

# Policy Influence: Do Public Pressure Campaigns Influence Bureaucratic Policymaking?

## Appendix and Replication Code

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## 1 Data

### 1.1 Testing the Theory

#### 1.1.1 Data: A Census of Public Comments

To examine the relationship between public pressure campaigns and lobbying success, I use an original dataset (introduced in Section ??) that combines several data sources on U.S. federal agency rulemaking.

The core data for this analysis are the texts of draft and final rules and public comments on these proposed rules published from 2005 to 2020. This includes all proposed rules from 161 agencies that were open for comment on regulations.gov between 2005 and 2020, received at least one comment from an organization, and saw a final agency action between 2005 and 2020. These 44,774 rulemaking dockets received a total of 58,380,146 comments.

I collected draft and final rule texts from federalregister.gov and comments submitted as digital files or by mail from regulations.gov. I also retrieve comments submitted directly on regulations.gov and metadata on rules and comments (such as the dates that the proposed rule was open for comment and whether the agency identified the organization submitting the comment) from the regulations.gov Application Programming Interface (API). I add additional metadata on rules (such as whether the rule was considered “significant”) from the Unified Agenda published by the Office of Information and Regulatory Affairs (reginfo.gov).

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 usually reverses or moves policy in the opposite direction of the previous administration. The same organizations often comment on both policies but with opposite positions. Support becomes opposition and vice versa.

**1.1.1.1 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 each comment text, 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 document for hand-coding.

I attempt to identify the organization(s) that submitted or mobilized each comment by extracting all organization names from the comment text. For comments that do not reference an organization, an internet search using portions of the comment’s text often identified the organization that provided the form letter text. I then identify lobbying coalitions both by hand and by textual similarity. Co-signed comments are

always assigned to the same coalition. Likewise, form-letter comments are always assigned to the same coalition.

Through the iterative combination of automated search methods and hand-coding described in Section ??, I attribute each comment to the organization behind it (its author if submitted by the organization or the mobilizing organization for form letters). I also identify comments submitted by elected officials, with special attention to members of the U.S. Congress.

Because my hypotheses are about the influence of organizations and coalitions, I collapse these data to one observation per organization or coalition per proposed rule for analysis. I then identify the main substantive comment submitted by each organization’s staff or lawyers, which are usually much longer than supporting comments like form letters.

**1.1.1.2 Hand-coded sample** To estimate the influence of public comments on policy, I use hand-coded comments on a random sample of rulemaking dockets. For each rule in the sample, almost all comments are hand-coded for their level of lobbying success. Hand-coding includes recording the type of organization, the lobbying coalition to which each comment belongs, the type of coalition (primarily public or private interests), their policy demands, and the extent to which the change between the draft and final rule aligned with their demands. This level of alignment between policy demands and policy outcomes is my measure of lobbying success. It does not identify a causal relationship (true policy influence), but it is the standard approach for assessing lobbying success with these kinds of observational data (see ?). For a more detailed description of the coding process, the codebook is available in Appendix ??.

I first selected a random sample of 69 proposed rules with both a mass-comment campaign and a final rule. I then selected all comments that were likely to be from organizations.<sup>1</sup> The hand-coding process included identifying the organization responsible for each comment submitted by an organization (e.g., a business, nonprofit, or government).

I then selected a sample of 43 proposed rules on which the same organizations commented without a mass comment campaign. While most studies of mass comment campaigns to date have focused on the Environmental Protection Agency, my combined sample rules come from 42 agencies. Additionally, my sampling approach includes rules with very small and very large numbers of comments that previous studies exclude.

I include all comments submitted as file attachments or emails, but only some comments typed in a text box. Sophisticated lobbying organizations almost always submit comments as file attachments. I include comments typed in a text box if they share text with other comments, indicating they are part of a pressure campaign. This includes nearly all comments on most rules. I exclude entirely unique textbox contents and comments shorter than ten words. Most textbox comments and nearly all extremely short comments are trivial (e.g., “This sucks”). While form letters are often short, they are very unlikely to be less than ten words. For comments sharing text, I code one sample document for all versions of the form letter.

My approach to measuring lobbying success starts with policy demands raised in comments. The dimensions of conflict on which I judge lobbying success are those issues identified by commenters. Unlike other studies, the issues I use to assess lobbying success do not come from first reading the policy or of any a priori concept of what each policy fight is about. Instead, I read the change between draft and final rule with an eye for alignment with commenters’ requests (including requests that specific parts of the draft policy do not change.)

Using commenter requests to identify the dimensions of the conflict has advantages and disadvantages. Compared to other potential measures of success, it is more likely to focus on things that commenters care about and miss policy issues that other, non-commenting segments of the public might care about.

Other approaches to identifying the commenter’s relationship with policy changes have different strengths and weaknesses. For example, one could measure success by the number of times a comment is mentioned

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<sup>1</sup>Through an iterative process described in ??, I developed software and methods to select comments that were most likely submitted by organizations rather than by individuals. For example, I include all comments submitted as file attachments rather than typed into the textbox.

Table 1: A Sample of Hand-coded Public Comments

Docket ID	Coalition	Comment type	Organization	Position	Success
DOT-OST-2018-0068	AAAE	Org	Finnair Plc	Supports Rule	2
FEMA-2016-0003	AASA	Org	Aasa. Aesa	Opposes Rule	2
FEMA-2016-0003	AASA	Org	Sam Walton	Opposes Rule	2
NPS-2018-0007	ACLU	Elected	Grace Meng	Opposes Rule	2
NPS-2018-0007	ACLU	Org	Justice First	Opposes Rule	1
PHMSA-2012-0082	AFL-CIO	Elected	Peter Defazio	Supports Rule	-1
PHMSA-2012-0082	AFL-CIO	Elected	Gordon Johnson	Supports Rule	1
ED-2016-OESE-0032	AFT	Org	Aft-New Mexico	Opposes Rule	1
WHD-2019-0001	ANCOR	Org	Easterseals	Supports Rule	-2
WHD-2019-0001	ANCOR	Org	Leadingage	Supports Rule	-2
USCIS-2006-0044	ARTS	Mass	Alia Agency	Opposes Rule	-2
USCIS-2006-0044	ARTS	Mass	Alabama Ballet	Opposes Rule	-2
USCG-2010-0990	BOATU.S.	Org	Boatu.s.	Opposes Rule	-1
CFPB-2019-0006	CFSA	Elected	Nolan Mettetal	Supports Rule	2
CFPB-2019-0006	CFSA	Elected	Mike Osburn	Supports Rule	2
IRS-2019-0039	CLC	Elected	Steve Bullock	Opposes Rule	-2
IRS-2019-0039	CLC	Org	Issue One	Opposes Rule	2
USCBP-2007-0064	EAA	Org	Sas Institute	Supports Rule	1
FWS-R9-ES-2008-0093	EARTHJUSTICE	Individual	Socalxj	Opposes Rule	-2
FWS-R9-ES-2008-0093	EARTHJUSTICE	Org	Niabi Zoo	Opposes Rule	-2

in the agency’s response to comments. However, this measure may be affected by 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 priori potential aspects of the policy. ? count five factors: (1) the number of regulated entities, (2) the 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, by starting with comments, my method relies on commenters to define the dimensions of conflict and highlight the issues they care most about. In this sense, my approach focuses on “the first face of power”—issues that are already on the agenda of the broader policy system.

The hand-coded sample includes 8,661 hand-coded documents representing over 29 million comments (including both mass comments and the sophisticated comments they support).

Table ?? shows a sample of hand-coded public comments. Docket ID is the identifier for each rulemaking. The Organization, Comment Type, and Coalition columns show how coders record the name and type of each organization or elected official, as well as the broader coalition to which they belong. The name assigned to each coalition is usually the name of one of the lead organizations.

The Position column in Table ?? is a collapsed version of the spatial position-coding described in Section ?? and Appendix ?. To create a binary measure of support and opposition, I collapse the coding of each comment’s spatial position into a dichotomous indicator of whether they ultimately support or oppose the rule. Finally, Lobbying Success—whether each comment got what it asked for in the change between a

Table 2: Organizations by Number of Rules on Which They Commented

Organization	Rules Lobbied On
Chamber Of Commerce	10
Natural Resources Defense Council	10
Oceana	10
Earthjustice	9
Sierra Club	9
National Audubon Society	8
American Petroleum Institute	7
Center For Biological Diversity	7
National Wildlife Federation	7
Pew Charitable Trusts	7
Edison Electric Institute	6
National Association Of Home Builders	6
National Mining Association	6
Port Gamble S'klallam Tribe	6
Public Citizen	6
Afl-Cio	5
American Bankers Association	5
Associated Builders And Contractors	5
Endangered Species Coalition	5
Environmental Defense Fund	5

draft and final rule—is coded on a five-point scale from 2 to -2. “2” indicates that most of the commenter’s requests were met. If the rule moved decidedly in the opposite direction as they would have liked it to move, this is coded as a “-2” (the opposite of total success). To measure these variables at the coalition level, I use the coding assigned to the lead organization or the average across coalition members. Because “lead” organizations are identified based on their leadership role in the coalition and the extent to which they represent the coalition’s policy demands, the lead organization’s coding is nearly the same as the average across coalition members in all cases.

Table ?? shows the organizations that commented on the most rules in this sample: 435 organizations lobbied on more than one rule in the hand-coded data, some on as many as 10 rulemaking dockets. Recall that this sample of rules is weighted toward rulemaking dockets that received more comments. Thus, the organizations lobbying on the most rules are not the same as those in the overall population. For example, recall from Table ?? that the American Petroleum Institute lobbied on nearly 400 rules, whereas the Pew Charitable Trusts lobbied on 120. Pew, however, used a public pressure campaign 5 percent of the time it lobbied, whereas the American Petroleum Institute used a public pressure campaign 0.3 percent of the time it lobbied. Thus, groups like Pew that more often use pressure campaigns are more likely to be lobbying on rules in this sample. While this sampling approach was necessary (a random sample of all rules would yield almost none with a pressure campaign), the statistical results should be interpreted as disproportionately reflecting variation in lobbying success in high-salience and contentious rulemakings.

Table 3: Hand-coded Data By Agency

Agency	Rules	Documents	Coalitions	Organizations	Comments
EPA	21	1,711	41	500	18,288,495
NOAA	8	363	28	190	578,545
FWS	7	1,013	24	564	5,050,397
IRS	6	57	8	49	77,479
BSEE	4	259	13	205	245,370
CFPB	3	1,944	19	949	1,109,808
USCIS	3	89	10	64	98
DOT	2	145	8	109	145
OCC	2	120	4	97	265
OFCCP	2	191	5	32	13,616
WHD	2	265	8	214	101,556
BLM	1	178	3	32	1,342,966
CEQ	1	506	5	444	425,432
DEA	1	16	3	16	16
DOI	1	47	3	38	54,002
EBSA	1	70	2	68	721,880
ED	1	141	16	135	141
FEMA	1	380	9	349	3,139
ICEB	1	303	4	65	303
MSHA	1	52	3	43	52

Table ?? shows the number of hand-coded rules, documents, the coalitions and organizations to which those documents belong, and the total number of comments they represent for a sample of agencies. As expected with a random sample, the agencies with the most rules in this sample are also those with the most final rules posted to regulations.gov (as shown in Figure ??). The Environmental Protection Agency (EPA), Fish and Wildlife Service (FWS), and National Oceanic and Atmospheric Agency (NOAA), Department of Transportation (DOT), and Internal Revenue Service (IRS) are all in the top ten agencies by the number of rulemaking dockets on regulations.gov. The Bureau of Safety and Environmental Enforcement, Consumer Financial Protection Bureau (CFPB), and Wage and Hour Division (WHD) of the Department of Labor are all above average and have a disproportionate number of rules with a large number of comments, making these agencies more likely to be selected into the weighted sample. Table ?? also illustrates how my method of collapsing documents with repeated text to one representative document allows me to reduce the number of documents requiring hand-coding by several orders of magnitude (compare the “Documents” and “Comments” columns).

Figure ?? shows hand-coded support and opposition to proposed rules by different types of commenters and presidential administration. Support and opposition coding come from the spatial position regarding the draft and final rule, as shown in Figure ?. Comments from a corporation (“Corp.”) were overwhelmingly opposed to Obama-administration policies and more supportive of Trump-administration policies. Elected officials more often write in opposition than in support of a proposed rule across administrations. In con-

trast, individuals, organizations, and the mass comments these organizations mobilized overwhelmingly supported Obama-administration policies and opposed Bush- and Trump-administration. Mass and individual comments are especially polarized. This reflects the partisan asymmetry in mobilizing organizations; the individuals (unique comments) and mass comments (form letters) mobilized by progressive public interest groups’ campaigns overwhelmingly supported Obama-era policies and opposed Trump-era policies.

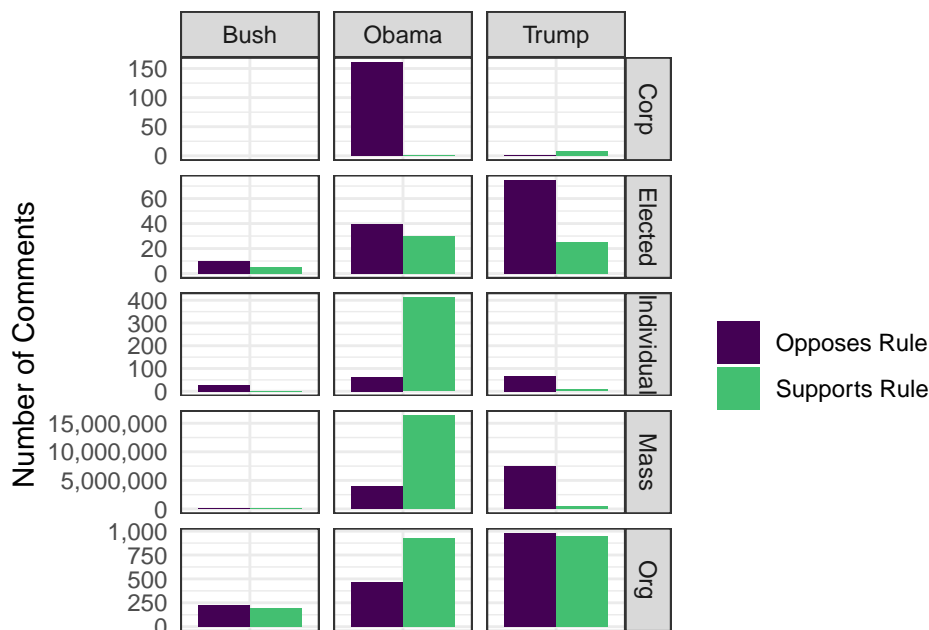


Figure 1: Hand-coded Comments By Type and Position on Proposed Rule

Most of these comments belong to lobbying coalitions and are thus not independent observations. When Friends of the Earth and the Sierra Club lobby together on a rule, the success of each depends on the other. Thus, I group comments into coalitions. The hand-coded sample includes 353 “coalitions,” 162 of which are single-organization “coalitions” (not coalitions), leaving 191 true coalitions of multiple organizations lobbying together.

Lobbying coalitions range in size from 2 to 217 organizations. Table ?? shows a sample of coded data, summarized at the coalition level. Even though the same organization may lead coalitions in multiple rule-makings, each rule’s lobbying coalitions are different, so I consider them separate observations. For example, the American Civil Liberties Union (ACLU) led a coalition in 2014 with a small number of organizations and a medium-size pressure campaign in support of a rule requiring additional Equal Employment Opportunity reporting from the Department of Labor’s Office of Federal Contract Compliance Programs (OFCCP). The ACLU also led a very different coalition in 2020 with a large number of organizations and a very small public pressure campaign against a rule rolling back regulations on banks published by the Office of the Comptroller of the Currency (OCC). Figure ?? shows that this sample is fairly balanced between coalitions that succeed and fail to get the changes they seek in the final rule.

Table ?? shows the number of coalitions coded as “public interest” and “private interest” by whether the majority of organizations in the coalition are for-profit businesses and trade associations or non-businesses (governments and nonprofits): 32 percent are majority business coalitions. 60 percent are public-interest coalitions. As Table ?? shows, the hand-coded “public interest vs. private interest” distinction is highly correlated with the share of businesses in the coalition but not perfectly. These two measures diverge in cases where public interest coalitions mobilize a large number of business allies or where private interest coalitions mobilize a large number of non-business allies. Thus, while the share of businesses and trade

Table 4: A Sample of Hand-coded Data Summarized by Coalition

Docket ID	Coalition	Position	Size	Businesses	Type	Mass
OCC-2020-0026	ACLU	Opposes Rule	75	2	Public	168
OFCCP-2014-0004	ACLU	Supports Rule	11	0	Public	7,141
ICEB-2015-0002	AFL-CIO	Supports Rule	5	2	Public	0
USCIS-2010-0017	AFL-CIO	Opposes Rule	2	0	Public	0
TREAS-DO-2007-0015	AHC	Supports Rule	1	0	Private	0
DEA-2018-0005	AMA	Supports Rule	3	3	Public	0
CEQ-2019-0003	AMWA	Opposes Rule	1	0	Public	0
USCIS-2006-0044	ARTS	Opposes Rule	12	0	Public	0
CFPB-2016-0025	CBC	Supports Rule	1	0	Public	0
CEQ-2019-0003	EOMA	Supports Rule	1	1	Private	0
WHD-2019-0001	EPI	Opposes Rule	55	5	Public	56,949
WHD-2019-0003	EPI	Opposes Rule	40	1	Public	44,352
CEQ-2019-0003	EPIC	Supports Rule	1	0	Public	0
DEA-2018-0005	HSCA	Opposes Rule	10	3	Public	0
DOT-OST-2018-0068	IAADP	Supports Rule	10	1	Public	0
ED-2016-OESE-0032	MCEC	NA	1	0	Public	0
OCC-2020-0026	MLA	Supports Rule	13	12	Private	0
USCIS-2010-0017	NCAPA	Supports Rule	14	5	Public	0
WHD-2019-0001	NCPA	Supports Rule	16	9	Private	0
FEMA-2016-0003	NCSL	Opposes Rule	2	0	Public	0

Table 5: Types of Lobbying Coalitions in the Hand-coded Sample

Coalition Type	Business led	Non-Business led	Mass Comments	No Mass Comments
Private	100	26	43	92
Public	12	155	82	130

Table 6: Comments from Elected Officials in the Hand-coded Data

Elected Official Type	n
State Elected Official	55
Senate	51
House	45
Local Elected Official	14
Governor	8

associations is more objective, the public-private distinction is likely a better measure of coalition type. I estimate alternative models in Section ?? with each measure.

Several coalitions may lobby on the same rule. 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 policy changes. However, by grouping organizations into coalitions, I account for many of the causally-related policy requests (those organizations lobbying on an issue *because* another organization is lobbying on that issue).

**1.1.1.3 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. Figure ?? shows the number of comments from members of Congress received during rulemaking by a sample of federal agencies. There is massive variation in the level of attention that members of Congress pay to different agencies and rules. The spikes in attention to each agency correspond with public pressure campaigns targeting rules from that agency. Oversight letters are frequently co-signed by multiple members from the Senate, House, or both chambers. Some of the rules on which members of Congress commented appear in the hand-coded sample. Table ?? shows the number of comments from the most common types of elected officials in the hand-coded data. Members of the U.S. House and Senate are the most common.

**1.1.1.4 The Dependent Variable: Lobbying Success** The dependent variable is the extent to which a lobbying coalition got the policy outcome it sought, which I measure in several ways.

First, on a sample of rules, I trained a team of research assistants to hand-code lobbying success for each organization or elected official, comparing the change between the draft and final rule to each organization’s demands on a five-point scale from “mostly as requested” to “significantly different/opposite from requested direction” as described in Section ?. Additionally, for each comment, coders identify the main overall policy demand, the top three specific demands, and the corresponding parts of the draft and final rule texts. This does not capture rule changes on which an organization did not comment.

Lobbying success on each specific demand was then coded for each organization and coalition. Both the overall score and average score across specific demands both fall on the interval from -2 (“significantly different”) to 2 (“mostly as requested”). A team of undergraduate research assistants then applied the



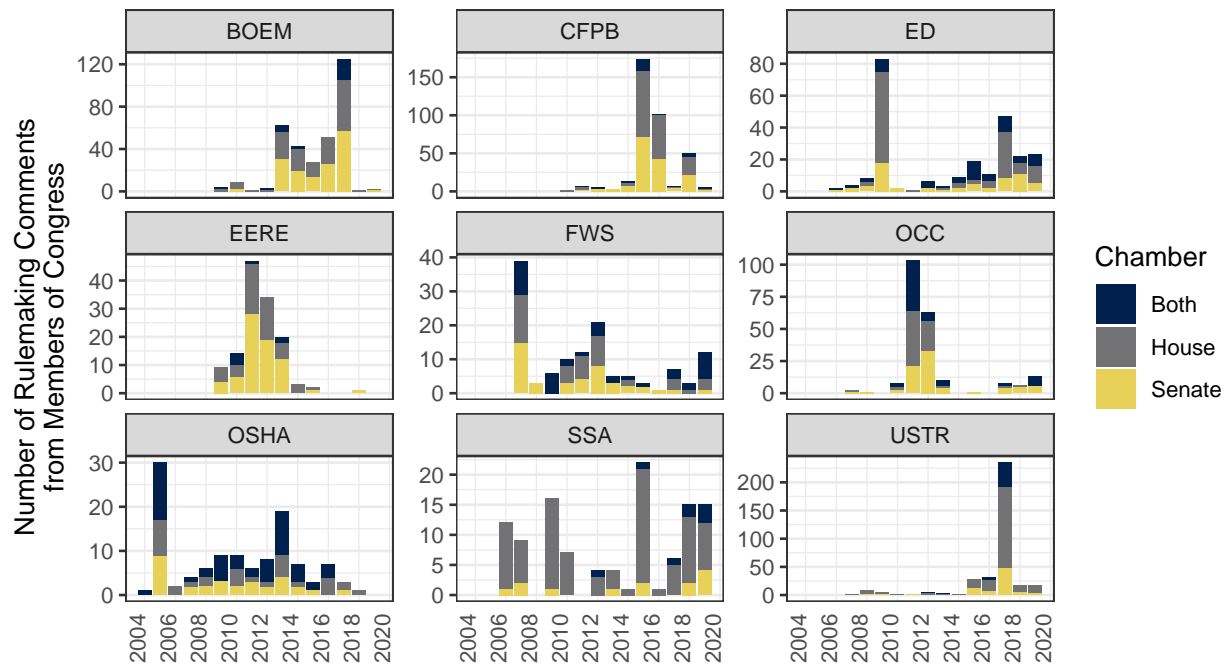


Figure 2: Number of Rulemaking Comments from Members of Congress per Year, 2005-2020 to the Bureau of Ocean Energy Management (BOEM), Consumer Financial Protection Bureau (CFPB), Department of Education (ED), Office of Energy Efficiency and Renewable Energy (EERE), Federal Aviation Administration (FAA), Fish and Wildlife Service (FWS), Office of the Comptroller of the Currency (OCC), Occupational Safety and Health Administration (OSHA), Social Security Administration (SSA), U.S. Trade Representative (USTR)

codebook to all comments likely to be from organizations or elected officials on a random sample of rules. Several rules were double-coded by the whole team.

In the models below, *coalition lobbying success* is the mean of hand-coded lobbying success on a five-point scale,  $\{-2, -1, 0, 1, 2\}$ .

The average hand-coded success per organizational comment is 0 ( $N = 8,661$ ). The average success for organizational comments with a mass comment campaign is -0.452 ( $N = 6,520$ ).

**1.1.1.5 The Main Predictor Variable** The number of supportive comments generated by a public pressure campaign (the main variable of interest) is a tally of all comments mobilized by each organization or coalition that ran a mass-comment campaign on a proposed rule. Because the marginal impact of additional comments likely diminishes, models typically include either the logged number of comments or a quadratic term to account for non-linear effects. If a coalition mobilizes more than 99 form-letter comments on a proposed rule, I code that coalition as having a mass comment campaign (*campaign* = 1). Where a coalition only submits technical comments from lawyers and does not mobilize public support, the binary measure, *campaign*, and the numeric measure, *mass comments*, are 0.

Figure ?? shows a scatterplot of the dependent variable (*lobbying success*) and main predictor (*mass comments*) for each coalition. Coalition lobbying success ranges from total success (2) to total loss (-2). The number of mass comments ranges from 0 to 3,012,281. The size of each point represents the size of each coalition (the number of organizations and elected officials). The color indicates whether the coalition is led by private or public interest groups. For example, one extremely large private coalition of payday lenders mobilized over a million comments during the Obama administration. This coalition was moderately successful at reducing the stringency of the regulation but did not stop it from going through.

The view of the data in Figure ?? does not show a clear relationship between public pressure and lobbying success. There were relatively more (and more successful) public interest campaigns in the Obama years. Likewise, there were more (and more successful) private interest campaigns in the Trump years. As predicted in ??, the largest campaigns are mostly public interest campaigns, and public interest campaigns are more frequent than private interest campaigns overall.

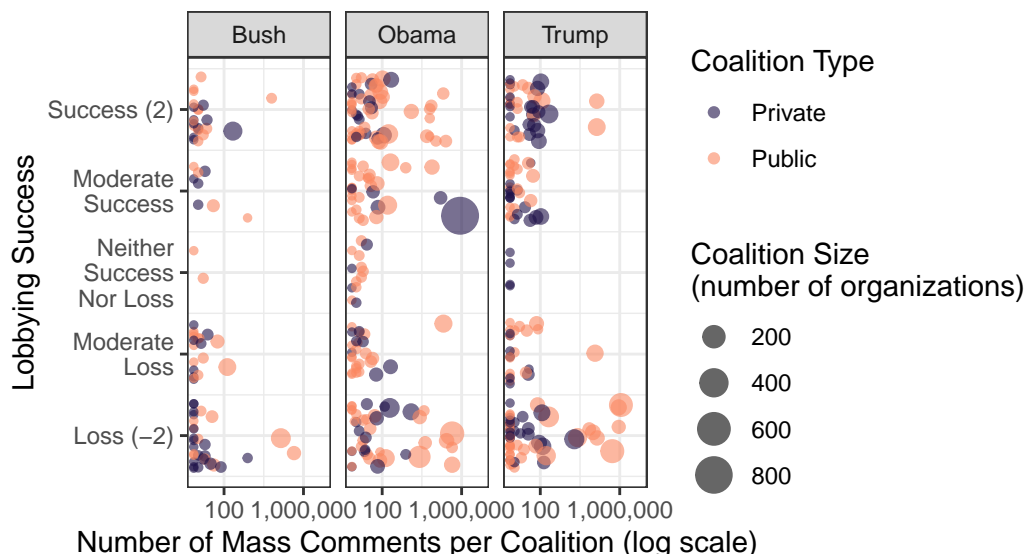


Figure 3: Lobbying Success by Number of Supportive Comments

This approach differs previous studies of mass comment campaigns in at least two ways. First, my methods allow me to identify coalitions consisting of multiple organizations. Previous studies measure mass comment

campaigns at the organization level. For example, ? analyzes “1,049 mass comment campaigns that occurred during 22 EPA rulemakings”—an average of nearly 50 “campaigns” per rule. By “campaign,” ? mean an organization’s campaign rather than a coalition’s campaign. Especially on EPA rules, there are rarely more than two or three coalitions engaging in public pressure campaigns—one of the environmental advocacy groups and their allies, another of regulated industry groups and their allies. Using organizations as the unit of analysis means that observations are far from independent. An analysis that counts one coalition’s campaign as 40 smaller “campaigns” with the same policy demands would count this one campaign as 40 observations.

In contrast, my methods allow me to measure levels of public pressure and lobbying success per organization *and* per coalition. Like previous studies, I identify the organizations responsible for mobilizing comments. Where other studies leverage the fact that the EPA gathers substantially similar comments, I am able to identify mass comment campaigns across dozens of federal agencies. Additionally, I further link common efforts by multiple organizations lobbying in a broader coalition. This allows for analysis with the lobbying coalition as the unit of analysis.

The second major difference between my approach and previous research is that I do not compare policymakers’ responses to sophisticated comments to policymakers’ responses to mass comments. Rather, I *attribute* mass comments to organizations and coalitions that also submit sophisticated technical comments. The set of comparisons one makes is critical to any study of responsiveness or policy influence. Researchers may reach different conclusions if they compare different things. Consider a study comparing how agencies respond to Sierra Club form letters to how they respond to the Sierra Club’s sophisticated comments. Now consider a study that compares responsiveness to the Sierra Club’s sophisticated comments between rules where they did and did not run a mass comment campaign. A study comparing the average influence of form-letter comments to the average influence of sophisticated comments is very different from a study that compares the influence of two sets of sophisticated comments with different *levels* of public pressure behind them. By measuring comments per coalition, both through hand-coding and text reuse, I capture different levels of public pressure than we would see if we were to look only at comments per organization.

**1.1.1.6 Other predictor variables** Other predictors of lobbying success in the models below include the *size* of the lobbying coalition, whether the coalition is a *business coalition*, and whether the coalition is lobbying *unopposed*. The number and type(s) of organization(s) is an attribute of each coalition (e.g., a *business* coalition with  $N$  organizational members). *Coalition size* is a count of the number of organizations lobbying together on the rule, i.e., the number of distinct commenting organizations in each coalition. For organizations lobbying alone, *coalition size* is 1. *Coalition* is an indicator variable for whether the organization is lobbying in a coalition. It takes a value of 0 when *coalition size* is 1 and 1 if *coalition size* is greater than 1. A coalition is *unopposed* when no opposing organizations comment. This is derived from the hand-coded spatial position of each comment. If an organization supports the proposed rule and others oppose it, they have opposition. Likewise, if an organization opposes a proposed rule and others support it, they have opposition. However, if multiple coalitions support (or oppose) the rule for different reasons (e.g., one coalition would like one provision added while another coalition would like a different provision added), a rule may have multiple unopposed lobbying coalitions.

I code a coalition as a *business* coalition if the majority of commenting organizations are for-profit businesses and trade associations. *Business* is binomial. Alternative models in the Appendix use the number and share of businesses in a coalition instead.

**1.1.1.7 Examples of hand-coded lobbying success** **A rule with a public pressure campaign: the 2015 Waters of the United States Rule:** In response to litigation over the scope of the Clean Water Act, the Environmental Protection Agency and Army Corp of Engineers proposed a rule based on a legal theory articulated by Justice Kennedy, which was more expansive than Justice Scalia’s theory. The Natural Resources Defense Council (NRDC) submitted a 69-page highly technical comment “on behalf of the Natural Resources Defense Council..., the Sierra Club, the Conservation Law Foundation, the League of Conservation Voters, Clean Water Action, and Environment America” supporting the proposed rule:

We strongly support EPA’s and the Corps’ efforts to clarify which waters are protected by the Clean Water Act. We urge the agencies to strengthen the proposal and move quickly to finalize it... ( [EPA-HQ-OW-2011-0880-16674](#))

I coded this as support for the proposed rule. Specifically, NRDC would like the EPA to move policy further in the same direction. NRDC makes four substantive requests: one about retaining language in the proposed rule (“proposed protections for tributaries and adjacent waters...must be included in the final rule”) and three proposed changes (“we describe three key aspects of the rule that must be strengthened”).<sup>2</sup> I also coded it as requesting speedy publication. These demands provide specific keywords and phrases for which to search in the draft and final rule text. By comparing the requested policy outcomes to the text of the final rule, I evaluate the extent to which NRDC got what it asked for.

A coalition of 15 environmental organizations mobilized over 944,000 comments. Over half (518,963) were mobilized by the four organizations mentioned in NRDC’s letter: 2421,641 by Environment America, 108,076 by NRDC, 101,496 by Clean Water Action, and 67,750 by the Sierra Club. Other coalition partners included EarthJustice (formerly a part of the Sierra Club, 99,973 comments) and Organizing for Action (formerly president Obama’s campaign organization, 69,369 comments). This is one of the larger campaigns in the dataset. This coalition made sophisticated recommendations and mobilized a million people in support of NRDC’s sophisticated lobbying.

The final rule moved in the direction requested by NRDC’s coalition, but to a lesser extent than requested—what I code as “some desired changes.” As NRDC et al. requested, the final rule retained the language protecting tributaries and adjacent waters and added some protections for “other waters” like prairie potholes and vernal pools. EPA did not alter the exemptions for ditches and waste treatment systems.

For this coalition, the dependent variable, *Lobbying success* is 1 on the scale from -2 to 2, *coalition size* is 15, *business* is 0, their position (*supports rule*) is 1, *campaign* is 1, and the number of *mass comments* is 943,931.

**2009 Fine Particle National Ambient Air Quality Standards:** In 2008, the EPA proposed a rule expanding air quality protections. Because measuring small particles of air pollution was once difficult, large particulates were allowed as a surrogate measure for fine particles under the EPA’s 1977 PM10 Surrogate Policy. EPA proposed eliminating this policy, requiring regulated entities and state regulators to measure and enforce limits on much finer particles of air pollution.

EPA received 163 comments on the rule, 129 from businesses, business associations such as the American Petroleum Institute and The Chamber of Commerce, and state regulators that opposed the rule. Most of these were short and cited their support for the 63-page comment from the PM Group, “an ad hoc group of industry trade associations” that opposed the regulation of fine particulate matter. Six state regulators, including Oregon’s, only requested delayed implication of the rule until they next revised their State Implementation Plans (SIPs) for Prevention of Significant Deterioration (PSD). EarthJustice supported the rule but opposed the idea that the cost of measuring fine particles should be a consideration. On behalf of the Sierra Club and the Clean Air Task Force, EarthJustice commented: “We support EPA’s proposal to get rid of the policy but reject the line of questioning as to the benefits and costs associated with ending a policy that is illegal.” The EarthJustice-led coalition also opposed delaying implementation: “EPA must immediately end any use of the Surrogate Policy—either by ‘grandfathered’ sources or sources in states with SIP-approved PSD programs—and may not consider whether some flexibility or transition is warranted by policy considerations.”

The final rule did eliminate the Surrogate Policy but allowed states to delay implementation and enforcement until the next scheduled revision of their Implementation Plans. I code this as the EarthJustice coalition getting most of what it requested, but not a complete loss for the coalition lobbying on behalf of the regulated industry.

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<sup>2</sup>NRDC’s three policy demands were: (1) “The Rule Should Categorically Protect Certain “Other Waters” including Vernal Pools, Pocosins, Sinkhole Wetlands, Rainwater Basin Wetlands, Sand Hills Wetlands, Playa Lakes, Interdunal Wetlands, Carolina and Delmarva bays, and Other Coastal Plain Depressional Wetlands, and Prairie Potholes. Furthermore, “Other ‘Isolated’ Waters Substantially Affect Interstate Commerce and Should be Categorically Protected Under the Agencies’ Commerce Clause Authority.” (2) “The Rule Should Not Exempt Ditches Without a Scientific Basis” (3) “The Rule Should Limit the Current Exemption for Waste Treatment Systems”

For the PM Group coalition, the dependent variable, *coalition lobbying success* is -1, *coalition size* is 129, *business coalition* is 1, *pressure campaign* is 0, and the number of *mass comments* is 0. For the State of Oregon’s coalition, the dependent variable, *coalition lobbying success* is 2, *coalition size* is 6, *business coalition* is 0, *pressure campaign* is 0, and the number of *mass comments* is 0. For the EarthJustice coalition, the dependent variable, *coalition lobbying success* is 1, *coalition size* is 3, *business coalition* is 0, *pressure campaign* is 0, and the number of *mass comments* is 0. These examples are broadly consistent with the overall data—lobbying success in these two examples is the same, despite the large difference in public pressure. This is not consistent with Hypotheses ?? or ?? that anticipated higher lobbying success with more public pressure.

Figures ?? and ?? show the distribution of values for coalition-level variables in the hand-coded data. Figure ?? shows a wide range of variation for *coalition size* and *lobbying success*, whereas the modal number of *businesses* is concentrated near 0. Most coalitions are between two and twenty members. About half have no business members, but a few have over 100. It is possible for the number of businesses to be larger than the coalition size where the same company sent in multiple comments. This occurs when franchised businesses mobilize local stores to send in letters. Because *coalition size* is the number of unique organizations, these are only counted once, but each is counted in the *businesses* variable.

Figure ?? shows that most coalitions in these data include no *members of Congress*, but some have as many as 27. The total number of *mass comments* is somewhat bimodal, reflecting the two random samples of rules from which these rules come. Most coalitions did not mobilize a pressure campaign and thus have no mass comments, but a few have over a million. The models below use either a binary indicator for mass comments, the logged value, or the number rescaled as hundreds of thousands of comments.

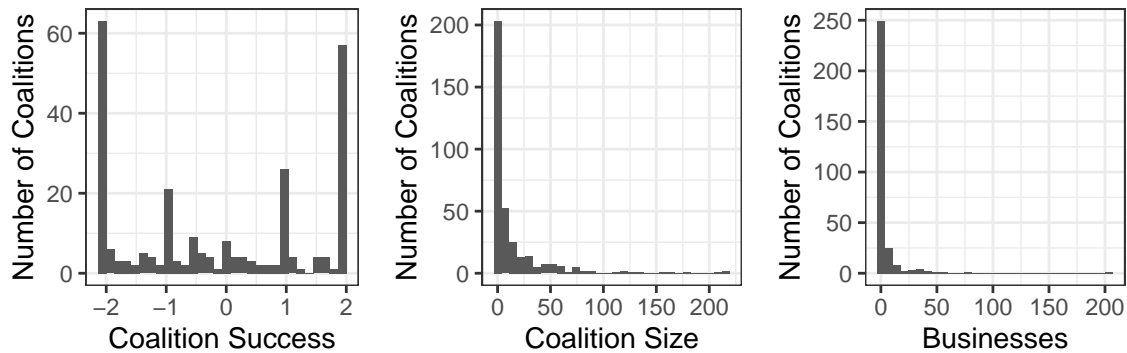


Figure 4: Hand-coded Data by Coalition

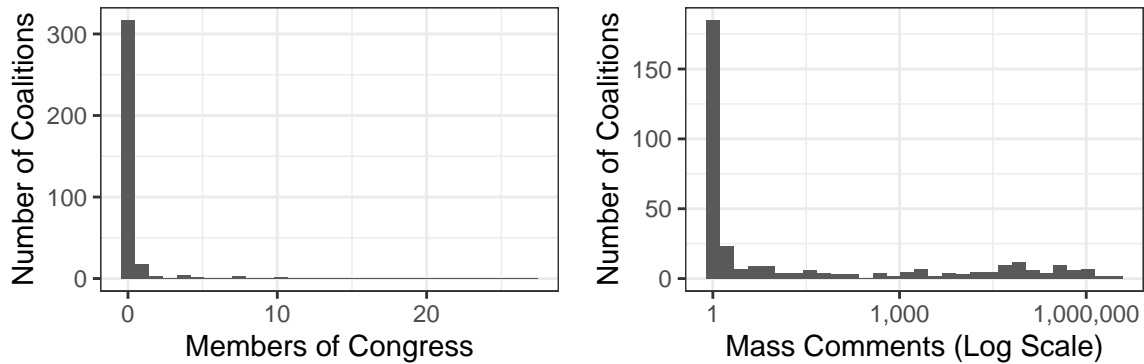


Figure 5: Number of Comments Linked to Hand-Coded Coalitions

**1.1.1.8 Limitations** The two main limitations of this design both bias estimates of public pressure campaign influence toward zero.

First, lobbying success may take forms other than changes in policy texts. Agencies may speed up or delay finalizing a rule, extend the comment period, or delay the date the rule goes into effect. Indeed, commenters often request speedy or delayed rule finalization, comment period extensions, or delayed effective dates. While I capture lobbying success concerning timing, my hand-coding approach prioritizes change in policy text, which is more difficult to achieve. Where commenters send both substantive and procedural (e.g., extended comment period) requests, I coded success concerning the substantive demands.

Second, bureaucrats may anticipate public pressure campaigns when writing draft rules, muting the observed relationship between public pressure and rule change at the final rule stage of the policy process. This is a limitation of all studies of influence during rulemaking comment periods.

## 2 Methods

### 2.0.1 Methods

The most direct way to assess the hypothesis that mass engagement increases lobbying success is to assess the relationship between the number of comments mobilized by a coalition and its lobbying success. The dependent variable for most analyses is the organization or coalition’s lobbying success, hand-coded on the interval between 2 (total success; the policy changed as requested) to -2 (total loss; the policy changed in the opposite direction requested). However, public pressure campaigns may only be effective under certain conditions. Specifically, pressure campaigns may help some types of coalitions more than others. Thus, I assess both the main relationship between pressure campaigns and lobbying success and the interaction between campaigns and coalition type. I then assess evidence for or against different potential causal pathways of influence. The main indirect pathway by which campaigns may influence agency policymaking is through engaging members of Congress.

These data have a hierarchical structure. Comment-level observations are nested within an organization, within a coalition, within a rule, within an agency, and an administration. I use a combination of fixed and random effects to account for dependence among observations at higher levels of analysis. The main models use data rolled up to the coalition level. Coalitions range from 1 to over 200 organizations in size and may include anywhere from 1 to over a million comments. Finally, I use a difference-in-difference design to assess variation in success *within* organizations that lobby on multiple rules.

#### 2.0.1.1 Modeling Coalition-level Lobbying Success

**2.0.1.1.1 The Direct Relationship Between Public Pressure and Lobbying Success** The dependent variable,  $Y$ , is the lobbying success of each coalition. To estimate the relationship between a coalition’s lobbying success and the scale of public pressure it mobilizes, I model the success of each coalition  $i$  lobbying a rule  $j$  published by an agency  $k$  under a president  $p$ . Each coalition is unique to a rule; each rule is unique to an agency (I assigned joint rules to the lead agency only) and presidential administration. I thus use the simpler notation  $y_i$  rather than the equivalent, more specific notation  $y_{ijkp}$ .

The main variable of interest is the total number of form-letter public comments that a lobbying coalition mobilized. The base model (Equation (??)) uses an indicator for whether coalition  $i$  used a public pressure campaign, i.e., mobilized mass comments (by definition, more than 99 mass comments).  $\beta_1$  estimates the difference in lobbying success when coalition  $i$  uses a pressure campaign compared to when it does not. Other models use either the logged number of comments or a quadratic term to account for the different marginal effects of additional public comments for smaller and larger campaigns.

$$Y_i = \beta_1 \text{Pressure campaign}_i + \beta_{2:n} X_i + \gamma_j + \delta_p + \epsilon_i \quad (1)$$

The base models include agency and president fixed effects ( $\gamma_k + \delta_p$ ) and control for other coalition-level factors that may affect a coalition's lobbying success,  $X_i$ . Controls include whether the coalition is lobbying unopposed, the coalition's size (the number of distinct organizations and elected officials), and the type of coalition (e.g., whether it is a business coalition or a public-interest coalition).  $\beta_{2:n}$  are the effects of these other coalition-level factors on lobbying success. I estimate these relationships using OLS regression.

**2.0.1.1.2 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) and the proportion of the total effect attributed to mediation through congressional support (comments or other communication from Members of Congress supporting the coalition's position on the proposed rule). As developed by Imai et al. (2010), this involves first estimating a model of the potential mediator as a combination of the main predictor, public pressure, and covariates,  $X_i$ .

The mediator model (Equation (??)) estimates the relationship between the scale of public pressure and the number of comments from members of Congress, who may receive political information (e.g., about the level of public attention or public opinion) from public pressure campaigns.

$$\text{Congressional Support}_i = \beta_0 + \beta_1 \text{Pressure Campaign}_i + \beta_{2:n} X_i + \gamma_k + \delta_p + \epsilon_i \quad (2)$$

The outcome model (Equation (??)) is the same as Equation (??), except that it now includes the number of supportive comments from members of Congress as a predictor.  $y_i$  is the Lobbying success of coalition  $i$  on a rule published by agency  $k$  under president  $p$ .  $\text{Pressure Campaign}_i$  is an indicator for whether the coalition organized a pressure campaign,  $\text{Congressional Support}_i$  is the number of members of Congress supporting the coalition, and  $X_i$  are other coalition-level predictors of lobbying success.  $\beta_{3:n}$  are the effects of these other coalition-level covariates.

$$Y_i = \beta_1 \text{Pressure campaign}_i + \beta_2 \text{Congressional Support}_i + \beta_{3:n} X_i + \gamma_j + \delta_p + \epsilon_i \quad (3)$$

The next section presents results from estimating the above models using the hand-coded data.

**2.0.1.2 Difference in Differences in Organization-level Lobbying 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), we can compare the lobbying success *within* the same organization *across* rules. This limits the analysis to organizations that lobby on multiple policies. The key variation of interest is when organizations lobby with a public pressure campaign versus when they do not.

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

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.

$$Y_{ij} = \alpha_i + \beta_0 + \beta_1 \text{Pressure Campaign}_{ij} + \beta_{2-n} X_{ij} + \gamma_k + \delta_p + \epsilon_{ij} \quad (4)$$

Equation (??) is similar to the model of coalition-level success except that  $y_{ij}$  is now the lobbying success of *organization*  $i$  in coalition  $j$  and  $X_{ij}$  is now a vector of organization- and coalition-level controls. Additionally, Equation (??) adds  $\alpha_i$ , a fixed effect for each organization. This fixed effect accounts for the organization's characteristics that do not vary over time as it lobbies on multiple rules. This difference-in-difference design ensures that coefficient  $\beta_1$  captures variation related to changes in levels of public pressure and other factors that vary within each organization, not other factors that may vary across organizations.