

Does Intolerance Dampen Dissent?

Online Appendix

Contents

1	Survey Item Wording	1
2	Measuring Macro-Tolerance	2
3	Measuring State-Level Protest Using GDELT	3
4	Modeling the Rate of Protest	6
5	Other Supplementary Tables	7

1. Survey Item Wording

Least-Liked Tolerance

Now let's consider [LEAST-LIKED GROUP / OTHER HIGHLY DISLIKED GROUP] a bit more. To what extent do you agree strongly, agree, are uncertain, disagree, or disagree strongly with the following statements about [LEAST-LIKED GROUP / OTHER HIGHLY DISLIKED GROUP]?

- LLT1:** [LEAST-LIKED GROUP / OTHER HIGHLY DISLIKED GROUP] should be allowed to make a speech in our community. (Agree strongly, agree, are uncertain, disagree, or disagree strongly)
- LLT2:** [LEAST-LIKED GROUP / OTHER HIGHLY DISLIKED GROUP] should be banned from running for public office.
- LLT3:** [LEAST-LIKED GROUP / OTHER HIGHLY DISLIKED GROUP] should be allowed to hold public rallies and demonstrations in our community.

Support for Civil Liberties

I am now going to read you a list of some policy positions that some people in the United States are talking about. For each policy, please tell me if you strongly support it, support it, oppose it, or strongly oppose it. The first one is

- SCL1:** Requiring everyone to carry a national identity card at all times to show to a police officer on request. (Strongly support, support, oppose, or strongly oppose)
- SCL2:** Allowing law enforcement officials to stop or detain people of a different race if these groups are thought to be more likely to commit crimes.
- SCL3:** Requiring that high school teachers defend America's policies in order to promote loyalty to our country.
- SCL4:** Allowing the government to record telephone calls and monitor e-mail in order to prevent people from planning terrorist or criminal acts.
- SCL5:** Allowing law enforcement officials to investigate people who participate in nonviolent protests against the U.S. government.

2. Measuring Macro-Tolerance

Table A1. Multilevel Model of Political Tolerance

	Baseline	MRP Model
Intercept	-.022 (.232)	-.064 (.235)
Percent Bachelor's degree		.522*** (.123)
Percent religious		-.252 (.131)
Percent Black		-.261* (.112)
AIC	8470.2	8459.8
BIC	8518.6	8526.3
<i>N</i> respondents	3133	3133
<i>N</i> MSAs	316	316
<i>N</i> regions	4	4
<i>N</i> education groups	5	5
<i>N</i> age groups	5	5
<i>N</i> race groups	4	4
<i>N</i> gender groups	2	2
Variance of MSA intercepts	.008	.004
Variance of education intercepts	.152	.145
Variance of age intercepts	.020	.020
Variance of race intercepts	.013	.014
Variance of gender intercepts	.025	.024
Variance of region intercepts	.009	.001
Variance of residuals	.849	.848

*** $p < .001$, ** $p < .01$, * $p < .05$. Standard errors in parentheses. All variables are standardized to range from 0 to 1.

MRP estimation begins with a multilevel model of individual opinion. Our model closely follows from those proposed by Park, Gelman, and Bafumi (2004) and Lax and Phillips (2009). In particular, we model respondents' general political tolerance factor scores as a function of five geographic and demographic categories. Because our measure of tolerance is continuous, we use a multilevel linear model:

$$\text{tolerance}_i = \beta^0 + \alpha_{g[i]}^{gend.} + \alpha_{r[i]}^{race} + \alpha_{a[i]}^{age} + \alpha_{e[i]}^{educ.} + \alpha_{m[i]}^{MSA} + \varepsilon_i$$

$$\varepsilon_i \sim N(0, \sigma_{tol}^2)$$

The grouping variables of gender, race, age, education, and MSA are modeled as random effects drawn from normal distributions with variances to be estimated from the data. The model for the race effects, for example, is:

$$\alpha_r^{race} \sim N(0, \sigma_{race}^2)$$

Our survey respondents hail from 316 of the 365 MSAs: these 316 MSA intercepts receive a more complex model because of the inclusion of random regional intercepts and MSA-level covariates:

$$\alpha_m^{MSA} = \alpha_r^{region} + \gamma^{deg.} \cdot degree_m + \gamma^{rel.} \cdot religious_m + \gamma^{black} \cdot black_m + u_m$$

$$u_m \sim N(0, \sigma_{MSA}^2)$$

Regional intercepts are then modeled in the same fashion as the race, age, etc., intercepts. A summary of the parameter estimates from this MRP model is provided in Table A1.

3. Measuring State-Level Protest Using GDELT

Using Google BigQuery, we gather GDELT data on protest in the United States from 2007 to 2011 by collecting all events:

1. Coded as having taken place in the United States (i.e., `ActionGeo_CountryCode = 'US'`),
2. Coded as occurring in the period 1/1/2007 to 12/31/2011, and
3. Classified as “protest” (category 14) in the CAMEO event taxonomy, which includes demonstrations or rallies, hunger strikes, strikes or boycotts, obstructions of public passage, violent protests or riots, and other forms of political protest.
4. That are specifically located in one of the 50 states. We drop events that are not located in one of the 48 states (i.e., `ActionGeo_ADM1Code != 'US',` or `'USDC'`).
5. Where protagonists are additionally identified as US-located. We drop events where the protagonist location (`Actor1Geo_ADM1Code`) is unknown or non-US.

We refer to the event counts obtained through the above procedure as the raw counts. Because of the prevalence of false positives in GDELT, we implement another three filters to remove as many false positives as possible:

1. Actor is not government, international, or media. Dropping events where the protagonist is categorized as government, international actor, or the media (i.e., `Actor1Type1Code` is one of the following: GOV, COP, JUD, LEG, MIL, MNC, IGO, SPY, UAF, IMG, UIS, or MED).
2. Root events. Remove events that are not mentioned in the first paragraph of a news article (i.e. `IsRootEvent = 0`).
3. More than one report. Remove events that are referenced by only one article (i.e., `NumArticles < 2`).

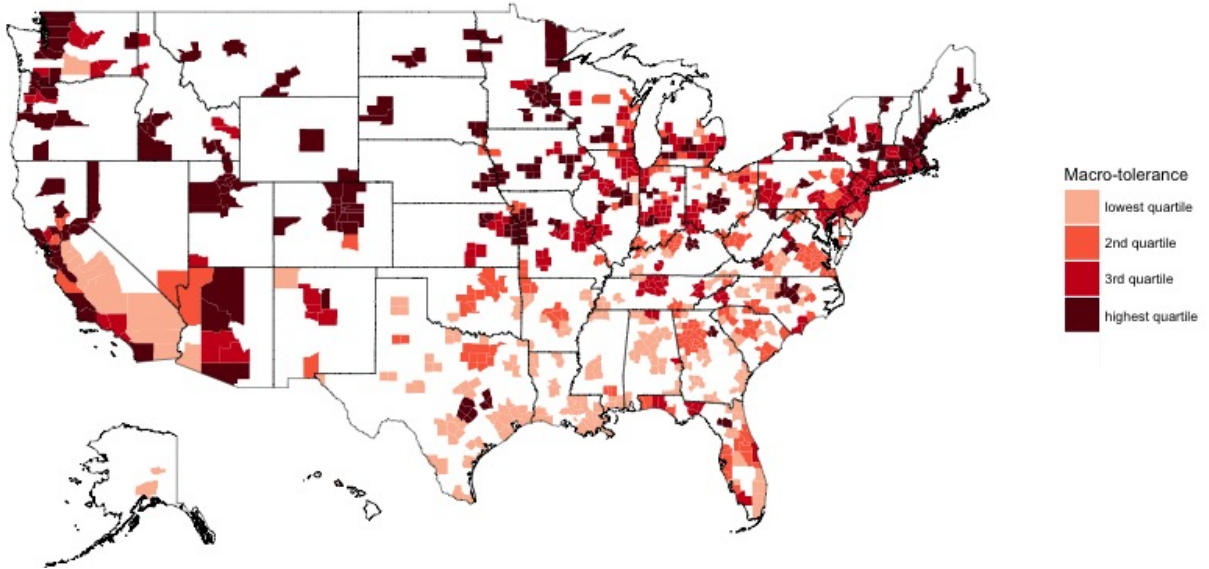
By applying all these filters, we arrive at the “filtered” measure that we use as our main measure of protest incidence throughout the paper.

Table A2 lists the ten most- and least-tolerant and the ten most- and least-protest prone MSAs. Figure A1 then plots the measures of macro-tolerance and rate of protest on maps of U.S. MSAs.

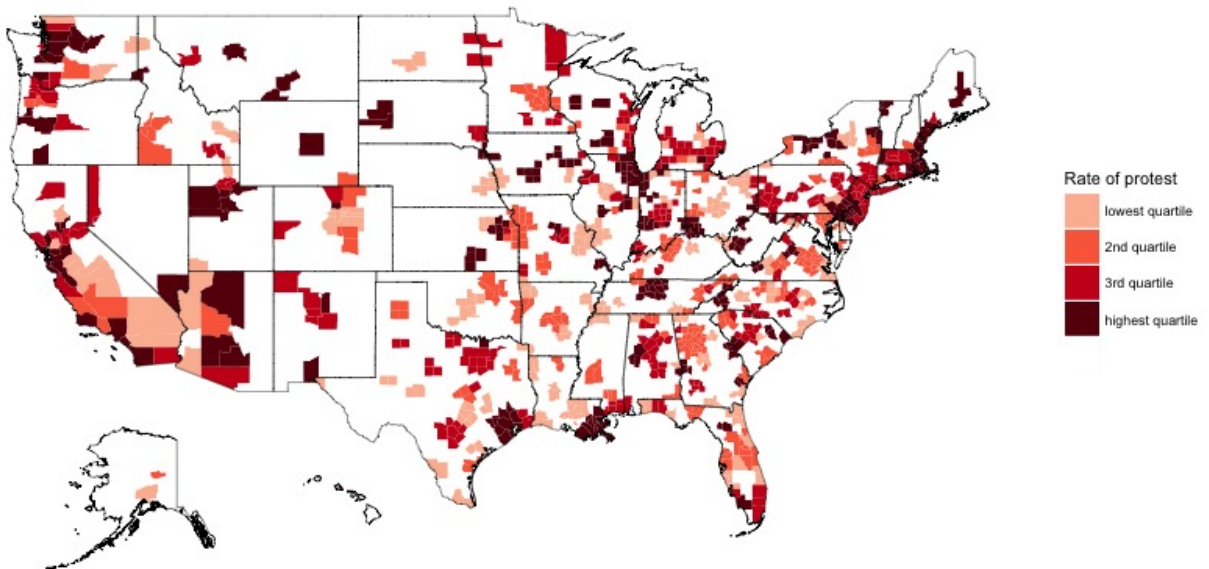
Table A2. Most and Least Tolerant and Protest-Prone Metropolitan Areas, 2007-2011

Rank	Macro-tolerance		Annual rate of protest (per million)	
	Metropolitan statistical area	Value	Metropolitan statistical area	Value
1	Boulder, CO	1.000	Carson City, NV	97.51
2	Ithaca, NY	.932	Topeka, KS	79.98
3	Corvallis, OR	.931	San Francisco-Oakland-Fremont, CA	71.28
4	Lawrence, KS	.882	Glens Falls, NY	65.15
5	Ames, IA	.843	Great Falls, MT	51.90
6	Ann Arbor, MI	.835	Boston-Cambridge-Quincy, MA-NH	49.14
7	Iowa City, IA	.819	Houma-Bayou Cane-Thibodaux, LA	47.25
8	Fort Collins-Loveland, CO	.807	Las Vegas-Paradise, NV	47.08
9	Missoula, MT	.785	Bangor, ME	45.63
10	Columbia, MO	.766	Longview, WA	45.14
...				
356	Beaumont-Port Arthur, TX	.089	McAllen-Edinburg-Mission, TX	1.06
357	El Paso, TX	.089	Yuma, AZ	1.03
358	Danville, VA	.087	Modesto, CA	.78
359	Sumter, SC	.073	Anderson, IN	.00
360	Rocky Mount, NC	.065	Coeur d'Alene, ID	.00
361	Pine Bluff, AR	.053	Elkhart-Goshen, IN	.00
362	Albany, GA	.044	Idaho Falls, ID	.00
363	Laredo, TX	.014	Jackson, TN	.00
364	McAllen-Edinburg-Mission, TX	.012	Midland, TX	.00
365	Brownsville-Harlingen, TX	.000	Winchester, VA-WV	.00

Figure A1. Macro-tolerance and Protest by Metropolitan Statistical Area



MRP estimates of macro-tolerance, 2007 to 2011. Non-metropolitan counties appear in white.



Annual rate of protest from 2007 to 2011 (annual incidence of protest divided by the MSA population in millions). Non-metropolitan counties appear in white.

4. Modeling the Rate of Protest

Our outcome variable is the annual incidence of protest in MSAs over the period 2007 to 2011. It is natural to model this variable as a count. Collective action is subject to diffusion effects (Andrews and Biggs 2006), with the consequence that the incidence of protest is not strictly independent across states. Count variables affected by spatial diffusion have increased dispersion. The negative binomial model, which includes a variance parameter, ω , to estimate dispersion, is thus appropriate for these data:

$$\begin{aligned} \text{protest}_i &\sim \text{Negative-Binomial}(\mu_i, \omega), \\ \ln(\mu_i) &= \beta_0 + \beta_1 \cdot \text{tolerance}_i + \varepsilon_i, \\ \exp(\varepsilon_i) &\sim \text{Gamma}(1, \omega). \end{aligned}$$

MSAs have very different population sizes. This implies that opportunities for participating in protest vary (e.g., the raw number of people who might conceivably engage in a protest). In such cases, it is necessary to include an “exposure” offset in count models. In our case, the size of the MSA population is an adequate offset variable. Adjusting for exposure, we get the negative binomial rate model, where the log of population is included with an offset, or fixed coefficient, of 1:

$$\begin{aligned} \ln\left(\frac{\mu_i}{\text{pop.}_i}\right) &= \beta_0 + \beta_1 \cdot \text{tolerance}_i + \varepsilon_i \\ \ln(\mu_i) &= \beta_0 + \ln(\text{pop.}_i) + \beta_1 \cdot \text{tolerance}_i + \varepsilon_i \end{aligned}$$

5. Other Supplementary Tables

Table A3. Descriptive Statistics

Variable	Min.	Max.	Mean	Std. Dev.
Incidence of protest	0	1530	53.75	174.98
Log of population	-2.89	2.93	-1.15	1.05
Macro-tolerance (MRP estimate)	0	1	.40	.17
Percent Obama vote 2012	0	1	.54	.18
Gini coefficient	0	1	.37	.17
Black-white segregation (dissimilarity index)	0	1	.46	.20
Ethnic fractionalization	0	1	.49	.24
Percentage population increase 2000-2010	0	1	.22	.10
Unemployment rate 2007-2011	0	1	.41	.17
Median household income	0	1	.31	.15
Percentage students	0	1	.20	.17
Percentage under 18 years old	0	1	.45	.14
Percentage with high school diploma	0	1	.73	.16
Charitable organizations per person	0	1	.31	.22
Religious congregations per person	0	1	.34	.19

All variables other than incidence of protest and log population, are rescaled to range from 0 to 1.

Table A4. Sources of Data

Variables	Source
Macro-tolerance	Freedom and Tolerance Surveys
Incidence / rate of protest	Global Database on Events Language and Tone (https://bigquery.cloud.google.com/table/gdelt-bq:full.events)
Number of religious congregations, Percentage religious	Association of Religion Data Archives census of religion 2010 (http://www.thearda.com/Archive/Files/Descriptions/RCMSMT10.asp)
Ethnic dissimilarity and isolation indices	John Logan's US2010 project (http://www.s4.brown.edu/us2010/SegSorting/Default.aspx)
Charitable organizations	National Center for Charitable Statistics (http://nccsweb.urban.org/) (note, in some cases, these data are for the main county, not the entire MSA)
Percentage Obama vote and turnout in 2012	The Guardian (https://www.theguardian.com/news/datablog/2012/nov/07/us-2012-election-county-results-download)
Ethnic fractionalization, age, employment, income, student status	2007-2011 American Community Surveys

Table A5. Confirmatory Factor Analysis of Political Tolerance

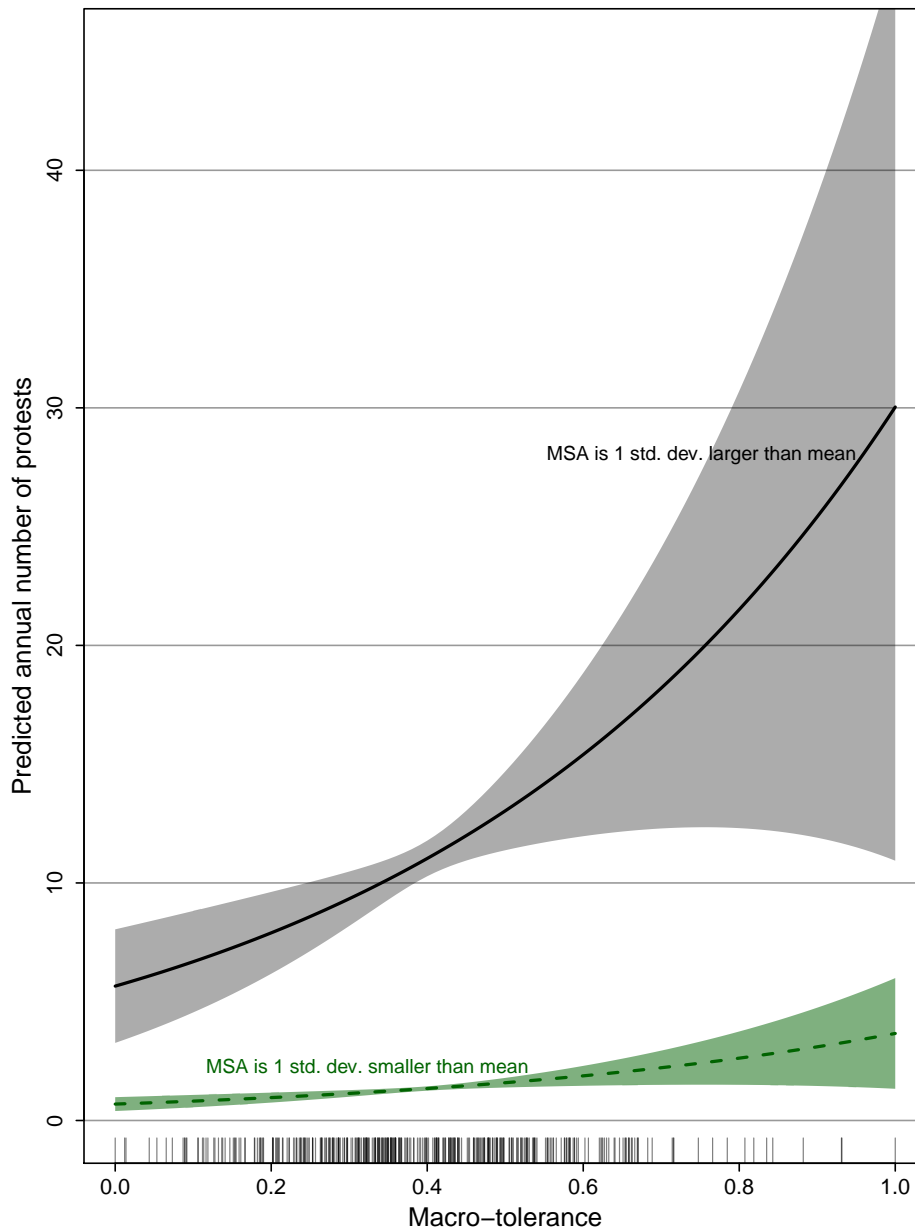
Indicators	Factor Loadings			Unique variances
	General tolerance	Least-liked tolerance	Support for civil liberties	
LLT1		.53		.49
LLT2		.49		.57
LLT3		.52		.51
SCL1			.38	.75
SCL2			.42	.70
SCL3			.43	.67
SCL4			.40	.72
SCL5			.40	.72
LLT	.89			1.00
SCL	.86			1.00
Model fit				
Test Statistic (χ^2)				134.38
df				17
<i>p</i>				.000
Comparative Fit Index				.978
Tucker-Lewis Index				.963
Reduction in Mean-Squared Error of Association				.041

$N = 4,102$. LL1–3: Least-liked tolerance items; SCL1–5: Support for civil liberties items. Confirmatory factor analysis for ordinal data estimated using diagonally weighted least squares and bootstrapped standard errors. Model is identified by constraining factor variances to one. The correlation between the LL1 and LL3 error terms is modeled ($r = .19$).

Table A6. Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Logged rate of protest													
2. Macro-tolerance (MRP estimate)	.35												
3. Percent Obama vote 2012	.25	.32											
4. Gini coefficient	.01	-.05	.13										
5. Black-white segregation (dissimilarity index)	-.03	-.25	.15	.24									
6. Ethnic fractionalization	-.05	-.27	.13	.32	.19								
7. Percentage population increase 2000-2010	-.16	.06	-.19	.01	-.41	.22							
8. Unemployment rate 2007-2011	-.17	-.40	.15	.08	.16	.33	.00						
9. Median household income	.25	.54	.31	-.23	.05	.21	.09	-.29					
10. Percentage students	-.27	-.42	-.18	-.19	-.05	.33	.28	.12	.03				
11. Percentage under 18 years old	.16	.53	.21	.29	-.21	-.02	.06	-.24	-.02	-.30			
12. Percentage with high school diploma	.26	.72	.11	-.25	-.06	-.35	-.11	-.42	.40	-.49	.26		
13. Charitable organizations per person	.07	.03	-.22	-.12	-.40	-.37	-.15	-.17	-.32	-.23	.15	.09	
14. Religious congregations per person	-.12	-.37	-.54	-.01	-.02	-.24	-.19	-.08	-.55	-.02	-.03	-.08	.40

Figure A2. Predicted Effects of Macro-tolerance in Large and Small MSAs



This figure displays the annual predicted number of protests as macro-tolerance varies from its lowest observed level (0) to its highest (1). The solid line shows the predicted incidence for a hypothetical metropolitan statistical area that is one standard deviation larger than the average, and the dashed line shows the predicted incidence for a hypothetical metropolitan statistical area that is one standard deviation smaller than the average. The accompanying shaded regions indicate the respective 95% prediction intervals. The negative binomial “protest incidence” model, as reported and discussed in the main paper, is used to generate these predicted effects. The “rug” of lines at the base of the graph show the observed distribution of metropolitan areas by their level of macro-tolerance.

Table A7. Additional Negative Binomial Models of MSA Protest Incidence, 2007-2011

	Unfiltered protest incidence	MRP ideology estimate added	Percent non-white added	Influential outliers dropped
Intercept	4.60*** (.49)	4.50*** (.51)	4.53*** (.65)	3.61*** (.52)
Macro-tolerance (MRP estimate)	1.75*** (.51)	1.61** (.54)	1.67** (.58)	2.01*** (.51)
Percent Obama vote 2012	.61* (.26)		.27 (.31)	1.05*** (.27)
Gini coefficient	-.39 (.27)	-.30 (.29)	-.26 (.30)	-.38 (.28)
Black-white segregation (dissimilarity index)	.04 (.24)	-.15 (.25)	-.05 (.26)	-.03 (.24)
Ethnic fractionalization	.57** (.22)	.54* (.23)		.71** (.23)
Percentage population increase 2000-2010	-.61 (.42)	-.89* (.45)	-.89 (.46)	-.64 (.44)
Unemployment rate 2007-2011	-.50 (.26)	-.37 (.28)	-.24 (.26)	-.65* (.28)
Median household income	.34 (.42)	.53 (.44)	.74 (.41)	-.01 (.42)
Percentage students	-.73* (.30)	-.69* (.33)	-.60 (.33)	-.91** (.31)
Percentage under 18 years old	-.84** (.33)	-.82* (.34)	-.90* (.38)	-.89** (.34)
Percentage with high school diploma	-.72 (.39)	-.59 (.42)	-.33 (.42)	-.63 (.41)
Charitable organizations per person	.56** (.20)	.52* (.21)	.52* (.22)	.43* (.21)
Religious congregations per person	.40 (.26)	.44 (.28)	.41 (.29)	.63* (.28)
Conservative ideology (MRP estimate)		-.58* (.27)		
Percentage non-white			.81 (.44)	
Variance parameter	2.81 (.23)	2.76 (.24)	2.74 (.24)	3.09 (.24)
AIC	3305.40	2822.40	2824.11	2758.06
<i>N</i>	365	365	365	362

*** $p < .001$, ** $p < .01$, * $p < .05$. Standard errors in parentheses. Models include log MSA population as an offset (i.e. with coefficient fixed to 1). All explanatory variables standardized to range from 0 to 1.

References

- Andrews, Kenneth, T., and Michael Biggs. 2006. "The Dynamics of Protest Diffusion: Movement Organizations, Social Networks, and New Media in the 1960 Sit-Ins." *American Sociological Review* 71(5): 752-77.
- Lax, Jeffrey R., and Justin H. Phillips. 2009. "How Should We Estimate Public Opinion in The States?" *American Journal of Political Science* 53(1): 107-21.
- Park, David K., Andrew Gelman, and Joseph Bafumi. 2004. "Bayesian Multilevel Estimation with Poststratification: State-Level Estimates from National Polls." *Political Analysis* 12(4): 375-85.