2.R
   - Inputs: CoppockJEPS.rdata
   - Outputs: CoppockJEPS_appendixfigure2.pdf, appendixfig2.rdata
8. CoppockJEPS_appendixfigure3.R
   - Inputs: CoppockJEPS.rdata
   - Outputs: CoppockJEPS_appendixfigure3.pdf, appendixfig3.rdata
9. CoppockJEPS_appendixfigure4.R
   - Inputs: CoppockJEPS.rdata
   - Outputs: CoppockJEPS_appendixfigure4.pdf, appendixfig4.rdata

10. CoppockJEPS_appendixfigure5.R
    - Inputs: CoppockJEPS.rdata
    - Outputs: CoppockJEPS_appendixfigure5a.pdf, CoppockJEPS_appendixfigure5b.pdf,
11. CoppockJEPS_appendixtable.R
    - Inputs: fig1a.rdata, fig1b.rdata, fig2.rdata, fig3.rdata, appendixfig2.rdata, appendixfig3.rdata, appendixfig4.rdata
    - Outputs: appendixtable1.tex, appendixtable2.tex