Policy Influence: Do Public Pressure Campaigns Influence Bureaucratic Policymaking?

Appendix and Replication Code

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Contents

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1 Data

Replication data are available in SQL and Rdata at https://github.com/judgelord/rulemaking

These data currently include 212,516 dockets, 134,927 rulemaking dockets from 1,909-02-10 to 2,020-12-17. These dockets received approximately 99,329,768 comments.

This analysis relies of rulemaking dockets from 2005 through 2020. These 44,583 rulemaking dockets received 75,614,762 comments.

1.1 Clustering with text reuse

My theoretical approach requires that I *attribute* form letter comments to the organizations, campaigns, and broader coalitions that mobilized them. To do so, I identify comments that share text. I find that a 10-word phrase repeated across more than a few comments is always either text copied from the proposed policy or a form letter provided by a campaign. Thus, for the text of each comment, I first remove all 10-word phrases that appear in the proposed rule (including the preamble and call for comments). Then, I identify all comments that share ten-word phrases with 99 or more other comments. Finally, I collapse these form letter comments to one representative sample for hand-coding.

For each comment on a rulemaking docket[1], I identify the percent of words it shares with other comments using a 10-word (or "10-gram") moving window function, looping over each possible pair of texts to identify matches.[2] When actors sign onto the same comment, it is clear that they are lobbying together. However, various businesses, advocacy groups, and citizens often comment separately, even when they are aligned. Text-reuse (using the same ten-word phrases) captures this alignment.

Figure 1 shows the percent of shared text for a sample of 50 comments on the Consumer Financial Protection Bureau's 2016 Rule regulating Payday Loans. Comments are arranged by the document identifier assigned by regulations.gov on both axes. The black on

[1]Where a new presidential administration used the same docket number to solicit comments on a proposed rule that a previous administration used, I count these as separate rulemaking dockets. I do so because the second policy is usually reversing or going in the opposite direction as the previous administration's policy solicited comments. The same organizations often comment but with the opposition positions. Support becomes opposition and vice versa.

[2]For more about n-gram window functions and comparisons with related partial matching methods such as the Smith-Waterman algorithm, see Casas, Denny, and Wilkerson (2017) and Judge-Lord (2017).

the diagonal indicates that each document has a perfect overlap with itself. Black squares off the diagonal indicate additional pairs of identical documents. For example, 100% of the words from Comment 95976 are part of some tengram that also appears in 95977 because the exact same comment was uploaded twice. The cluster of grey tiles indicates a coalition of commenters using some identical text. Comments 91130 through 91156 are all partial or exact matches. All are part of a mass comment campaign by Access Financial. The percent of the identical text is lower than many mass-comment campaigns because these are hand-written comments, but the n-gram method still picks up overlap in the OCRed text in the header and footer. Tengrams that appear in 100 or more comments indicate a mass comment campaign. Some agencies use similar "de-duping" software [CITE] and only provide a representative sample comment. In these cases, my linking method assumes that the example comment is representative, and I link these comments to others based on the text of the sample comment provided.

1.2 Hand-coded sample

To estimate the influence of public comments on policy, I code almost all* comments on a random sample of rules, recording the type of organization, the lobbying coalition to which each belongs, the type of coalition (primarily public or private interests), their policy demands, and the extent to which the change between draft and final rule aligned with their demands. This level of alignment between policy asks and policy outcomes is my measure of lobbying success. It does not identify a causal relationship–true policy influence, but it is state of the art with these kinds of observational data (see Yackee and Yackee (2006)).

*On each selected rule, I code all comments submitted as file attachments or emails, but only some comments typed in a text box. I include comments typed in a text box if they share text with other comments (see above). This includes nearly all comments on most rules, excluding entirely unique text-box content, which is marginal both qualitatively and quantitatively. For comments sharing text, I code one sample document for all versions of the form letter.

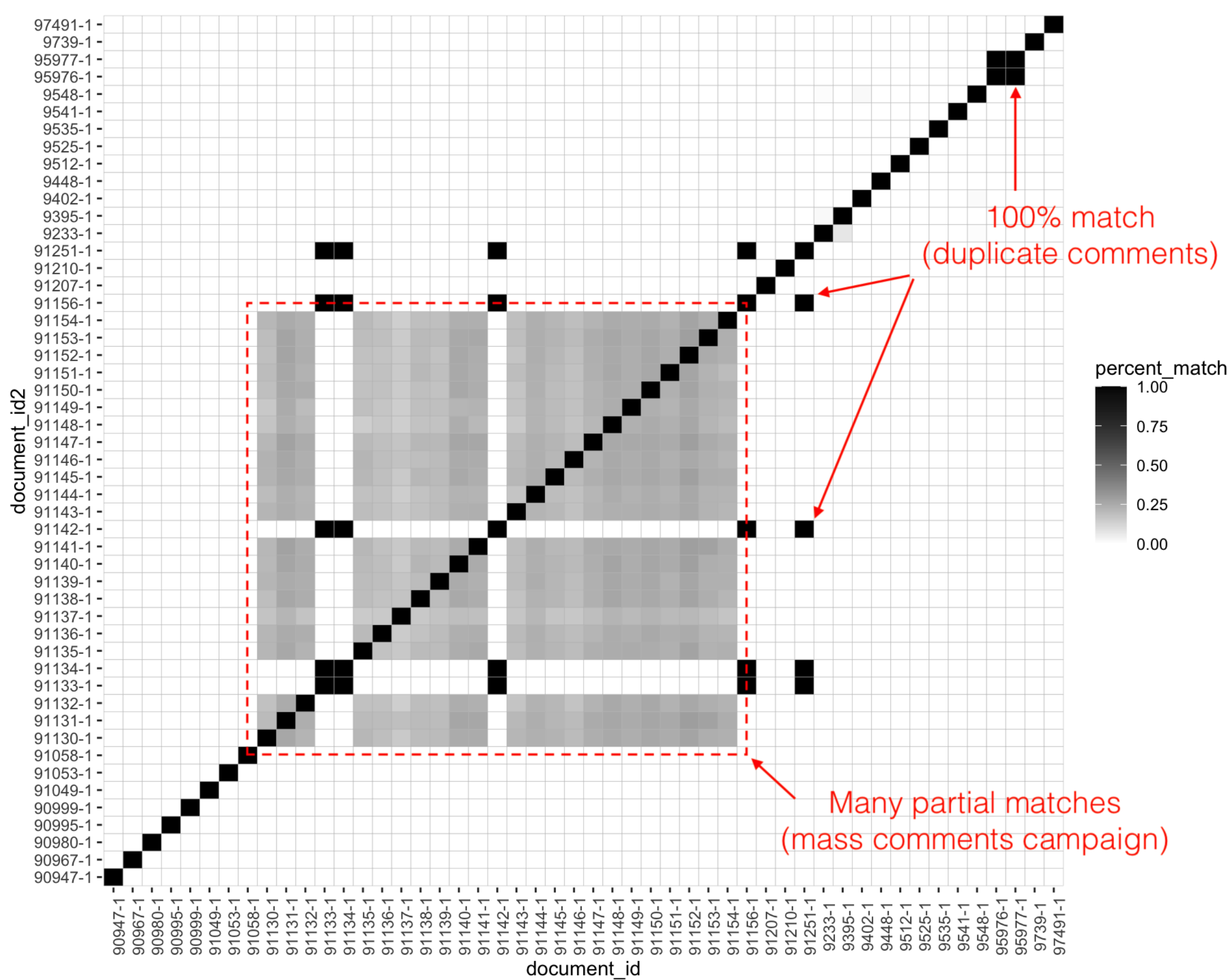

Figure 1: Percent of Matching Text in a Sample of Public Comments

My approach to measuring lobbying success starts with policy demands raised in comments. I code the general regulatory/deregulatory direction of the policy change, but the dimensions of conflict on which I judge lobbying success are those identified by commenters. They do not emerge from a reading of the policy or not any a priori concept. Instead, I read the change between draft and policy with an eye for alignment with commenters' requests (including requests that specific parts of the draft policy do not change.)

My approach of identifying the dimensions of the conflict by comments has benefits and downsides. Compared to other potential measures of success, it is more likely to focus on things that commenters care about. For example, one could measure success by the number of times a comment is mentioned in the agency's response to comments. However, this may capture strategic responsiveness by agencies choosing to discuss some issues more than others. It also counts explicit rejections toward the measure of responsiveness. One could also measure success by focusing on a-priory potential aspects of the policy. Balla et al. (2020) count five factors: (1) the number of regulated entities, (2) number of activities or substances being regulated, (3) the level of pollution standards, (4) the compliance and effective deadlines of the regulation, and (5) the monitoring and reporting requirements. Each takes one value (increasing or decreasing), and each is weighted equally in the analysis. In contrast, starting with comments allows commenters to highlight the issues they care most about.

1.2.1 By organization

Organization-level data sample:

document_id	comment_type	comments	org_name
FEMA-2016-0003-0170	org	1	state of alaska
CFPB-2019-0022-5924	mass	1	NA
WHD-2019-0003-12782	org	1	national association of home builders
NPS-2018-0007-71052	org	1	institute for free speech
ICEB-2015-0002-41564	org	1	southeast missouri state university
FWS-HQ-NWRS-2012-0086-0094	org	1	alaska oil and gas association
DEA-2018-0005-1537	org	1	association for accessible medicines
ED-2016-OESE-0032-19253	NA	1	new york state council of school superi
PHMSA-2012-0082-0327	org	1	dakota gasification company
NOAA-NMFS-2013-0101-1828	org	1	forked river tuna club
IRS-2016-0015-0141	mass	1	american federation of government emp
WHD-2019-0001-59320	org	1	partnership for medicaid home based c
CEQ-2019-0003-346818	org	1	cahto tribe
BSEE-2017-0008-0595	org	1	dnv gl
CFPB-2016-0025-211877	org	1	michigan cbc host committee
PHMSA-2012-0082-0317	org	1	village of elburn
USCBP-2007-0064-0358	org	1	international flying samaritans
DOI-2015-0005-4423	org	1	kapolei community development corpo
DOI-2015-0005-4332	org	1	democratic party of hawaii hawaiian af
NOAA-NMFS-2013-0101-1881	org	1	diane marie fishery
USCG-2010-0990-1744	org	1	aep river operations
FWS-HQ-ES-2018-0097-107766	mass	72178	humane society
NOAA-NMFS-2018-0035-0319	org	1	center for sportfishing policy
TREAS-DO-2007-0015-0032	org	1	center for regulatory effectiveness
NOAA-NMFS-2008-0096-0019	org	1	united national fishermen's assoc.
NOAA-NMFS-2018-0035-0329	org	1	blue water fishermen's association
FWS-HQ-ES-2018-0097-57575	org	1	montezuma county
TREAS-DO-2007-0015-0112	elected	1	congressman joe pitts
CFPB-2019-0006-5717	org	1	coachella valley housing coalition
TREAS-DO-2007-0015-0091	[illegible]	1	[illegible]

Summary counts:

org_type	n
ngo	1418
gov	652
corp	452
corp group	438
NA	21
org	8
elected	4
coalition	2
corp groups	2
corp gorup	1
corp grop	1
general assembly-md	1
gov association	1
maryland house of delegates	1
new jersey mayor	1
ngos	1
other	1
senate-md	1

org_type_detailed	n
ngo;advocacy	379
gov;local	205
gov;state	192
corp;group	77
ngo;legal	77
ngo;professional	67
ngo;credit union	61
ngo; advocacy	48
ngo;university	46
gov;tribe	44
gov;tribe;ej	38
corp;corp	37
ngo;coalition	37
ngo;faith	34
gov;federal	32
ngo;union	31
gov;federal;regional	25
ngo;membership	24
ngo;advocacy;membership	19
ngo;thinktank	19
corp group;coalition	17
corp;law firm	17
ngo;membership;advocacy	17
gov;local;coalition	15
corp;bank	14
corp;small corp	14
ngo;legal;advocacy	14
ngo;environmental	13
ngo;pressure group	13
	11

1.2.2 By coalition

Coalition-level data sample:

docket_id	coalition_comment	coalition_type	coal
BSEE-2012-0005	pew	public	
BSEE-2012-0005	offshore operators committee	private	
BSEE-2013-0010	shell	private	
BSEE-2013-0011	shell	private	
BSEE-2013-0011	pew	public	
BSEE-2017-0008	center for biological diversity	public	
BSEE-2017-0008	american petroleum institute	private	
BSEE-2018-0002	earthjustice	public	
BSEE-2018-0002	american petroleum institute	private	
CEQ-2019-0003	partnership project	public	
CEQ-2019-0003	liuna	private	
CFPB-2016-0025	wcbc	public	
CFPB-2016-0025	axcess financial	private	
CFPB-2019-0006	true	public	
CFPB-2019-0006	true	NA	
CFPB-2019-0006	true	private	
CFPB-2019-0022	lshv	public	
CFPB-2019-0022	aca international	private	
DEA-2018-0005	hsca	public	
DEA-2018-0005	phrma	public	
DOI-2015-0005	blanket crew	public	
DOI-2015-0005	support and assist	public	
ED-2016-OESE-0032	department of education	public	
ED-2016-OESE-0032	public schools	public	
ED-2016-OESE-0032	public schools	NA	
FEMA-2016-0003	pew	public	
FEMA-2016-0003	nema	public	
FWS-HQ-ES-2018-0006	defenders of wildlife	public	
FWS-HQ-ES-2018-0006	national endangered species act reform coalition	private	
FWS-HQ-ES-2018-0007	defenders of wildlif	public	

Histograms of coalition variables

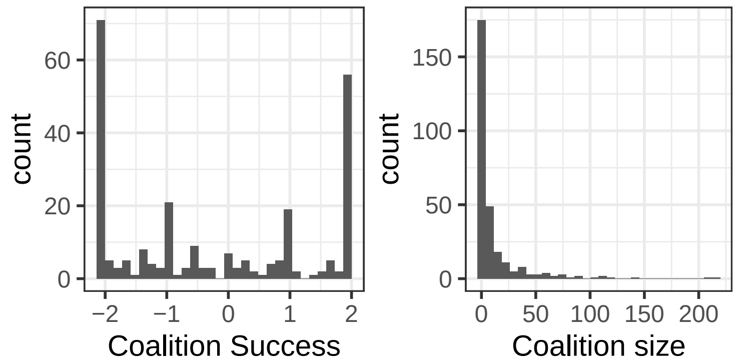

Figure 2: Hand-coded Data by Coalition

Number of comments

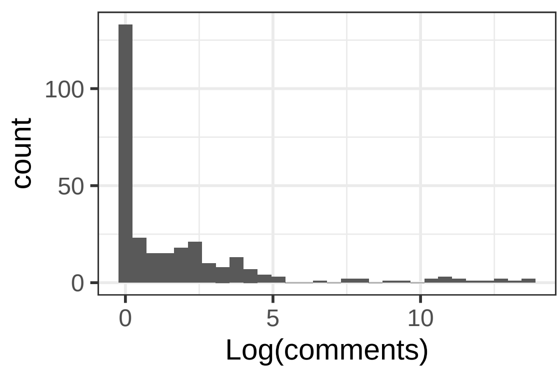

Figure 3: Number of Comments Linked to Hand-Coded Coalitions

Coalitions by type (public interest vs. private interest)

1.2.2.1 Number of supportive comments

1.2.2.2 Coalition Size (number of supportive organizations)

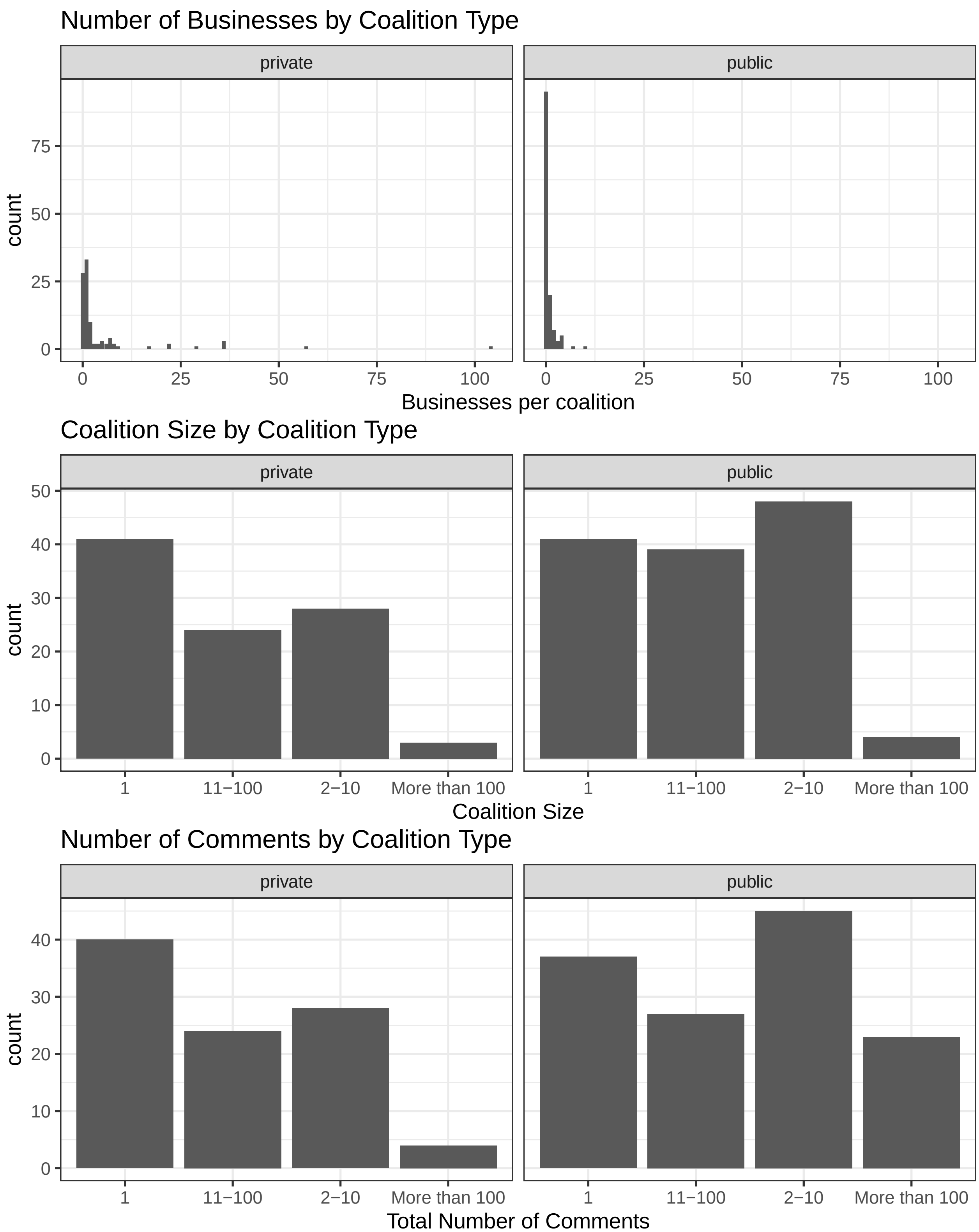
Number of Businesses by Coalition Type
private
public
count
Businesses per coalition
Coalition Size by Coalition Type
Coalition Size
1
11−100
2−10
More than 100
Number of Comments by Coalition Type
Total Number of Comments

Figure 4

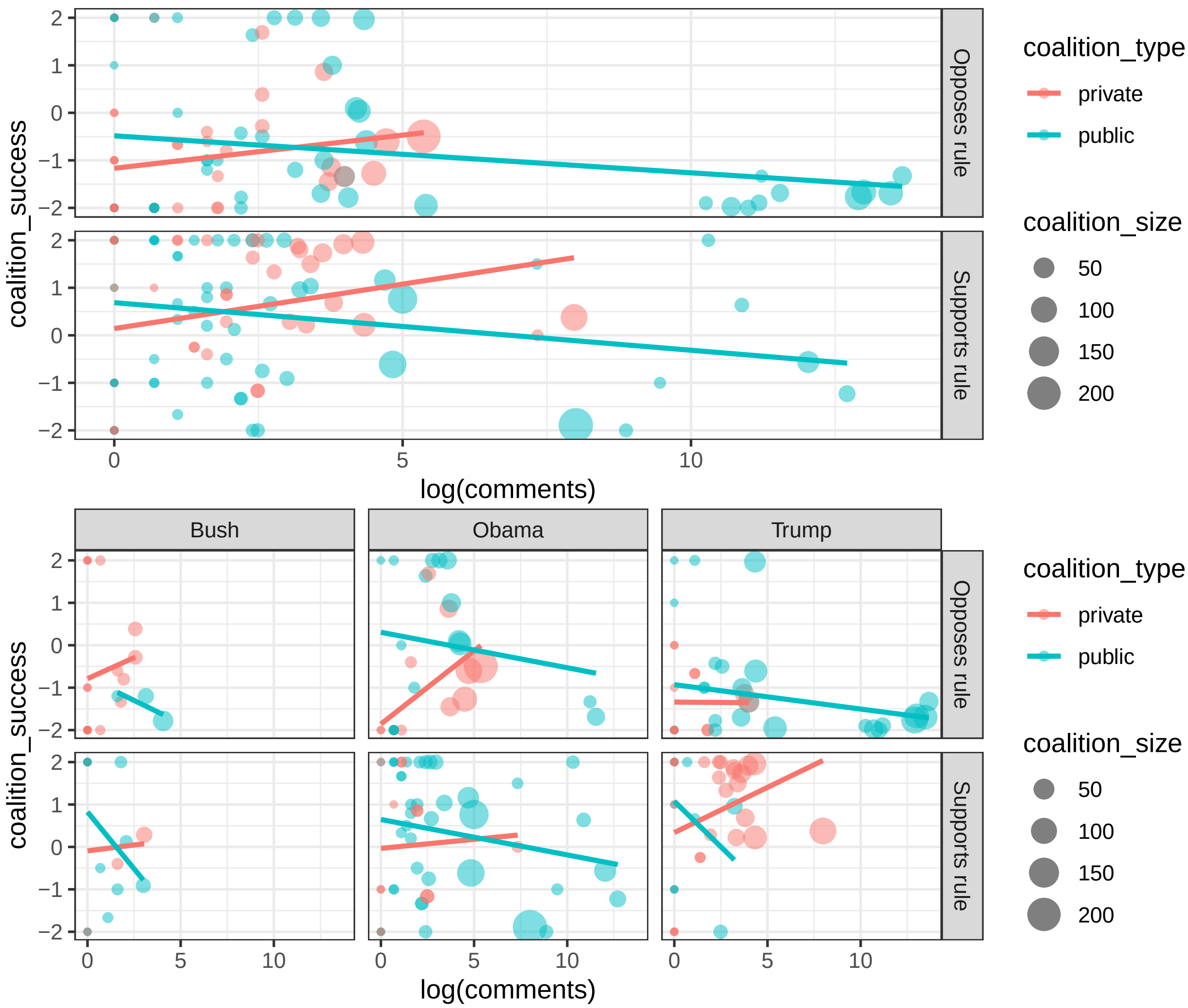

Figure 5: Lobbying Success by Number of Supportive Comments

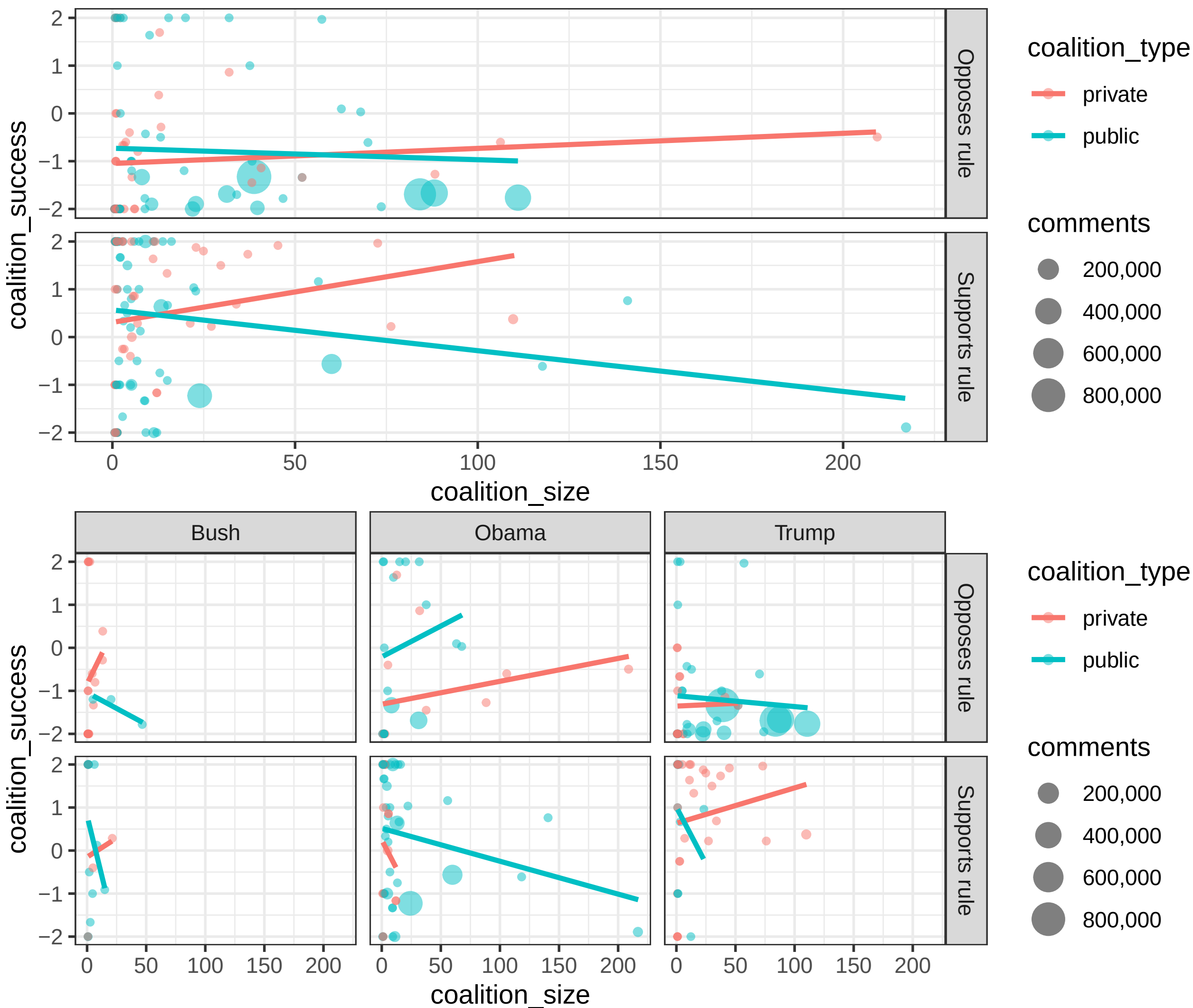

Figure 6: Lobbying Success by Number of Supportive Comments

1.3 Machine-coded Data

IN PROGRESS

Dependent variable: *The percent change in policy text...*

Explanatory variables: The *total number of comments...*

1.4 Comments from legislators

One mechanism by which campaigns may influence policy is by mobilizing members of Congress. Thus, I identify comments submitted by members of Congress and count the number of legislators in each lobbying coalition.

elected_type	n
house	26
senate	16
congress	5
gov	5
florida	4
governor	4
maryland	4
mayor	4
mississippi	4
representative	4
alaska	3
illinois	3
senator	3
senators	3
texas	3
NA	3
california	2
city	2
oklahoma	2
state	2
attorney	1
baltimore	1
berkeley	1
carbondale	1
carver	1
elected	1
georgia	1
iowa	1
jersey	1
[illegible]	[illegible]

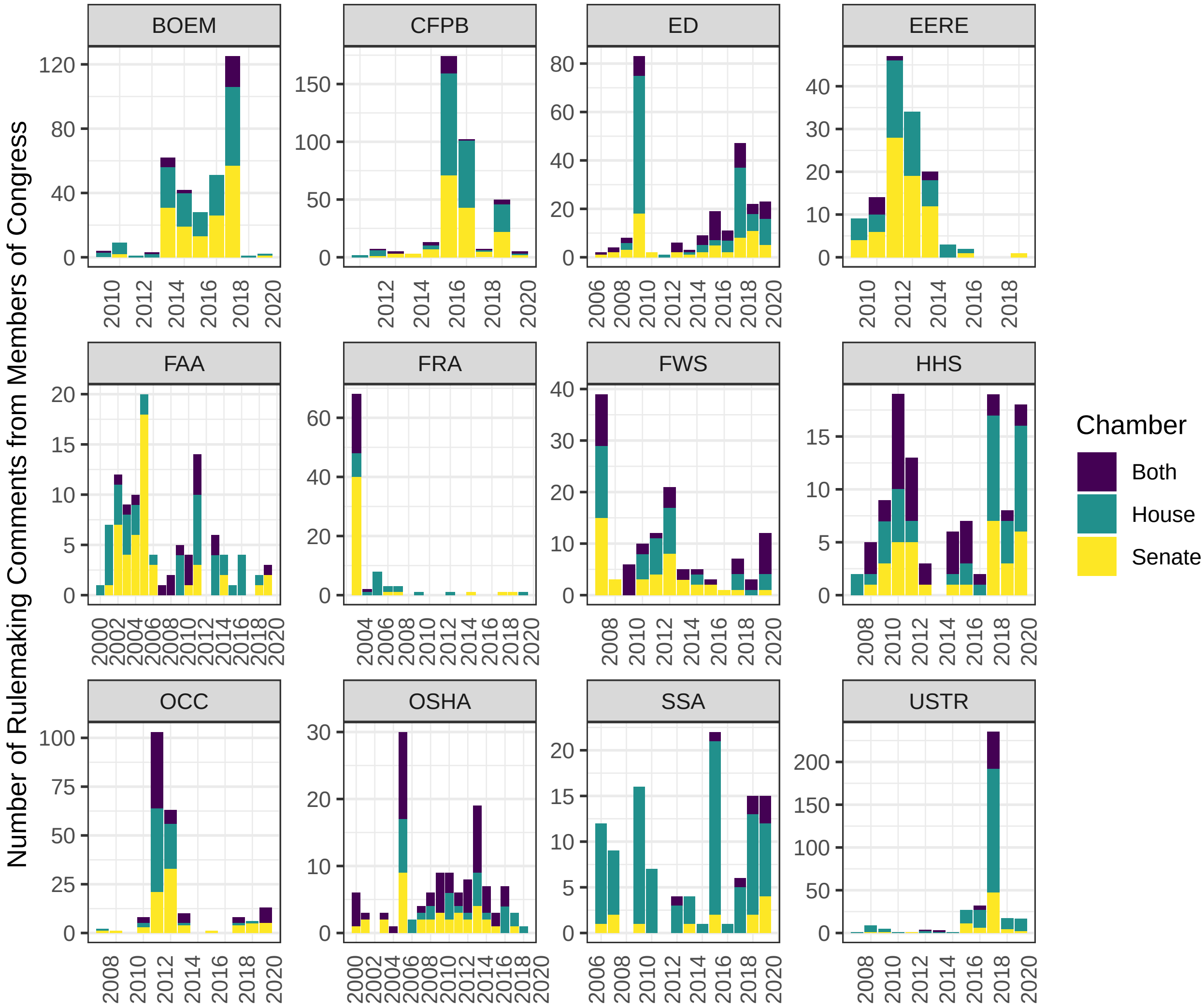

Figure 7: Number of Letters from Members of Congress Received During Rulemaking per Year

2 Descriptives

Hypothesis 2.1. Most people engage in national policy processes as a result of organized public pressure campaigns.

Hand-coded sample [in progress]

comment_type	n
coalition	1
elected	126
individual	531
mass	3395900
org	3006
NA	0

Full data [in progress]

mass	n
FALSE	13639400
TRUE	69515059

Hypothesis 2.2. Public pressure campaigns are organized by *coalitions* that include groups that engage in sophisticated technical lobbying.

> Nearly all mass comments in the hand-coded rules were mobilized by a group that also engaged in sophisticated lobbying.

> Organizations (if any) affilitated with different types of comments in the hand-coded data:

docket_id	coalition	coalition_comments	c
FWS-HQ-ES-2018-0097	center for biological diversity	856518	p
FWS-HQ-ES-2018-0007	defenders of wildlife	702687	p
FWS-HQ-ES-2018-0006	defenders of wildlife	440844	p
CEQ-2019-0003	partnership project	400085	p
PHMSA-2012-0082	sierra club	330381	p
NOAA-NMFS-2013-0101	pew charitable trusts	168293	p
NOAA-NMFS-2012-0059	pew	102875	p
NOAA-NMFS-2013-0050	pew	74818	p
BSEE-2018-0002	earthjustice	71627	p
BSEE-2017-0008	center for biological diversity	59410	p
FWS-HQ-NWRS-2012-0086	defenders of wildlife	53271	p
WHD-2019-0003	epi	44391	p
IRS-2016-0015	americans for tax fairness	29853	p
NOAA-NMFS-2018-0035	gulf restoration network	28488	p
NOAA-NMFS-2011-0117	oceana	12887	p
OFCCP-2014-0004	aclu	7152	p
PHMSA-2012-0082	NA	3084	N
FEMA-2016-0003	pew	2982	p
CEQ-2019-0003	liuna	2896	p
NOAA-NMFS-2013-0101	american sportfishing association	1542	p
BSEE-2012-0005	pew	1530	p
OCC-2020-0026	aclu	222	p
PHMSA-2012-0082	american petroleum institute	214	p
ICEB-2015-0002	NA	183	N
CFPB-2016-0025	wcbc	148	p
PHMSA-2012-0082	barrington and illinois trac coalition	125	p
CFPB-2016-0025	axcess financial	112	p
ICEB-2015-0002	nafsa	109	p
BSEE-2013-0011	shell	90	p
[illegible]	[illegible]	[illegible]	[illegible]

Hypothesis 2.3. Public interest group coalitions mobilize *more often* than private interest group (e.g., business-led) coalitions.

Yes, but not as much as I expected.

Hypothesis 2.4. Public interest group coalitions mobilize *more successfully* than private interest group (e.g., business-led) coalitions.

Yes, by far.

Hypothesis 2.5. Public pressure campaigns targeting national policy are most often run by large national policy advocacy organizations.

Yes.

Hypothesis 2.6. If narrow private interest groups (e.g., businesses) launch public pressure campaigns, it is a response to an opposing campaign.

Yes.

3 Models of influence/success

3.1 DV = Comments from members of Congress

Hypothesis 3.1. The scale of public engagement moderates elected officials' engagement in agency rulemaking engagement.

The simplest model of the relationship between congressional attention and public attention would be to model the count of legislator letters as a function of features of the rulemaking, including the total number of public comments. The number of letters from members of congress would be a count process; this would be a Poisson or negative binomial regression.

In equation (3.1), y_j is a count of the number of legislator comments on a proposed rule j, β_1 is the effect of a one-unit increase in the logged number of public comments on proposed rule j, and η is a vector of coefficients on other factors (X_j) that may lead legislators to comment.

$$y_j = \beta_0 + \beta_1 \text{log(Public comments)}_j + \eta X_j + \epsilon_j$$

Alternatively, if we want to control for legislator characteristics that may make them more or less likely to comment on a rule, we can make members of Congress the unit of analysis. The dependent variable is now whether or not a given legislator i commented on proposed rule j. The relationship between public engagement and legislator engagement can be modeled by Equation (3.1), where $Pr(Comment_{ij})$ is the probability that legislator i comments on a proposed rule j, β_1 is the effect of a one-unit increase in the logged number of public comments on proposed rule j, and η is a vector of coefficients on other factors (X_{ij}) that may affect whether a legislator engages.

$$logit(Pr(\text{Legislator comment}_{ij})) = \beta_0 + \beta_1 \text{log(Public comments)}_{ij} + \eta X_{ij} + \epsilon_{ij}$$

Hypothesis 3.2. Public pressure campaigns attract oversight from allies. The more comments supporting a position, the more likely principals holding that position are to engage.

Hypothesis 3.3. Public pressure campaigns reduce oversight from opponents. The more comments opposing a position, the less likely principals holding that position are to engage.

The simplest model of the relationship between congressional attention and public support or opposition to a proposed rule would be to model the net count of legislator letters supporting and opposing the proposed as a function of features of the rulemaking, including the net number of public comments supporting and opposing. As the number of letters from members of congress would be a count process, this would be Poisson or negative binomial regression.

The model is the same as equation (3.1) except that y_j is now the *net* number of legislator comments supporting a proposed rule j, and β_1 is now the effect of a one-unit increase in the logged *net* number of public comments supporting proposed rule j.

With a measure of the likely position on each rule (for example, if promulgated by a co-partisan administration), the individual legislator can be the unit of analysis. The probability that legislator i will comment on rule j, given their position p_{ij} on a proposed rule j ($Pr(Comment_{ij}i|p_{ij})$), is modeled in equation (3.1). Hypothesis 3.2 implies that β_1 is positive and Hypothesis 3.3 implies that β_2 is negative.

$$logit(Pr(\text{Legislator Comment}_{ij}|p_{ij})) = \beta_0+\beta_1\text{Comments supporting } p_{ij}+\beta_2\text{Comments opposing } p_{ij}+\eta X_{ij}+$$

3.2 DV = Lobbying success

For all three measures of lobbying success, I assess the relationship between lobbying success and mass comments by modeling coalition i's lobbying success in a rulemaking j, y_{ij} as a combination of whether the coalition is unopposed, the coalition's size, whether it is a business coalition, and the logged number of mass comments. I estimate these relationships using OLS regression.

$$Y_{ij} = \boldsymbol{\beta}_1\mathbf{log(Comments)}_{ij} + \beta_2\text{Size}_{ij} + \beta_3\text{Unopposed}_{ij} + \beta_3\text{Coalition Type}_{ij} + \epsilon_{ij}$$

I use two related measures of coalition type. Models 1 and 3 use my classification of coalitions as primarily public or private interests. Models 2 and 4 below use a related measure: the share of coalition members that are businesses or trade associations. Models 3 and 4 include interacting each measure of the coalition's type with a dummy for president

Trump rather than President Obama's administration. Bush-era rules are dropped from these models for simplicity.

Challenges for inference

Non-independence

Organzations lobbying in coalitions The hand-coded sample includes 4,577 hand-coded documents representing 3,399,682 comments. However, many of these comments belong coalitions and are thus not independent. When Friends of Earth and the Sierra Club lobbying together on a rule, the success of each depends on the other. Thus, I group comments into coalitions. The hand-coded sample includes 291 "coalitions," 141 of which are single organizations (not really coalitions), leaving 150 true coalitions of groups lobbing together.

3.2.0.1 Coalitions lobbying on rules The fact that several coalitions may lobby on the same rule creates a lesser form of dependence among observations. One coalition's lobbying success is correlated with another coalition's lobbying success to the extent that they are asking for the same or contradicting things. Because we have grouped organizations into coalitions, the causally-related asks (those organizations lobbying *because* another organization is) are largely accounted for.

4 Results

4.0.1 DV = Coalition success

Note: these models include coalitions of 1 (organizations lobbying alone), but results are similar if I exclude them, except that coalition size has a much weaker correlation with success.

NOTE: At this time, the sample mostly rules that received an unusual number of comments, so these results are based on variation with high-salience rulemakings.

TODO: Add specification with agency fixed effects?

	Model 1	Model 2	Model 3	Model 4
(Intercept)	-0.377*	-0.288**	-0.645**	0.050
	(0.194)	(0.132)	(0.318)	(0.194)
log(comments)	-0.152***	-0.138***	-0.147***	-0.141***
	(0.052)	(0.052)	(0.051)	(0.052)
coalition_typepublic	0.317		0.910**	
	(0.226)		(0.358)	
log(coalition_size)	0.245**	0.261**	0.255**	0.247**
	(0.104)	(0.110)	(0.106)	(0.114)
coalition_unopposedTRUE	-1.623	-1.712	-1.355	-2.050
	(1.563)	(1.584)	(1.527)	(1.552)
coalition_business		-0.003		-0.016
		(0.013)		(0.013)
presidentTrump			0.538	-0.543**
			(0.376)	(0.223)
coalition_typepublic × presidentTrump			-1.420***	
			(0.485)	
coalition_business × presidentTrump				0.054**
				(0.027)
Num.Obs.	206	254	166	211
R2	0.051	0.035	0.122	0.083
R2 Adj.	0.032	0.019	0.088	0.056
AIC	772.3	959.6	613.1	790.0
BIC	792.3	980.8	638.0	816.8
Log.Lik.	-380.144	-473.804	-298.558	-386.976
F	2.711	2.229	3.666	3.062

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

My preferred model is model 3:

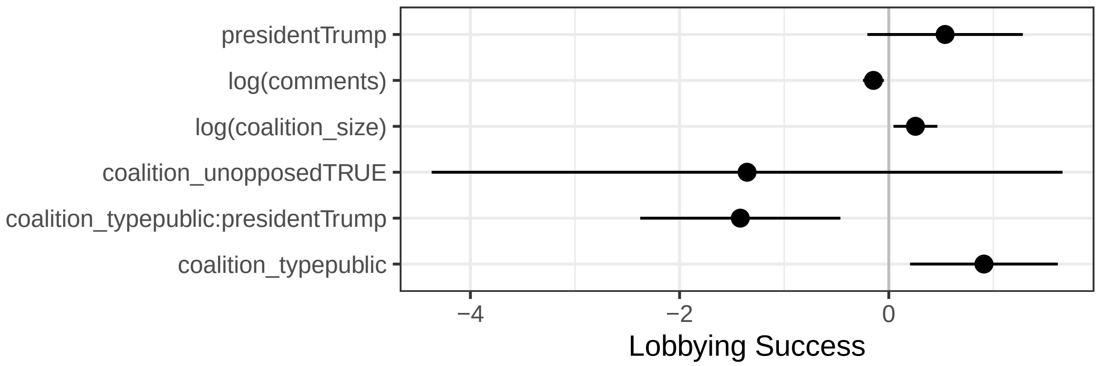

Figure 8: OLS Model of Coalition Lobbying Sucess with Hand-coded Data

4.0.1.1 Modeling Congressional Support as a Mediator of Lobbying Success

To assess congressional support as a mediator in the influence of public pressure campaigns on rulemaking, I estimate the average conditional marginal effect (ACME, conditional on the number of comments from Members of Congress) and average direct effect (ADE) of mass comments using mediation analysis. Model 3 in table 1 replaces the dependent variable (lobbying success) with the mediator variable (the number of supportive members of Congress). Model 1 is the same as Model 1 above. Model 2 is the same but includes the proposed mediator, the number of supportive comments from members of Congress.

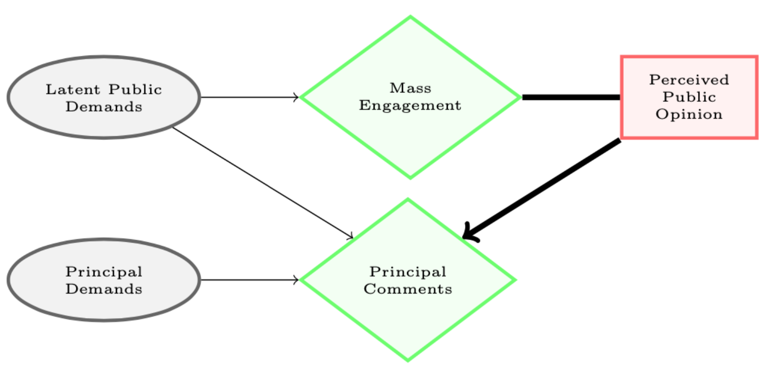

Figure 9: The Mediator Model: The Relationship Between Public Pressure and Congressional Oversight

4.0.1.1.1 Mediator model (4.0.1.1.1):

$$\text{Congressional support}_{ij} = \beta_0 + \beta_1 log(\text{Comments}_{ij}) + \beta_{2-n} X_{ij} + \epsilon_{ij}$$

	Members of Congress in Coalition (OLS)	Members of Congress in Coaliti
(Intercept)	-0.078*	-25.472
	(0.043)	(2989.342)
log(comments)	-0.016	-0.248
	(0.011)	(0.167)
coalition_typepublic	0.084*	19.180
	(0.050)	(2989.341)
log(coalition_size)	0.073***	1.582***
	(0.023)	(0.391)
coalition_unopposedTRUE	0.078	3.169
	(0.346)	(42352.794)
Num.Obs.	206	206
R2	0.070	
R2 Adj.	0.051	
AIC	151.5	59.5
BIC	171.4	76.2
Log.Lik.	-69.730	-24.761
F	3.765	

* p < 0.1, ** p < 0.05, *** p < 0.01

4.0.1.1.2 Outcome model (y_{ij} = Lobbying success$_{ij}$) (4.0.1.1.2):

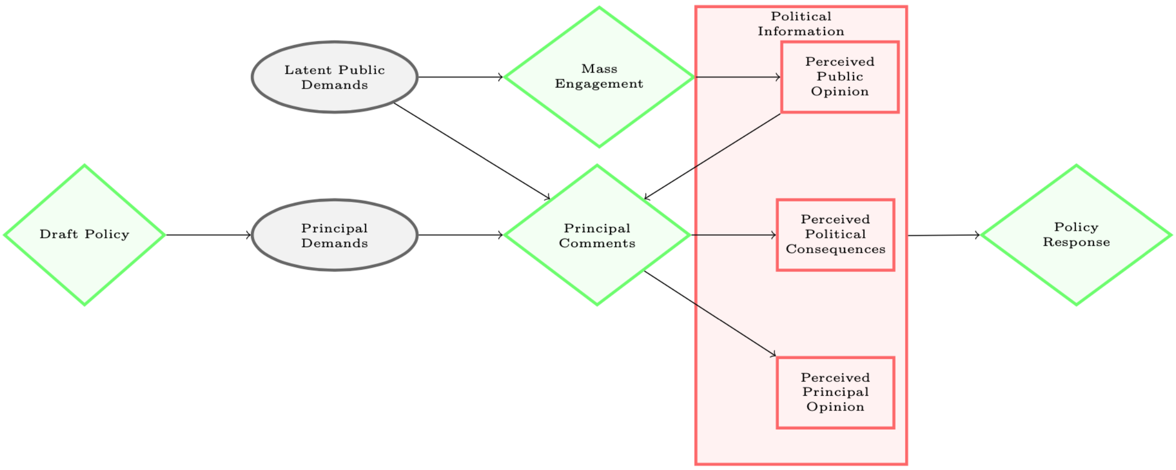

Figure 10: Integrating Public Pressure and Congressional Oversight into a Model of Lobbying in Bureaucratic Policymaking

$$y_{ij} = \beta_0 + \beta_1 log(\text{Comments}_{ij}) + \beta_2 \text{Congressional support}_{ij} + \beta_{3-n} X_{ij} + \epsilon_{ij}$$

```
##
## Causal Mediation Analysis
##
## Quasi-Bayesian Confidence Intervals
##
##                 Estimate 95% CI Lower 95% CI Upper p-value
## ACME             0.00401     -0.00664         0.02   0.522
## ADE             -0.15783     -0.26460        -0.06   0.002 **
## Total Effect    -0.15381     -0.25927        -0.05   0.002 **
## Prop. Mediated -0.01752     -0.17824         0.05   0.520
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sample Size Used: 206
```

Table 1: Lobbying Success and Congressional Support

	1	2	3
Dependent Variable	**Lobbying Success**	**Lobbying Success**	**Members of Congress in C**
(Intercept)	0.022	-0.397**	-0.078*
	(0.307)	(0.196)	(0.043)
log(comments)	-0.138***	-0.157***	-0.016
	(0.047)	(0.052)	(0.011)
coalition_typepublic	-0.006	0.338	0.084*
	(0.258)	(0.228)	(0.050)
log(coalition_size)	0.159	0.264**	0.073***
	(0.121)	(0.106)	(0.023)
coalition_unopposedTRUE	NA	-1.603	0.078
	()	(1.564)	(0.346)
coalition_congress		-0.259	
		(0.319)	
Num.Obs.	136	206	206
R2	0.067	0.054	0.070
R2 Adj.	0.046	0.031	0.051
AIC	484.1	773.6	151.5
BIC	498.7	796.9	171.4
Log.Lik.	-237.051	-379.804	-69.730
F	3.160	2.297	3.765

* p < 0.1, ** p < 0.05, *** p < 0.01

```
##
##
## Simulations: 1000
```

> Mediation analysis will require adding cases where coalitions lobbied unopposed, which we are much more likely to see in the sample of rules without mass comments.

The average effect of the logged number of comments, conditional on letters from members of congress (the ACME) is 0, with a p value of 0.522.

The average direct effect (ADE) of the logged number of comments on lobbying success is -0.16, with a p-value of 0.002.

The Total Effect of a one-unit increase in the logged number of comments is -0.15, with a p value of 0. -0.02 of this is mediated through mobilizing congressional attention (p-value = 0.52).

4.0.2 DV = organzation success

While it would not be appropriate to compare the lobbying success of organizations *within* a rulemaking (because many organizations belong to the same coalition), it may be appropriate to compare the lobbying success *within* the same organization *across* rules. This limits the analysis to organizations that lobbying on multiple policies. The key variation of interest is when organizations lobby with a large amount of public support versus when they do not.

There is still a (lesser) problem with the i.i.d. assumption here because two organizations lobbying in a coalition on one rule may mobilize each other to lobby in coalition in a different rule (in my data, lobbying coalitions are at the policy-level, since they differ from policy to policy).

org_name	n
Natural Resources Defense Council	9
Sierra Club	9
Earthjustice	8
Oceana	8
Pew Charitable Trusts	7
Center For Biological Diversity	6
American Bankers Association	5
American Petroleum Institute	5
Associated Builders And Contractors	5
Association Of Oregon Counties	5
County Of Siskiyou	5
Edison Electric Institute	5
Environmental Defense Fund	5
International Association Of Drilling Contractors	5
International Bancshares Corporation	5
Materion Brush Inc.	5
National Association Of Home Builders	5
National Audubon Society	5
National Employment Law Project	5
National Mining Association	5
National Wildlife Federation	5
Nez Perce Tribal Executive Committee	5
Ocean Conservancy	5
Port Gamble S'klallam Tribe	5
Quinault Indian Nation	5
Afl-Cio	4
American Bird Conservancy	4
Blue Water Fishermen's Association	4
Chamber Of Commerce	4
Confederated Tribes Of Warm [illegible]	4

384 organizations lobbied on more than one rule in the hand-coded data, some on as many as 9 rulemaking dockets. This yields a total of 986 observations of an organization lobbying on a docket that also lobbied on some other docket. (Note: this is a undercount due to imperfect standardization of organization names).

At the organization level, the appropriate analysis is a difference-in-difference design. We know the success of each organization when it does and does not participate in a lobbying coalition that mobilizes public pressure (at least each organization that I can use for this analysis). The difference within an organization is now the key variation.

$Y_{ij} = \boldsymbol{\beta}_1 \textbf{Comments}_{ij} + \gamma_i + \beta_2 \text{Coalition Size}_{ij} + \beta_3 \text{Support}_{ij} + \beta_4 \text{President}_j + \epsilon_{ij}$

Where Y_{it} represents the level of success that organization i. γ_{ij} is a fixed effect for the organization. This fixed effect accounts for the organization's characteristics. This difference-in-difference design ensures that coefficient $\boldsymbol{\beta}_1$ captures variation related to changes in levels of public pressure, not other factors that may vary across organizations.

β_2 captures the effect of coalition size on lobbying success of organization i on rule j. β_3 captures the difference in the success of organization i when they support proposed policy j rather than oppose it. $President_j$ is a dummy for whether policy j was proposed by President Trump rather then-president Obama's administration.

Assuming that organizations have parallel trends in their level of success given a level of support, $\boldsymbol{\beta}$ represents the average effect of changing levels of public pressure on an organization's lobbying success.

Estimates in the table below show the results of this model. It suggests that the same organization was less effective when it mobilized more comments, more successful when they supported the rule, and less successful under president Trump than President Obama.

The negative correlation between lobbying success and the number of mass comments is likely due to campaigns "going down fighting"–not trying to influence policy. The fact that organizations are more likely to get the outcome they seek when they already support the rule makes sense because the agency is more likely to be sympathetic to their requests. The fact that the average organization was less likely to see its desired policy changes under President Trump is likely due to asymmetry in mobilizing organizations, with more organizations on the left than the right in this sample of rules. (Note: this may change in the broader sample.)

	Lobbying Success
log(coalition_comments)	-0.094**
	(0.043)
coalition_size	0.001
	(0.004)
PositionSupports rule	0.609**
	(0.252)
presidentTrump	-0.566**
	(0.234)
Num.Obs.	1892
R2	0.915
R2 Adj.	0.412
R2 Within	0.094
R2 Pseudo	
AIC	6204.6
BIC	15182.6
Log.Lik.	-1483.303
FE: org_name	X
Std. errors	Clustered (org_name)

* p < 0.1, ** p < 0.05, *** p < 0.01

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