Hall of Mirrors: Corporate Philanthropy and Strategic Advocacy

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Abstract

Information is central to designing effective policy and policymakers often rely on competing interests to separate useful from biased information. In this paper we show how this logic of virtuous competition can break down, using a new and comprehensive dataset on U.S. federal regulatory rulemaking for 2003-2016. For-profit corporations and non-profit entities are active in the rule-making process and are arguably expected to provide independent viewpoints. Policymakers, however, may be less than fully aware of the financial ties between some firms and non-profits – grants that are legal and tax-exempt, but hard to trace. We document three patterns which suggest that these grants may distort policy. First, we show that, shortly after a firm donates to a non-profit, that non-profit is more likely to comment on rules on which the firm has also commented. Second, when a firm comments on a rule, the comments by non-profits that recently received grants from the firm's foundation are systematically closer in content to the firm's own comments, relative to comments submitted by other non-profits. Third, the final rule's discussion by a regulator is more similar to the firm's comments on that rule when the firm's recent grantees also commented on it. We discuss two interpretations of the evidence. While the negative welfare consequences of a "comments-for-sale" scenario are immediate, we show that, even if corporate grants' only effect is to relax the grantee's budget constraint, this can also lead to distorted policy making.

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1 Introduction

Economists and political scientists have long studied – both theoretically and empirically – the role interest groups play in the formation of laws and regulations (Olson, 1965; Grossman and Helpman, 2001). In the U.S., as in many democracies, there are well-established channels through which interest groups can try to influence the laws and rules that may impact their communities, their businesses, and society at large. Through means such as lobbying, grassroots campaigns, testimonies, and public advocacy, interested parties inform politicians and bureaucrats of the costs and benefits of government action.

While interest groups may have expertise on topics of direct relevance to them, they may also be tempted to present information that is tainted by their self-interest. This logic is at the core of the literature on informational lobbying.[1] Government officials must therefore weigh both the quality of information and its impartiality, based in part on its source. As such, policymakers may view information provided by for-profit corporations as less credible if that information is not corroborated by other groups with non-aligned interests. Non-profit organizations often represent interests that are unaligned with business.[2] Some non-profits – such as research groups and think tanks – are providers of nonpartisan, technical expertise and are commonly expected to offer a more neutral perspective. Other non-profits – such as environmental groups, social welfare organizations, and advocacy groups – may have opposing interests to business, to the extent that laws or regulations that benefit their members constrain business profits. Overall, non-profit organizations may therefore play an important balancing role in the informational lobbying process. This role can be subverted, however, by the financial ties between corporations and non-profits, when unbeknownst to regulators and lawmakers.

There exists anecdotal evidence that these concerns are well-founded. Across a range of issues and regulatory agencies, researchers and journalists have documented cases of companies using charitable contributions to co-opt ostensibly neutral and even non-aligned non-profits. Notably, Peng (2016) describes the efforts of telecommunications firms to win merger approvals from the Federal Communication Commission (FCC), in part by assembling diverse and vocal coalitions of supporters. Peng quotes Crawford (2013) on the Comcast-NBCU merger, in which *"[t]he company*

[1] By informational lobbying, we refer to the broad literature on strategic information transmission, which encompasses cheap talk and costly signalling models in the context of lobbying. For a complete discussion, see chapters 4-6 in Grossman and Helpman (2001). Early examples include Potters and Van Winden (1992), Austen-Smith (1993), Austen-Smith (1995) and Lohmann (1995).

[2] As Rose-Ackerman (1996) suggests for interactions with consumers, a rationale is that they "may favor non-profits because they believe that they have less incentive to dissemble because the lack of a profit motive may reduce the benefits of misrepresentation." Easley and O'Hara (1983) also emphasize the role of informational asymmetries. However, ameliorating informational problems is only one of the benefits of not-for-profit status. Other organizational rationales are explored in Glaeser and Shleifer (2001) and Glaeser (2002).

encouraged letters to the FCC from more than one thousand non-profits...including community centers, rehabilitation centers, civil rights groups, community colleges, sports programs, [and] senior citizen groups." For the AT&T/T-Mobile merger, Peng similarly documents letters of support addressed to the FCC from non-profits that, at first glance, would appear to have little interest or expertise in telecommunications policy, including a homeless shelter in Louisiana, a special needs employment agency in Michigan, and the Gay & Lesbian Alliance Against Defamation (GLAAD). The non-profits were all AT&T Foundation grantees (in the case of the homeless shelter, the donation had come in just five months before the merger was announced). In no case did the non-profits disclosed their AT&T funding in their comments to the FCC, and in at least one instance, the comments did not appear to represent the views of the non-profit membership. According to Peng, "*GLAAD's president and six board members resigned when its merger endorsement made headlines and revealed that the organization had received AT&T funds.*"

Journalists and medical experts have documented similar persuasion-via-donation in public health debates. Jacobson (2005) describes a ("no-strings attached") $1 million donation from Coca-Cola Foundation to the American Association of Pediatric Dentistry (AAPD). The gift was accompanied by a shift in the tone of AAPD statements on sugary beverages, from describing soft drinks as "a significant factor" in tooth decay, to describing the scientific evidence of the relationship as "unclear".[3] Similar concerns have been raised with respect to the role of donations from corporations to university research hospitals.[4]

Investigative journalists have also documented many instances of companies influencing the policy statements of "neutral" non-profits that are meant to provide evidence-based analysis on matters of public interest. Confidential memos and documents suggest that some think-tank reports are discussed with corporate donors before the research is complete, allowing donors to potentially shape the final reports, so that the resulting "scholarship" can be used to corroborate their parallel lobbying efforts. In her 2017 book *Dark Money*, journalist Jane Mayer, provides one prominent example, documenting how the philanthropic activities of the billionaire industrialist brothers Charles and David Koch furthered their efforts to influence political discourse: "*[The Koch brothers] subsidized networks of seemingly unconnected think tanks and academic programs*

[3]A more direct link to policy can be found in the soda industry's efforts against New York City's ban on large sugary drinks in the 2010s. In his decision to strike down the Bloomberg administration policy, the presiding judge cited amicus briefs filed by two New York non-profits (the local chapter of the NAACP and the Hispanic Federation), which argued that the ban would disproportionately affect ethnic and racial minority groups. Both non-profits were recipients of funds from Coca-Cola and PepsiCo. See "Minority Groups and Bottlers Team Up in Battles Over Soda." *The New York Times* March 12, 2013. Aaron and Siegel (2017) show that 95 national public health organizations received funding from Coca-Cola and PepsiCo during 2011-2015; the study does not, however, look at the effect on organizations' publicly stated positions.

[4]See, for example, Gardiner Harris, "Top Psychiatrist Failed to Report Drug Income," *The New York Times,* October 3, 2008; Charles Piller and Jia You, "Hidden conflicts? Pharma payments to FDA advisers after drug approvals spark ethical concerns," *Science News,* July 5, 2018. See also Ross et al. (2000).

and spawned advocacy groups to make their arguments in the national political debate. [...] Much of this activism was cloaked in secrecy and presented as philanthropy, leaving almost no money trail that the public could trace. But cumulatively it formed, as one of their operatives boasted in 2015, a 'fully integrated network'."

The context of U.S. Federal Regulation, with its far-reaching economic implications and its carefully documented record of communication between private organizations and government agencies, offers an ideal setting to establish evidence pertinent to the interactions of for-profit and not-for-profit entities vis-à-vis the government. U.S. Federal agencies are legally required to publish proposed rules in the Federal Register, accept public comments on those proposed rules, and consider these comments before rules are finalized.[5][6] While there is no legal requirement for agencies to act on feedback received in the comments, the agencies themselves often attribute changes between proposed and final rules to arguments made via rulemaking.[7] As emphasized by Sunstein (2012), public commentary is also a valuable source of feedback to preempt regulatory mistakes "*when the stakes are high and the issues novel.*" We focus on this environment for our analysis.

The government repository regulations.gov provides the largest source for comment information on proposed rules. Our comprehensive dataset includes the vast majority of the comments submitted in the rulemaking process since 2003 and all related regulatory material. For each comment, we observe the specific proposed rule pertinent to that document, as well as the content of the comment and the identity of the commenter. We use natural language processing and machine learning tools (most of them customized to our environment) to standardize, clean, and analyze the corpus of all the comments and rules in our sample.

We complement the commentary data with information on corporate foundations and their beneficiaries, using data on charitable donations by foundations linked to corporations in the S&P 500 and Fortune 500 between 1995 and 2016 through detailed tax forms filed with the Internal Revenue Service (IRS).

We document three robust patterns. First, we show that non-profits are more likely to comment on the same regulation as their donors, and that this "co-commentary" is most strongly associated

[5] The Administrative Procedures Act of 1946, 5 U.S.C. 553(c) states: "*. . . the agency shall give interested persons an opportunity to participate in the rule making through submission of written data, views, or arguments with or without opportunity for oral presentation. After consideration of the relevant matter presented, the agency shall incorporate in the rules adopted a concise general statement of their basis and purpose.*" https://www.law.cornell.edu/uscode/text/5/553. Last accessed 5/1/2020.

[6] There are some exceptions for urgent actions or cases in which the change is so trivial that the agency does not expect comments, but in general, agencies which fail to publish a sufficiently informative proposal or fail to follow the commenting procedure can have their regulations vacated in court.

[7] For instance, the U.S. Food and Drug Administration states on their website: "*these suggestions can, and do, influence the agency's actions*". See https://www.fda.gov/drugs/drug-information-consumers/importance-public-comment-fda Last accessed 4/28/2020.

with donations in the year immediately preceding the comments. This result survives the inclusion of firm-grantee fixed effects and hence controls for the general tendency of some firm and non-profit pairs to be both financially connected and active on similar regulatory issues. The effect is large: a donation in the preceding year is associated with a 76% increase in the likelihood of co-commentary.

In our second set of results, using natural language processing tools, we show that the content of comment pairs from firms and non-profits linked via charitable donations tend to be more similar relative to any other pairs of comments on the same proposed rule. Importantly, the timing of this relationship parallels that of our first set of findings: co-comments in the year immediately following a donation are the most similar, even controlling for the average tendency of a given grantee-firm pair to share similar language. We also investigate the semantic orientation of the comments and show that the comment similarity for firm-grantee pairs does not result from comparably worded comments that express opposing sentiment.

Our third main empirical finding is that co-commenting relationships matter for the rules eventually finalized in the U.S. Code of Federal Regulations. Focusing on all comments made by firms in our dataset, we show that, if the recipient of a recent donation commented on a the same proposed regulation as its donor firm, the language of the agency discussion of the final rule is more closely aligned with the firm's comment than the comments of other firms. This result is also confirmed when we focus on whether the regulator cites that specific firm in its discussion of the final rule. At the very least, it appears that the firm is able to obtain more attention from the regulator in finalizing the rule.

The welfare consequences of the patterns we document depend crucially on the theoretical mechanism that produces them. We believe there are two primary theoretical interpretations of our findings that deserve discussion:

(i) A "comments-for-sale" view offers the least benign interpretation (in social welfare terms) of our results. Grantees may be simply be "for sale" and willing to change the content of their comments to regulators in exchange for corporations' financial support. Under this interpretation, donations buy comments of certain non-profits. Some of the examples discussed above in the text underscore this mechanism.

(ii) A "comments facilitation" view is more benign. Donations may serve to relax the budget constraints of selected grantees. As new regulations are proposed, a firm precisely targets with donations non-profits that happen to be aligned with its interests at that particular point in time. This funding does not result from an expectation that grantees will change the content of their comments in a quid-pro-quo sense, but because the firm wishes to financially buttress non-profits presenting an independently similar viewpoint to regulators.

With regard to this second, more benign mechanism, we make two observations. First, in section 4 we observe a greater similarity in co-comments between a firm and its grantees following a donation, even relative to the average co-comments made by the same pair when not immediately preceded by a donation. This is also observed when looking within a relatively narrow set of regulatory issues. We acknowledge that these findings admit the possibility that, even within a narrow category of issues, a firm may support non-profits only when a topic of particular alignment suddenly arises. However, the likelihood of such precise targeting needs to be taken into account in evaluating its plausibility. Second, we show that there still may be negative welfare consequences under this more benign interpretation if the donation affects the *probability of commenting*. A parsimonious theoretical framework in section 7 illustrates this last point. Even absent a change in the content of comments, when regulatory agencies are not aware of the financial ties between firms and grantees, they misread the signal from a grantee's decision to comment. We show that, as long as the regulator has a less than perfect knowledge of these financial ties (a realistic assumption given the complexity of the data), welfare losses are to be expected under theoretically plausible circumstances. These results do not hinge on the outright distortion of the stance of beneficiary non-profits, but result from the the selective subsidy of communications only offered to a favorable subset of third-party advocates. This simple framework also illustrates conditions under which welfare losses from subsidizing non-profit commentary may be less of a concern and when they can be ameliorated by disclosure.

Our findings, first and foremost, provide a contribution to the literature on the mechanisms by which interest groups seek to influence government policy (for canonical early contributions see, for example, Grossman and Helpman (1994, 2001) and for a more recent discussion Baumgartner et al., 2009; Bertrand et al., 2014; Drutman, 2015). We differ from much of this prior work in our focus on influence via expert commentary, rather than through financial contributions and, much more importantly, in documenting one mechanism by which private interests may cloak biased advice by inducing its provision by a non-obviously aligned party. This has implications for how we model the process of governmental information acquisition (Austen-Smith, 1993; Laffont and Tirole, 1993), and is also of direct policy relevance for corporate disclosure requirements (Bebchuk and Jackson, 2013; Peng, 2016).

Our work is also related to prior research that has shown the value of coalitions of diverse interest groups in the adoption of government policy. The benefits of counteracting advocacy have an established rationale within information economics and political economy. Early theoretical explorations include Becker (1983), Austen-Smith and Wright (1994), Dewatripont and Tirole (1999), and Krishna and Morgan (2001). Empirical applications include work focused on the rulemaking phase of Title IX of the Dodd-Frank Act of 2010 (Gordon and Rosenthal, 2018). In another study on legislation introduced in Congress between 2005 and 2014, Lorenz (2017) shows that bills supported by interest-diverse coalitions are more likely to receive committee consideration; in contrast, Lorenz (2017) finds no association between committee consideration and lobbying coalitions' size or their interests' PAC contributions. Generalizing beyond the lawmaking process, this prior work complements our findings, in that it suggests that corporations can expect some return for the type of charitable "investments" we uncover in this paper.[8]

From a welfare perspective, we wish to understand potential subversion of the regulatory and rule making process due to distortions in information and beliefs. These are concerns that add to issues of pure regulatory capture (Stigler, 1971; Peltzman, 1976) and are complementary to issues of enforcement vis-à-vis the courts (Glaeser and Shleifer, 2003). Our analysis may also contribute to the understanding of the complex problem of cognitive or cultural capture of regulators, highlighted by Johnson and Kwak (2010) and Kwak (2014), in providing a mechanism through which regulators' and special interests' beliefs become more strongly aligned.

Finally, our paper expands on earlier work highlighting how corporations may strategically use their corporate philanthropy as an undisclosed tool of political influence. Bertrand et al. (2018) show that corporations allocate more of their charitable giving to congressional districts that are more relevant to the corporations due to the committee assignments in the House of Representatives of their elected representatives. We identify in this paper another, independent, mechanism for "strategic" corporate philanthropy (Baron, 2001) in the government arena.[9]

2 Institutional context and the data

2.1 Rulemaking process

The rulemaking process of U.S. federal agencies provides a context in which we may observe both the presence and the content of communication by different entities with interests in influencing the policymaker. While lobbying at the federal or local level does not come with statutory requirements of disclosure of the content or even the exact target of communication,[10] the rulemaking process consists of a series of codified procedures that regulate the activity of federal agencies in the production of "rules" under the Administrative Procedure Act (APA) of 1946.

The subject of policy deliberation is a rule "*designed to implement, interpret, or prescribe law or policy,*" according to the APA. The process of rulemaking may be set in motion by the

[8]Other papers that focus on the returns to lobbying include Bombardini and Trebbi (2011, 2012); Kang (2016); Kang and You (2016).

[9]For a broader review of corporate philanthropy and corporate social responsibility, see also Kitzmueller and Shimshack (2012).

[10]Under the Lobbying Disclosure Act of 1995, lobbying registration and reporting forms only require lobbyists to list the topic and the agency lobbied (e.g., Trade, the Senate of the United States), in addition to clients and payments. See Vidal et al. (2012); Bertrand et al. (2014).

passage of a new law in Congress which then requires implementation, or by an agency itself, upon surveying its area of legal responsibility and identifying areas that need new regulations.[11] The rulemaking process starts with a Notice of Proposed Rulemaking (NPRM), which includes the objective of the rule and how it would modify the current Code of Federal Regulations. The NPRM is published in the Federal Register, at which point the agency specifies a period of 30 to 60 days during which the public can submit comments on the proposed rule.

This notice and comment process is designed to alleviate the informational problem in federal regulatory agencies. These provisions explicitly delineated in the APA are fundamental to U.S. public administration rulemaking (Strauss, 1996), providing an opportunity for protection of consumer and private interests in an environment in which regulators are typically non-elected and not directly accountable to voters (Besley and Coate, 2003).

After comments have been received and additional information collected, the agency may proceed to publish a final rule in the Federal Register or issue a Supplemental Notice of Proposed Rulemaking if the initial rule was modified substantially, in which case further comments are invited. This notice-and-comment procedure aims to include the general public and all interested parties in the crafting of the new rule. Importantly, accompanying the final rule, the agency also provides a discussion of the goals and rationale of the policy, and how the comments were incorporated into the final rule; this discussion is published in the rule's Supplementary Information section. Upon finalization of the rule, comments represent part of the official record, and rules can be challenged judicially on procedural or substantive grounds based on comments filed by entities that participated in the rulemaking process. Judicial review is an important constraint to rulemaking activity in the United States in that it effectively forces regulators to attend to opinions expressed via commentary.

2.2 Data

We now introduce our sources and provide a brief overview of the data. For further details we refer to Appendices A and B.

2.2.1 Charitable giving by foundations

The starting point for our sample is the set of corporations that have appeared at any point during the period 1995 to 2016 in the Fortune 500 and/or S&P 500 lists, which collectively include 1,398 firms.[12] Data on charitable donations by corporate foundations come from FoundationSearch, which digitizes publicly available Internal Revenue Service (IRS) data on the 120,000 largest

[11] Agencies may decide to engage in rulemaking under the recommendation of congressional committees, other agencies, or following a petition from the general public.

[12] The initial number of firms is 1,434, but we combine firms that merge during the sample period.

active foundations in the U.S. We find 629 active foundations that can be matched by name to 474 of the initial list of 1,398 firms, some of which have more than one foundation.[13]

Each charitable foundation must submit Form 990/990 P-F "Return of Organization Exempt From Income Tax" to the IRS annually, and this form is open to public inspection. Form 990 includes contact information for the foundation, as well as yearly total assets and total grants paid to other organizations. Schedule I of Form 990, entitled "Grants and Other Assistance to Organizations, Governments, and Individuals in the United States," specifically requires the foundation to report all grants greater than $5,000. For each grant, FoundationSearch reports the amount, the recipient's name, city and state, and a giving category created by the database.[14]

While the IRS assigns a unique identifier (Employer Identification Number, EIN) to each non-profit organization, Schedule I does not include this code, so we rely on the name, city and state information to match a grantee to a master list of all non-profits. This list, called the Business Master File (BMF) of Exempt Organizations, is put together by the National Center for Charitable Statistics (NCCS) primarily from IRS Forms 1023 and 1024 (the applications for IRS recognition of tax-exempt status). The BMF file reports many other characteristics of the recipient organization, including address, assets and non-profit sector code called the National Taxonomy of Exempt Entities (NTEE). The results of the matching between all public charities, private foundations or private operating foundations (designated as 501(c)3 organizations for tax purposes) in the BMF and the recipients of charitable giving by Fortune 500 and S&P 500 companies is described in detail in Bertrand et al. (2018).

Finally, note that direct charitable giving by firms (that is, not through their charitable foundations) or large charitable grants by executives of the firms are unfortunately not traceable and are excluded from the analysis.

2.2.2 Comments and rules

The source of data on regulatory comments is regulations.gov, a website through which the majority of U.S. federal agencies collect public comments in the notice-and-comment phase of rulemaking.[15] The regulations.gov API provides a search function for document metadata which allows us to identify all comments submitted and stored on the site. Our initial comment sample consists of

[13]As noted in Brown et al. (2006), larger and older companies are more likely to have corporate foundations, which may partly result from the fixed cost of establishing a foundation. They also find that state-level statutes – in particular laws relating to shareholder primacy and the ability of firms to consider broader interests in business decisions – predict establishment of a foundation. Various endogenous financial variables are also predictive of foundation establishment. The analysis in Brown et al. (2006) is cross-sectional, so their variables are absorbed by the various fixed effects in many of our analyses.

[14]The ten broad categories are: Arts & Culture, Community Development, Education, Environment, Health, International Giving, Religion, Social & Human Services, Sports & Recreation, Misc Philanthropy.

[15]For the complete list, see Appendix tables D.7 and D.8.

all comments posted to regulations.gov in the years 2003-2016. We use a custom machine learning tool to extract organization names from the comment metadata. The algorithm identified 981,232 comments that appear to be authored by organizations (as opposed to private individuals) and we downloaded the full text of these organization comments. We are particularly interested in comments submitted by non-profits and by corporations that we observe in our FoundationSearch sample. The comments are linked to corporations' and grantees' names through a custom name matching tool that implements multiple types of fuzzy matching and manual corrections.[16]

Comments on regulations.gov are organized into rulemaking folders (dockets) created by agencies to hold comments on a narrow topic (often a single proposed rule). For example, docket FNS-2006-0044 from the Food and Nutrition Service (FNS) contains comments on a proposed rule 06-09136, "Fluid Milk Substitutions in the School Nutrition Programs."[17] We rely on the agencies' classification and refer to each of these dockets on a homogeneous topic as a *rule*.

In the last section of the paper, we examine the wording of the discussion of final rules as a function of corporate and non-profit comments. Rulemaking documents such as proposed rules, rules, and notices are published in the Federal Register. We collect these documents in bulk XML format from the Government Print Office website, and obtain additional identifiers and metadata from the federalregister.gov website API.

Linking comments to specific rules requires additional steps, which we describe in more in section 5 and online Appendix A.

2.2.3 Basic data facts

Recall that our sample starts with the set of companies that appeared at least once in the Fortune 500 or S&P 500 lists between 1995 and 2016. Of the 1,398 firms in that sample, we find 909 that have commented at least once in the period 2003-2016.[18] This is the sample of firms that forms the basis of our regressions. We have a total of 22,654 firm comments over 5,792 rules. Of these 909 firms, 414 have a foundation. To generate the set of non-profits for our analysis, we start from the 225,180 entities that received at least one grant from any foundation in our sample over the period 1998-2015. Our sample consists of the 11,531 of these grantees that comment at least once at any point during the period starting in 2003. We have a total of 318,841 comments on 8,729 rules from these grantees.

There is vast heterogeneity among firms in their activity in the commenting phase. The most actively commenting firm, Boeing, provided comments on 1,284 rules. On average each firm

[16] Available at https://github.com/bradhackinen/nama

[17] There are also complex dockets that contains multiple proposed rules and notices, but they still constitute a homogeneous topic. See, for example, docket EPA-HQ-OAR-2008-0699, the Environmental Protection Agency's review of the National Ambient Air Quality Standards for Ozone.

[18] We only consider comments starting in 2003 because this is when the comments database is complete.

comments on 18 rules, but the distribution is skewed: the median firm comments on 6 rules, while the firms at the first and third quartile comment on 2 and 17 rules, respectively. The distribution of comments among grantees is even more skewed. On average each grantee comments on almost 5 rules, but the median is 1 and the third quartile is 3 rules. The most active grantee (Center for Biological Diversity) comments on 905 rules.

Appendix Table D.3 lists the agencies that receive the highest number of comments from grantees and firms.[19] At the top of the list for firms are the EPA (Environmental Protection Agency), the FAA (Federal Aviation Administration) and the FDA (Food and Drug Administration). The top three agencies as recipients of grantees' comments are the FWS (Fish and Wildlife Service), the NOAA (National Oceanic and Atmospheric Administration), and HHS (The Department of Health and Human Services). It is worth noting that the EPA, the FAA and the FDA feature in the top 10 agencies for grantees as well.

Tables 1 and 2 provide summary statistics for the 2008-2014 period (period during which our data are most complete) on firm and grantee commenting and what we define as "co-comments," which are instances in which firms and grantees comment on the same rule. Table 1 summarizes the firm side: there is a total of 1,457.8 comments by firms in an average year (by an average number of firms commenting annually of 384.4, a figure not reported in the table). On average a firm comments on 1.9 rules per year. Of these rules, 1.3 receive comments from non-profits. Of particular interest is the further subset of 0.3 rules that received comments from the firm's grantees (the number is 0.2 if we consider grantees that received recent donations[20]). Overall, about 10% of the average firm's comments have a co-comment by grantees they recently supported.

Table 2 presents the analogous breakdown of commenting for grantees. We note that, of the average annual number of comments (5,073 from 2,516.7 annual grantees, the latter figure unreported in the table), 1,255.6 (almost 25%) come from grantees that have received at least one donation from our sample of firms, and 645.6 (almost 13%) come from those that received a recent donation. It is interesting to compare the total number of annual comments by firms (1,457.8) to the number of comments by recent grantees (645.6), who, as we will see, submit comments with similar content.

Finally, Table 3 presents annual donations, which average \$9 million per firm, and the donations associated with grantees that comment on the same rules as the firm, which average \$700,000. The average firm contributes 8% of its funds to grantees who comment on the same rules (16% to grantees commenting to the same agency). We can conclude that co-commenting represents a meaningful share of both firms' and grantees' activity. Appendix Tables D.1 and D.2 report the same firm commenting and co-commenting quantities for the set of rules that has been classified

[19] Agency acronyms are listed in Appendix tables D.7 and D.8.

[20] Recent, as discussed later, refers to a donation occurring in the year of the comment or the year before.

as "significant" under Executive Order 12866, because of the scale of their impacts.[21] Significant rules make up approximately 10% of all rules that receive at least one organization comment, but they receive almost half of all firm comments. Within significant rules, for every five firm comments received by a regulator, the regulator also receives three comments from non-profits with a financial tie to the firms they are co-commenting with, roughly half of these involving a donation in the concurrent or previous year.

It is useful to compare the dollar amounts of these donations with federal lobbying expenditures, using a dataset maintained by the Center for Responsive Politics.[22] The amount that firms in our sample spent lobbying all federal institutions during our reference period (2003-2014) was $772 million per year. Assuming that money was split evenly between all of the institutions listed in each lobbying report filing, we obtain a rough estimate of $538 million per year spent by our sample firms lobbying our sample agencies. The equivalent estimate for the total amount of money donated to non-profits that co-comment with their donor firms is $251 million, or about 47% of total federal lobbying expenditures. For an additional comparison, firm political action committee (PAC) campaign contributions in a typical congressional cycle average 10% of total lobbying expenditures, or about a fifth of the donations we consider.

3 Evidence based on charitable giving and non-profit commenting on regulations

This section focuses on the link between firms and non-profits through charitable grants, and establishes a relationship between firm-grantee financial ties and their tendency to comment on the same regulations. We denote firms/foundations by $f \in F$ and grant-receiving non-profits (grantees) by $g \in G$. Let D_{fgt} be an indicator function that takes a value of 1 if we observe a donation from firm f to grantee g in year t, and 0 otherwise. The indicator function C_{frt} is equal to 1 if firm f comments on rule r in year t, and 0 otherwise. The indicator function C_{grt} is defined similarly and is equal to 1 if grantee g comments on rule r in year t, and 0 otherwise. We define $CC_{fgrt} = C_{frt} \times C_{grt}$ as an indicator equal to 1 when donor f and grantee g comment on the same rule r at time t. We adopt two types of specifications: a "co-commenting" specification and a "rule" specification.

[21] One common reason for being classified as significant is that the rule has "an annual effect on the economy of $100 million or more."

[22] See https://www.opensecrets.org/federal-lobbying. Last accessed 4/30/2020.

3.1 Co-commenting specification

We begin by relating the event of a firm and a grantee commenting on the same rule to a recent financial tie between the two in the form of a charitable donation. In particular, we examine whether co-commenting is more likely in the year immediately following a donation.

Let $CC_{fgt} = I\left(\sum_r CC_{fgrt} > 0\right)$ indicate whether firm f and grantee g comment on the same rule at time t. Our benchmark specification is:

$$CC_{fgt} = \beta_0 + \beta_1 D_{fgt-1} + \delta_{fg} + \delta_t + \varepsilon_{fgt} \tag{1}$$

where δ_{fg} indicates firm-grantee pair fixed effects, δ_t time fixed effects, and D_{fgt-1} is equal to 1 if we observe a donation from f to g in the concurrent (t) or preceding ($t-1$) year of the comments, and 0 otherwise. We group together years t and $t-1$ donations due to the coarseness of the data along the time dimension. We only observe the year of comment, so it is possible for a comment to be made in, say, January of 2006 and a donation in June 2006; hence we can only be certain that the lagged-year donation took place prior to co-commenting.[23]

The four columns in Table 4 report different sets of fixed effects in order of increasing stringency. In column (1) we only include time fixed effects δ_t, while in column (2) we include separate grantee, firm, and time fixed effects, which account for the average tendency of certain firms and grantees to be more active in grant-making and receiving, and also in commenting on rules.

One may still be worried that the pattern of co-commenting may result from firms contributing to non-profits that share similar objectives and views, or non-profits that operate in similar sectors. For instance, the Bayer Science & Education Foundation associated with Bayer US, a pharmaceutical company, may be more likely to donate to healthcare-related research non-profits, and both Bayer and healthcare-related non-profits may be more likely to comment on healthcare-related regulations than an average organization. For this reason, our preferred specification in column (3) of Table 4 includes firm-grantee fixed effects and time fixed effects. In this specification, β_1 is estimated employing only within-pair variation over time in donations and co-commenting. In particular, β_1 will detect whether, controlling for the average tendency of a certain firm f to co-comment with and donate to a specific non-profit g, we observe co-comments occurring immediately after a donation from f to g. Column (4) is an even more demanding specification, as we introduce grantee-year and firm-year fixed effects, which control for firm- and grantee-specific changes in commenting and giving/receiving over time. Standard errors are clustered at the grantee-firm pair level for all columns.

We find a robust and economically significant association between recent donations and the

[23]In Appendix Table D.4 we separate contemporaneous and lagged donations and find that lagged donations strongly predict co-commenting, while contemporaneous donations are a weak predictor of co-commenting.

likelihood of co-commenting. Co-commenting is sparse when considering all possible firm-grantee-year triples: 0.175% feature co-commenting. In column (3) a recent donation is associated with a 76% increase in the likelihood of co-commenting, even after controlling for the general propensity of a specific firm to give to as well as co-comment with a specific grantee. Even in the saturated specification of column (4), a recent donation increases the probability of co-commenting by 46%.

As a further robustness exercise, Appendix Table D.4 includes, along with dummies for donations at time t and $t-1$, a dummy for whether firm f donated to g in year $t+1$. The set of fixed effects in this table is analogous to Table 4. In column (4) of that table, with the most restrictive set of fixed effects (i.e. pair, grantee-year and firm-year fixed effects), we find that donations made immediately after the commenting period are not associated with co-commenting, whereas only immediately preceding donations are. This pattern further confirms the particular timing we emphasize here, with co-commenting more prevalent only after we observe a recent donation from firm to grantee.

3.2 Rule specification

In the specifications we have considered thus far, we have aggregated co-commenting across different rules at the firm-grantee-year (fgt) level. For robustness, we now present an alternative approach that allows us to control for the average level of commenting on a given rule r. This "rule" specification relates the probability of commenting by a grantee on r to donations received:

$$C_{gr} = \beta_0 + \beta_1 \underbrace{I\left(\sum_f D_{fg} \times C_{fr} > 0\right)}_{DonorComment_{gr}} + \delta_g + \delta_r + \eta_{gr},$$

where C_{gr} is equal to 1 if g comments on rule r (0 otherwise) and $DonorComment_{gr} = I\left(\sum_f D_{fg} \times C_{fr} > 0\right)$ is equal to 1 if g receives a donation from any firm that comments on r, and 0 otherwise. In its most saturated version, this specification includes rule fixed effects δ_r, which capture the extent to which certain rules are subject to more intense commenting, and grantee fixed effects δ_g, to account for factors like resources and size of the non-profit, which may make g both more visible (to corporate donors) and more likely to comment on any rule.

Table 5 reports estimates of β_1 under different fixed effects and with two-way clustered standard errors at the grantee and rule level. Our preferred specification in column (4) has rule and grantee fixed effects. When considering all the possible pairs of grantees and rules, we find a comment in 0.043% of cases. It is not surprising that this number is small, since the universe of all possible grantee-rule pairings involve non-profits like, say, the Red Cross, that we would not expect to comment on, say, financial regulation. Starting from this baseline probability of commenting on a specific rule, we find that the probability that a non-profit comments on a particular rule is 3 to 5.5 times higher when a donor firm commented on the same rule, a quantitatively sizable result that accords with our previous results under specification (1).

3.3 Heterogeneity in co-commenting effects by grantee attributes

We conclude this section by presenting further results on how the link between grants and co-commenting behavior varies by a grantee's attributes. We consider two main dimensions of heterogeneity that may be informative as to the types of non-profits that may be most susceptible. Specifically, we consider research-focused organizations, and organizations focused on shaping policy, both by influencing public opinion and directly lobbying governments on legislation. In both cases, differences in the effect of money on co-commenting behavior is ambiguous. Consider first research-focused organizations. On the one hand, such entities ostensibly provide neutral expert input on regulations that lie within their purview; on the other hand, research organizations such as think tanks may be targeted with donations from firms which exploit preexisting sympathies to nudge them toward providing supportive comments.[24] Advocacy organizations share a similar ambiguity, as a result of forceful prior policy positions which, on the one hand, should make them less persuadable, but may also lead to donations that aim to nudge them toward supportive commentary.

We define research- and advocacy-focus based on the IRS's National Taxonomy of Exempt Entities (NTEE) code, a three-digit activity classification system for non-profits. The first digit, a letter, denotes the organization's main area (e.g., arts, medical, environment, etc), whereas the second two are numerical digits which capture the type of activity. For example, A denotes all arts organizations, while A50 is the category for museums. We define *Research* as an indicator variable that takes on a value of 1 for each of the following groups: all non-profits in the main areas of medical (H), science (U), and social science (V); non-profits across all main sectors with the activity code for Research Institutes & Public Policy Analysis (05); and institutions of higher education with a research focus (B43 and B50, universities offering graduate programs, and graduate/professional schools respectively). We will further distinguish between comments from higher education organizations (B43 and B50, in which case the commenter is usually a faculty member) and all other research-focused entities. The indicator variable *Advocacy* captures all non-profits with the activity code for Alliances and Advocacy (01)[25] as well as all non-profits in the main area

[24] See, for example, "How Think Tanks Amplify Corporate America's Influence," *The New York Times*, August 7, 2016.

[25] The definition of this category is as follows – for the education category it reads, "Organizations whose activities focus on influencing public policy within the Education major group area. Includes a variety of activities from public education and influencing public opinion to lobbying national and state legislatures." The definition is similar for other major area (first-digit) groups.

of Civil Rights, Social Action & Advocacy (R).

In Table 6, we present results that parallel those of Table 4. We add to this specification a series of interaction terms to explore heterogeneous effects of grants on co-commenting. Standard errors are clustered at the grantee-firm pair level for all columns. First, in column (1) we present results with only year fixed effects, to examine differences in the average level of co-commenting for research and advocacy organizations. We also include as a control $log(Income)$ of the grantee, to control for size. As expected, advocacy organizations –which, recall, are defined by a mission of affecting policy– are far more likely to co-comment on regulations, a direct result of their frequent commenting more generally. Similarly (though of a much smaller magnitude) research-focused organizations are more likely to co-comment. Co-commenting is also correlated with size, as expected.

Column (2) examines whether there is differential co-commenting behavior for *Research* organizations; this specification includes firm-grantee fixed effects.The interaction term is negative, marginally significant ($p < 0.10$), and large in magnitude – its value, -0.213, is almost identical to that of the direct effect of lagged grants, indicating a zero correlation between the receipt of a grant and co-commenting for research-focused organizations. In column (3) we disaggregate *Research* into universities versus all others and, while neither coefficient is statistically significant, we find that the two are both negative (though the university research interaction is more negative). Finally, column (4) looks at differential behavioral for *Advocacy* organizations. The interaction term is negative and, while not significant, very large in magnitude, more than double the size of the direct effect of grant receipt. Recall that overall advocacy organizations are relatively frequent commenters; one possible interpretation of this result is a "hush money" effect, with firms paying advocacy firms to stifle would-be comments. We explore this issue further in section 6.

4 Quantifying the similarity in content across regulatory comments

Thus far our analysis has demonstrated that financial connections between firms and non-profits are associated with an increase in the propensity to co-comment on the same rules. We now show that the content of non-profits' messages to regulators are also related to these non-profits' financial connections to firms.

To build intuition (and without intent to claim any deliberate deception by the parties involved in this particular instance), consider the example of Bank of America's $150,000 donation to the Greenlining Institute in 2010. Bank of America is the second largest bank in the United States by total assets and is a central player in housing finance; the Greenlining Institute is a non-profit focused on improving access to affordable housing and credit to low-income families and minorities (African American, Asian American, and Latino, in particular). In 2011 both organizations commented on the Office of the Comptroller of the Currency's Credit Risk Retention (CCR) rule, Docket ID OCC-2011-0002 initiated under the Dodd-Frank Act of 2010 (Title IX, Subtitle D, Section 941). CCR, also known as the "skin in the game" rule, imposed a 5% retention requirement on all mortgage loans originated by lenders in the United States to moderate "originate-to-distribute" moral hazard problems pervasive in the build-up to the 2008 financial crisis. The main comment submitted by Bank of America[26] observed that, in relation to relaxing the definition of qualified mortgages exempted from retention requirements on the issuing bank's balance sheet (i.e., of mortgages deemed safe enough to warrant exemption from the restriction): "*...the PCCRA provision will cause some borrowers to be unable to obtain a loan at all. In the currently tight private residential mortgage market, borrowers already must provide significant down payments.*" The Greenlining Institute provided a similar assessment in its comment,[27] expressing the opinion that "*by raising the barrier to affordable home ownership with an unreasonable 20% down payment requirement, we will not only keep families from rebuilding after foreclosure, but we will prohibit an entire generation of first time borrowers from owning a home, despite lower home prices across the country.*" In sum, both organizations appeared to advocate openly for laxer definitions of the CCR exemptions, limiting the rule's bite, and allowing assets with substantially lower quality and higher risk to be exempt.[28]

In this section, we provide a framework for examining the content and textual similarity of comments filed by non-profits and firms, and show that, upon receipt of a donation from a firm's foundation, comments by a non-profit are more similar to those of its donor, suggesting that the Bank of America-Greenlining example may hold more broadly in the data.

We compute approximate measures of semantic similarity of pairs of public comments using Latent Semantic Analysis (LSA) with bag-of-words features. LSA is an established technique in the natural language processing (NLP) literature and it has been shown to perform well on a variety of document classification and retrieval tasks.[29] In our own tests, we found LSA worked significantly better than some alternatives on a benchmark classification task we developed with our data (see Appendix B for details). We proceed in three steps in the construction of our measures. First, we collect all comments from all organizations with at least two comments in all

[26] Document ID OCC-2011-0002-0141

[27] Document ID OCC-2011-0002-0353

[28] These efforts ultimately succeeded in entirely defanging the rule. For a discussion, see Floyd Norris for the *New York Times*, Oct. 23, 2014, Page B1 "Banks Again Avoid Having Any 'Skin in the Game"', available at https://www.nytimes.com/2014/10/24/business/banks-again-avoid-having-any-skin-in-the-game.html Last accessed 4/1/2020.

[29] See Dumais et al. (1988) and Deerwester et al. (1990). For a discussion of latent semantic analysis, see Dumais (2004).

rules, and collapse the documents to organization-rule-year level observations by concatenating the text from all attachments and submissions from a single organization on a given rule in a particular calendar year. Next, we apply LSA to construct a document vector for each rule-year comment which summarizes the distribution of words in each comment. As is common in LSA, we use term-frequency inverse-document-frequency (TF-IDF) weighting to emphasize the importance of words which appear in a small number of documents. Finally, we construct a scalar similarity measure from the cosine angle between the document vectors corresponding to firm and grantee comments, and scale this measure to have a standard deviation of one across all firm-grantee co-comment pairs.

Our benchmark comment similarity specification is:

$$S_{fgr} = \beta_0 + \beta_1 D_{fgt-1} + \delta_{fg} + \delta_r + \varepsilon_{fgr} \tag{2}$$

where S_{fgr} is the similarity of comments of grantee g and firm f commenting on the same rule r finalized in year t, D_{fgt-1} is indicator variable that equals 1 if firm f donated to grantee g in either year t or year $t-1$ and 0 otherwise, and the coefficient of interest is β_1. As each rule r is finalized in a specific year t, year fixed effects are spanned by rule fixed effects and are therefore omitted. The dataset we employ for this analysis includes all possible firm-grantee pairs of comments conditional on commenting on the same rule r.

The results for equation (2) with separate firm, grantee and rule fixed effects are presented in column (1) of Table 7. We find that firm and grantee comments are 4.7% of a standard deviation more similar after a recent donation.

One potential concern is that the results in column (1) are driven by firms preferentially donating to grantees that have more similar comments on average. We thus include a firm-grantee pair fixed effect in column (2). This specification, with more restrictive fixed effects, exploits only variation within a firm-grantee pair over time and thus measures whether the similarity of comments is higher than average *for a specific pair* when there is a recent donation linking the two. A recent donation in this specification is associated with an increase in the similarity of comments by 6.1% of a standard deviation, a significant effect.

Even though we find similarity increasing after a recent donation in the fixed effect specification, it is conceivable that donations may happen only at the exact time when the firm and the grantee serendipitously agree on a specific topic of regulation. A more stringent bar to clear would be to hold the topic constant and test whether a non-profit's comments become more similar to those of the firm after receiving a donation, relative to their standard level of similarity when commenting on that specific topic. To put it differently, we would ideally assess whether a grantee changes its position on the identical topic on which it typically comments just after receiving a donation, along the lines of the Coca-Cola and AAPD example discussed in the introduction.

By construction, we do not have multiple comments on the same rule by the same entities. However, the specification in column (3) aims to approximate this thought experiment, by adding fixed effects for agency (a proxy for the topic) times sector (NAICS 6 digit code) of the firm times IRS's National Taxonomy of Exempt Entities Classification (NTEEC) code of the non-profit. This specification therefore exploits only variation in similarity and donations within a set of firms, grantees and issues that are homogeneous. We find that even in this specification, recent donations are associated with an increase in similarity.[30]

In columns (4)-(6), we maintain the specifications in columns (1)-(3) with an additional modification to the document vectors that is intended to correct for potential bias introduced by similarities in the firm's and grantee's commenting style. Here, we use the term "style" broadly to mean any aspect of the comment text that tends to be repeated across comments by the same organization. For example, there can be large differences in the amount of technical language and jargon employed by different commenters. Our solution is to control for each organization's style by subtracting their mean comment document vector from all of their comments before computing cosine similarities between document vectors (see Appendix B for details). The resulting similarity measure then focuses on the parts of comments that vary over time rather than fixed aspects of commenting style. We find that controlling for style in this way only increases the implied association between a recent donation and co-comment similarity.

In Appendix D we also present analyses that underscore the very specific timing of the link from donation to comment similarity. In particular, we modify our definition of donations to focus on the period immediately *after* the regulatory commenting phase. Appendix Table D.5 reports these results, using specifications that parallel those presented for the co-commenting results. The estimated coefficient on future donations is much smaller in magnitude than that of recent donations, though for this set of results neither coefficient is generally statistically significant. If we run the same comment similarity regressions on future donations alone, the estimated coefficients are small and never statistically significant (in contrast to recent donations). This placebo exercise is informative along several dimensions. As future donations are close in time to the commentary activity, but statistically and economically insignificant, these findings further assuage the concern that our results may be driven by some underlying shared tendencies of firms and grantees operating in related areas. The systematic timing of excess similarity between comments' texts just following the disbursement of a charitable grant offers more support to the view that donations provide firms with some influence over grantees' expressed viewpoints.

[30]Although not shown for the sake of brevity, most variation in the results with different fixed effects is due to the regression specification rather than changes in the sample. The difference in results in columns (4) and (5) are one exception: the estimated change in similarity associated with a recent donation is 7.1% when using the specification from column (4) and sample from column (5).

It is natural to ask whether an increased similarity of the text of comments necessarily implies more similar positions on an issue. We construct a test to assess the possibility that firms and grantees may employ a similar terminology, while nonetheless delivering opposing messages to regulators. Our test is based on an analysis of comment sentiment, which relies on established NLP scholarship. Semantic orientation exercises are common in the NLP literature (e.g., the unsupervised classification of book reviews as positive or negative), including applications to economics and finance, for example in the classification of monetary policy announcements as hawkish or dovish, in the study of the tone of financial news, or in partisan speech (Lucca and Trebbi, 2009; Gentzkow et al., 2019).[31] Using these tools, our goal is to rule out the possibility that the comments of non-profits receiving grants may use similar words, but express views that are in opposition to their corporate donors.

Table 8 maintains the same design and structure of fixed effects as Table 7, but replaces the similarity score S_{fgr} with a semantic orientation concurrence score W_{fgr} as our dependent variable. The construction of this variable relies on polarity scores defined for each comment based on the popular AFINN sentiment lexicon, with valence scores ranging between -5 (negative) and 5 (positive) for each labeled word. For each comment we construct the sum of valence scores divided by the number of words with non-zero valence scores. W_{fgr} is defined as the negative absolute difference between this measure for the pair of comments from firm f and from grantee g on rule r. The interpretation of the coefficient of interest β_1 is therefore the effect of a charitable donation on the alignment of sentiment across firm and non-profit (i.e., the excess co-movement of sentiment in the two comments relative to any randomly generated pair of firm and grantee comments on that rule).

The data do not support the view that donations systematically reach grantees expressing opposing views to the firm providing the grant relative to a random grantee. The sign of β_1 is inconsistent across specifications and never statistically significant. Overall, we conclude that there is no systematic relationship between comment sentiment and donations, and that our findings are unlikely to be explained by firm and grantee comments carrying similarly worded but antagonistic messages. We wish to be explicit that this conclusion comes with the caveat that the methodology employed, which was developed for microblogging (Twitter), may be less directly applicable for the highly sophisticated text that appears in our comment data.

[31] In general, by semantic orientation we refer to the direction (polarity) of words, phrases or longer pieces of text in a semantic space or context (e.g., friendly/adversarial, dovish/hawkish, positive/negative) calculated based on a reference lexicon of words or n-grams over which directionality is carefully labeled by a pool of researchers.

5 Comments and final rules

The evidence provided so far points to firms and their recent grantees commenting more often on the same rules and with more similar language. Circling back to our initial motivation, these patterns may be of concern only if they have an impact on final regulations.

At this point it is important to distinguish between two very different pieces of text that appear in the Federal Register when the final rule is published: i) the *final regulatory text* is designed to formulate, amend, or repeal sections of the Code of Federal Regulations (5 U.S.C. § 551(5)) and is written with a terminology and structure, at times dictating a change in a single word, that makes it very different from comments submitted and hence unsuitable to our analysis; ii) the *discussion of the rule* tends to be longer and presents arguments in favor of, or against, specific choices that may have been brought forward by firms, non-profits, and other entities in their attempt to persuade the regulator. We therefore focus on this latter part of the final rule.[32]

Typically, it is extremely hard to assess the effects of lobbying on policy outcomes (Kang, 2016). Much lobbying activity is designed to block change (so no policy differences are observed in equilibrium) and information flows are immaterial and undisclosed (e.g., meetings and phone calls). In our context, though, it is possible to measure the weight placed on each firm's comments by employing two proxies: the similarity between the final rule discussion by the regulatory agency and the firm's own comments, and the frequency with which a firm is cited by name in the agency's discussion of the final rule. We aim to assess whether, when a firm's grantee comments on the same rule as the firm, the published discussion of the final rule by the regulator appears more similar to the firm's comments, and whether the regulator cites that firm more frequently in its discussion.

As an example, consider the concern expressed by Wells Fargo, one the largest depository institutions in the U.S., on a specific regulatory burden that the bank believed was implied by the proposed version of the so-called Volcker Rule of the Dodd-Frank Act of 2010. The Volcker Rule aimed to prohibit depository institutions from engaging in the use of part of their depository funding for speculative trading (proprietary trading).[33] Wells Fargo expressed the concern that the proposal required transaction-by-transaction oversight: "*We also do not believe that the Proposed Rule's transaction-by-transaction approach, which would require analyzing permitted customer trading, market making, underwriting and hedging activities on a transaction-by-transaction basis, is the best way for the Agencies to implement the Proposed Rule...*"[34] The OCC addressed

[32]The discussion of the rule is found in the Supplementary Information section, which is part of the preamble to the final rule and typically constitutes its most important component. See https://www.federalregister.gov/uploads/2011/01/the_rulemaking_process.pdf Last accessed 4/1/2020.

[33]79 FR 5535

[34]Document ID OCC-2011-0014-0285

this concern directly and conceded some changes to the rule: "*A number of commenters expressed general concern that the proposed underwriting exemption's references to a 'purchase or sale of a covered financial position' could be interpreted to require compliance with the proposed rule on a transaction-by-transaction basis. These commenters indicated that such an approach would be overly burdensome. ... [T]o address commenters' confusion about whether the underwriting exemption applies on a transaction-by-transaction basis, the phrase "purchase or sale" has been modified to instead refer to the trading desk's "underwriting position.""* The two texts appear related.[35]

We begin by constructing S_{fr}, the similarity score between the discussion of rule r and firm f's comment, using the same LSA-based approach as for our co-comment similarity analysis.[36] In contrast to the similarity score constructed in section 4, S_{fr} measures the similarity between a comment and the discussion of comments in the final rule, rather than the similarity between the texts of two comments on a proposed rule. We interpret S_{fr} as a proxy for the salience and effectiveness of the firm's comment in shaping the regulator's decisions.

Let us posit that S_{fr} is a function of the commenting efforts of the firm and of grantees connected to the firm by donations:

$$S_{fr} = \beta_1 GranteeCocomment_{fr} + \delta_f + \delta_r + \varepsilon_{fr} \tag{3}$$

The variable of interest is the dummy $GranteeCocomment_{fr} = I\left(\sum_g \sum_t C_{grt} \times D_{fg,t-1} > 0\right)$, which is equal to 1 if we observe that a grantee commenting on the same rule as the firm also received a donation from the firm in the same or previous year as the grantee submitted their comment, and 0 otherwise. If there is excess similarity between rule discussion and a firm's comment when grantees connected to the firm by donation also comment on that rule, β_1 should be positive. We interpret an increase in S_{fr} as a proxy that, at a minimum, captures the firm having the attention of the regulator. We note, however, that S_{fr} could conceivably correlate with influence in shaping the content of the final rule or in keeping out certain provisions.

We also examine whether firms are cited more often in final rule discussions in which we observe a comment by one of their grantees, employing $log(1 + citations)$. Firm fixed effects in this specification capture the extent to which certain firms are systematically more likely to be cited by regulators across all rules. Similarly, rule fixed effects control for the fact that some rule discussions may include on average more numerous references to firms' comments.

Table 9 presents our regression results. We find that the similarity between firm comments and the rule discussion is 16% of a standard deviation higher when at least one grantee commenting

[35] Interestingly, the Black Economic Council, a recent Wells Fargo grantee, also expressed concerns on the same rule on grounds of excessive complexity. Document ID OCC-2011-0014-0024

[36] Because of the specific focus on the exact wording of the discussion of rule r, in this section we take r to refer to each separate final rule discussion, including the minority of cases where there are multiple final rules in a docket. Appendix A provides more details on the correspondence between rules and dockets.

on the same rule has received a recent donation from the firm. Similarly, firms are cited more frequently (5% more often) within each rule, and are 2% more likely to be cited at all, though this last estimate is not statistically significant. Notice here that one possible reason why citations are a more noisy proxy is that certain agencies appear to deliberately avoid naming commenters in their final discussions.[37]

One of the main difficulties with interpreting these results as causal is that we do not observe all channels of communication from the firm to the regulator (a form of omitted variable bias). However, we do have information about lobbying contacts between the firm and regulator from lobbying disclosure reports filed with the Senate's Office of Public Records.[38] For columns (2), (4), (6), and (8), we control for the estimated expenditure on lobbyists hired to communicate with the agency that published the rule in question.[39] Our results are robust to controlling for lobbying expenditures over the same time period as donations, adding weight to the interpretation that the channel of influence we capture in our analysis is through the submitted comments.

As with our co-commenting and comment similarity results, these rule outcomes do not appear to be driven by future donations. In Appendix Table D.6 we add an indicator for future donations to grantee co-commenters. When both variables are included, it is the variable based on recent donations that predicts final rule similarity.

6 Getting paid not to comment: The role of hush money

Sections 3-5 focus on the role of donations from corporations to non-profits in generating additional messages that are more similar to the donor's position. This section examines whether corporations also use donations for a distinct strategic purpose: to silence opposing opinions.

It is plausible to envision an informational lobbying environment in which agents supporting a specific action opposed by a counterparty may be motivated to suppress the opposing viewpoint (and compensate the counterparty for its silence). For example, in a discussion of the strategies employed in the multi-year campaign of the tobacco industry against greater regulation, Lando (1991) writes: "*The tobacco industry has been effective in purchasing what has been described as 'innocence by association'. Tobacco industry sponsorship of sports events is notorious. The industry has also contributed substantially to the arts, to women's groups, and to organizations*

[37] One reason for this behavior is that generically discussing comments instead of exactly naming commenters may appear safer in case of ex post legal action against the regulator. An instance is action brought for arbitrary and capricious behavior arising for agency's failure to address dissenting comments to a proposed rule.

[38] We use bulk lobbying data that has been cleaned and organized by the Center For Responsive Politics, available through www.opensecrets.org.

[39] Lobbying disclosure reports do not contain per-agency expenditures, but each filing lists the branches of government contacted, and the total amount spent. We divide total expenditures for each filing evenly between all branches listed. In practice, our results are not sensitive to how this lobbying amount is constructed.

representing minorities. These types of pernicious industry activities have been successful in buying the silence or the tacit support of some groups that have suffered a disproportionate share of the tobacco burden." Payment in exchange for inaction and silence is commonplace in the market (e.g., noncompete and nondisclosure agreements, non-disparagement clauses, etc.) and such private agreements or clauses do not represent *per se* invalid contracts or violations of free speech. They may be, however, private agreements that are undisclosed to regulators, who may interpret the silence of some parties to the regulatory process as informative.[40]

The role of such "negative" strategies is thought to be crucial to the success of special interest groups in politics. Blocking unfavorable bills from ever seeing the light of day (committee discharge) in the U.S. Congress is as much a part of lobbying as facilitating the passage of bills favorable to an industry. Similarly, interest group comments in rulemaking often aim to kill unfavorable provisions or stall the implementation of rules. ("Nothing happening" is almost always the desirable policy outcome for incumbent firms; see Baumgartner et al., 2009.)

To test for the presence of "hush money" in rulemaking, we propose an extension of our empirical framework in section 3. In particular, we modify the rule specification in section 3.2 as follows:

$$C_{gr} = \beta_0 + \beta_1 DonorComment_{gr} + \beta_2 DonorComment_{gr} \times Comments_{ga} + \delta_g + \delta_r + \eta_{gr} \quad (4)$$

where $DonorComment_{gr}$ is equal to 1 if grantee g received a donation from a firm that also commented on the same regulation, and 0 otherwise, and $Comments_{ga}$ is a measure of how frequently g comments to regulatory agency a. We consider three different measures for $Comments_{ga}$: the total number of comments submitted by g to a, the share of g's comments that are submitted to a, and the share of all comments submitted to a that come from g.

To understand the intuition behind this test, observe that certain non-profits may have particular expertise or focus in a specific area of regulation, which we approximate by the identity of the agency overseeing the rule (e.g., the Sierra Club commenting on rules proposed by the EPA).[41] Interacting $Comments_{ga}$ with the donation from a commenting firm, $DonorComment_{gr}$, aims to establish whether such donations have a differential effect on the likelihood of commenting for grantees that typically comment on rules considered by agency a, versus grantees that normally do not comment on rules by a. We argue that this interaction is useful for assessing the potential role of hush money, since within the set of issue experts (high $ShareComments_{ga}$) it is more likely that donations are made with the aim of inducing silence and muting expert commentary. A

[40] Absence of a signal is in fact informative in games of incomplete information in which Bayesian agents are assumed. For an application to political campaigns, see Kendall et al. (2015).

[41] Bertrand et al. (2014) follow a similar approach to define issue expertise of individual lobbyists from federal lobbying reports.

plausible null hypothesis supporting the presence of hush money is therefore $\beta_2 < 0$, as charitable donations may be more likely to be hush money for grantees that routinely comment on rules from a.

Our results based on this specification suggest that hush money is not a common strategy in our setting. In Table 10 we present results using all three measures of $Comments_{ga}$ with and without rule fixed effects. The evidence points clearly in the direction of donations increasing co-commenting from grantees that routinely comment on rules from the regulator proposing r. The coefficient $\beta_2 > 0$ is systematically positive and highly statistically significant, indicating that firms are more likely to induce – rather than stifle – comments from such grantees. While this does not rule out the existence of hush money, it nevertheless suggests that this behavior might be less prevalent than the co-commenting behavior documented in sections 3-5.

7 A simple framework to illustrate welfare considerations

This section lays out a conceptual framework to explore the potential welfare consequences of what we have learned about the grantees' commenting behavior. In the introduction of the paper we posit two intuitive interpretations of our results so far. The least favorable interpretation (in terms of welfare consequences) is a "comments-for-sale" scenario in which grantees are willing to modify the content of their comments in exchange for corporations' financial support. A more benign interpretation, which we refer to as "comments facilitation", is that firms donate to non-profits that happen to be aligned with their interests on a particular issue, not because they expect grantees to change their comments, but instead because these firms wish to financially support such non-profits in presenting their own viewpoint to regulators.

Our goal in this section is to show that even the more benign interpretation, with no change in the comment content, may also imply welfare losses. Specifically, we wish to demonstrate that, within a straightforward textbook framework that reflects the setting we study, the distortion in information resulting from firms shifting grantees' commenting behavior through a relaxation of their budget constraint may be a concern worthy of attention. We recognize that other models with distinct assumptions may not necessarily generate identical welfare losses. Our purpose in this exercise is to take standard assumptions, appropriate for the empirical environment under consideration, to their logical conclusion and offer a discussion that is useful for welfare considerations.

We formalize the interactions of firms, grantees, and regulatory agencies in an informational lobbying model. We model these interactions via costly signaling rather than cheap talk (e.g., Krishna and Morgan, 2001) because costly signaling more accurately reflects our setting: comments are often dozens of pages long, the product of careful work by large teams of skilled (and costly to employ) professionals. Furthermore, focusing on a costly signaling model is more conservative in the sense that the model's predictions will not depend on distortion in the content of messages.

Consider the basic setup of Grossman and Helpman (2001, ch. 5), which itself is based on Potters and Van Winden (1992). There are three players: a firm f, a non-profit grantee g, a regulatory agency a. The agency wishes to set a policy p according to a continuous state of the world θ, distributed uniformly on the interval $[0, 1]$. We assume that a is benevolent, in the sense that the agency maximizes social welfare. The objective function for the agency is given by a standard quadratic loss function $U_a = -(p - \theta)^2$, whereas the grantee and firm have policy preferences given by $U_i = -(p - \theta - \delta_i)^2$, where $i = f$ (firm) or g (grantee), and δ_i reflects i's bias relative to the policymaker.

There is a fixed cost, $l_i > 0$, of sending a comment, and we further assume that the grantee and the firm both observe the true state of the world θ, whereas the agency must rely on information transmitted by firm and grantee in setting its policy. In this setting, information can be conveyed credibly by the mere presence of a costly signal (i.e., the act of sending a comment), without specifying its content.

We proceed to discuss several variants on this framework to establish that a "comment subsidy" – a transfer from firm to grantee that reduces l_g – can lead the regulatory agency to select a policy that is further from its optimum relative to the no-subsidy case. We will compare three scenarios: (1) the case in which transfers do not occur; (2) the case in which transfers occur unbeknownst to the agency a; (3) the case in which transfers occur and are fully observed by a. Case (1) describes instances in which transfers are prohibited or in which transfers are not incentive-compatible for the firm to give out or the grantee to accept. Case (2) describes instances in which the regulator is unaware of or ignores these grants, or is only partially aware of their magnitude; we believe this scenario best captures current policy, absent systematic data on this phenomenon and the complexity of tracing direct charitable donations by f and g's tax forms back to each firm. Case (3) addresses the instance of full disclosure. Full disclosure is relevant as a benchmark, as it is often considered an essential remedy in political agency discussions of money in politics, most prominently in U.S. Supreme Court's cases on campaign finance legislation (e.g. *Buckley v. Valeo*[42]).

Note that in this model, the firm *cannot* affect the content of the message, but only the costly action of the grantee. We are therefore not relying on a mechanism akin to the example of the Coca-Cola and AAPD discussed in the introduction. We show that even when we rule out this most obvious source of welfare loss through misrepresentation, a "comment subsidy" from firm to grantee that reduces l_g can lead the agency –if unaware of the subsidy– to select a policy that

[42] *Buckley v. Valeo*, 424 U.S. 1 (1976) is a salient U.S. Supreme Court ruling, pertinent to the limitations of election spending and political giving vis-à-vis First Amendment issues of freedom of speech.

is further from its optimum. Interestingly, however, we also show that the disclosed-subsidy case yields, at least for some parameters, higher payoff to the agency relative to the case in which transfers are prohibited.

Case 1: Baseline of no Transfers Between Firm and Grantee

In the presence of a single sender, it is straightforward to show that there exists a pure strategy equilibrium in which sender i sends a costly message if and only if the state of the world $\theta \geq \theta_i$ and the agency sets $p = \frac{\theta_i}{2}$ if it does not receive a comment and $p = \frac{1}{2} + \frac{\theta_i}{2}$ if it does receive one. The threshold state θ_i derives from the indifference condition of sender i between sending a comment and achieving a payoff $-\left(\frac{1+\theta_i}{2} - \theta - \delta_i\right)^2 - l_i$ and not sending a comment, with payoff $-\left(\frac{\theta_i}{2} - \theta - \delta_i\right)^2$, where $\theta_i = \frac{1}{2} - 2\delta_i + 2l_i$.

Under this baseline case the expected utility of the agency is given by

$$U_a(\theta_i) = \int_0^{\theta_i} \left[-\left(\frac{\theta_i}{2} - \theta\right)^2 \right] d\theta + \int_{\theta_i}^1 \left[-\left(\frac{1+\theta_i}{2} - \theta\right)^2 \right] d\theta. \tag{5}$$

To build intuition, consider the set of circumstances in which the firm is the sender and it has a large bias. In this case f may not credibly communicate any information to the agency. For instance, we can assume that the firm's bias is $\delta_f = \frac{3}{4}$ and cost of sending a comment $l_f = \frac{1}{2}$, so that f cannot credibly communicate information because $\theta_f \leq 0$.

Assuming a lower bias for the grantee, $\delta_g = \frac{7}{16}$, and a comment cost for the grantee that is the same as for the firm, i.e., $l_g = \frac{1}{2}$, we can see that, in contrast to the firm, g can credibly comment to a ($\theta_g = \frac{5}{8}$).

Case 2: Undisclosed Comment Subsidies from Firm to Grantee

Let us now allow the firm to subsidize the cost of sending a comment for the grantee, i.e., to lower the comment cost from l_g to $l'_g < l_g$ (i.e., the firm provides a grant of size $l_g - l'_g$ to the grantee). Given the lack of disclosure requirements, we model this subsidy as unbeknownst to the agency, or at least underestimated (taking l_g as a's belief of the equilibrium comment cost of g).

Under this assumption, a believes that the grantee behaves according to the threshold strategy $\theta_g = \frac{1}{2} - 2\delta_g + 2l_g$, following the logic in Case (1). However, the presence of a lower cost of commenting for the grantee implies a different, lower equilibrium threshold θ'_g, implicitly defined by the following equation:

$$-\left(\frac{\theta_g}{2} - \theta'_g - \delta_g\right)^2 = -\left(\frac{1+\theta_g}{2} - \theta'_g - \delta_g\right)^2 - l'_g.$$

This yields $\theta_g' = \frac{1}{2} - 2\delta_g + l_g + l_g'$.

There are several important implications that warrant discussion. Going back to the numerical example, let us set $l_g' = \frac{1}{4}$, so that the firm pays half the cost of the grantee's subsidy, and thus $\theta_g' = \frac{3}{8}$. The first implication is that, under unobserved comment subsidies, the agency will choose a policy p' that is on average distorted relative to the baseline case. In the absence of subsidy, the policy choice p is on average unbiased, i.e., $p = \frac{1}{2}$. It is straightforward to verify that here instead $p' = \frac{1}{2} + \frac{\theta_g - \theta_g'}{2}$ and that $\theta_g - \theta_g' = l_g - l_g' > 0$, so that the policy is distorted on average toward the preferences of the firm and grantee. In this numerical example, the distortion is $\frac{1}{8}$.

It is similarly straightforward to show that the agency is worse off under the equilibrium with comment subsidies than in the baseline case. In this case the expected payoff for the agency is given by $U_a' = \int_0^{\theta_g'} \left[- \left(\frac{\theta_g}{2} - \theta \right)^2 \right] d\theta + \int_{\theta_g'}^1 \left[- \left(\frac{1+\theta_g}{2} - \theta \right)^2 \right] d\theta$. Note that the agency's payoff changes both as a result of the policy distortion, as well as the different information partition, since the new threshold θ_g' is different from θ_g and certain partitions are more informative than others.

In addition, both f and g are better off in the subsidy case. The firm's expected payoff with subsidy is given by:

$$U_f' = \int_0^{\theta_g'} \left[- \left(\frac{\theta_g}{2} - \theta - \delta_f \right)^2 \right] d\theta + \left[\int_{\theta_g'}^1 - \left(\frac{1+\theta_g}{2} - \theta - \delta_f \right)^2 \right] d\theta - \left(1 - \theta_g'\right) \left(l_g - l_g'\right). \quad (6)$$

In our numerical example, $U_f' - U_f = \frac{1}{64}$, so that in this case the firm benefits from the positive distortion in policy. The expected utility of the grantee is given by:

$$U_g' = \int_0^{\theta_g'} - \left(\frac{\theta_g}{2} - \theta - \delta_g \right)^2 d\theta + \int_{\theta_g'}^1 - \left(\frac{1+\theta_g}{2} - \theta - \delta_g \right)^2 d\theta - l_g' \left(1 - \theta_g'\right),$$

so that the gain for g is $U_g' - U_g = \frac{1}{8}$. The grantee also benefits from the policy distortion of $\frac{1}{8}$, which is not excessive relative to its preference bias δ_g.

Different model assumptions and distinct parameter configurations do not necessarily yield the same loss – our purpose here is illustrative. At the same time, let us also emphasize that this result is intuitive and the modeling approach is conservative. The grantee never acts contrary to its principles – the subsidy merely lowers the threshold for comments which, if unrecognized by the agency, distorts the agency's perceived signal of the optimal policy. That is, even under a scenario where the firm does not condition its financial contribution to the content of the message and there is thus no explicit quid-pro-quo transaction, comments lead to distorted policy decisions and lower payoffs for the regulator as a result.

Case 3: Full Disclosure of Comment Subsidies from Firm to Grantee

Consider now the case in which a can perfectly observe transfers from f to g. The policy analog is straightforward: grantees that comment on regulation are required to publicly disclose their corporate funding sources to a.

The analysis of this case is similar to case (1): the agency is aware that the grantee faces a lower (subsidized) commenting cost, and conditions its policy rule on the subsidized cost l'_g. This leads to a different threshold $\theta''_g = \frac{1}{2} - 2\delta_g + 2l'_g$, such that if $\theta > \theta''_g$ the grantee sends a comment to the agency. The agency's utility is calculated similarly to the baseline case and is given by $U_a\left(\theta''_g\right)$. The expected utility of firm and grantee are given, respectively, by the following two expressions:

$$U''_f = \int_0^{\theta''_g} \left[-\left(\frac{\theta''_g}{2} - \theta - \delta_f\right)^2 \right] d\theta + \left[\int_{\theta''_g}^1 -\left(\frac{1+\theta''_g}{2} - \theta - \delta_f\right)^2 \right] d\theta - \left(1 - \theta''_g\right)\left(l_g - l'_g\right).$$

$$U''_g = \int_0^{\theta''_g} \left[-\left(\frac{\theta''_g}{2} - \theta - \delta_g\right)^2 \right] d\theta + \left[\int_{\theta''_g}^1 -\left(\frac{1+\theta''_g}{2} - \theta - \delta_g\right)^2 \right] d\theta - \left(1 - \theta''_g\right) l'_g.$$

It is tempting to conclude that, under full disclosure, the firm may no longer have an incentive to subsidize the grantee's commenting activity. This may not be the case, however, because the lower commenting cost of the grantee may induce a more informative partition of the state space relative to the baseline case. The next proposition aims to provide some insight into the particular conditions under which full disclosure in fact improves welfare.

Generally, Proposition 1 below establishes that full disclosure improves the agency's welfare relative to both the baseline case as well as the undisclosed/unknown subsidy case, if both firms and grantees are better off under disclosed transfers than under no transfers at all (i.e., the baseline case). More formally, the following holds:

Proposition 1. *If $U'_f > U_f$, $U'_g > U_g$, $U''_f > U_f$ and $U''_g > U_g$, then $U''_a > U'_a > U_a$.*

Proof. In Appendix. □

Note that the first two conditions ($U'_f > U_f$ and $U'_g > U_g$) plausibly describe the current status quo, in which (undisclosed) transfers *do* occur on the equilibrium path, so it is reasonable to presume that firms and grantees are better off than under the no-transfer case.

The proposition also establishes that, if firm and grantee are better off under full disclosure, then welfare would actually *decline* if transfers were prohibited. This feature highlights the important distinction between prohibiting transfers versus requiring their public full disclosure. This result arises from the improvement in informational quality under disclosed transfers that can occur because, for example, the costs of commenting were initially excessively high for the grantee. Under such circumstances, comment subsidies with full disclosure may be the best policy prescription.

8 Conclusions

Politicians (and voters) are frequent targets of messages aimed at persuading them of the merits of specific policy positions. While in most cases the identity of senders is disclosed, allowing an assessment of the bias and interests of the originators of the message, in other cases it may not be available or even is deliberately obscured. These situations range from the use of dark money in U.S. electoral politics in the aftermath of the Supreme Court's *Citizens United v. Federal Election Commissio*n and *McCutcheon v. Federal Election Commission* cases, to the circulation of white papers by think-tanks and other non-profits.

Apparently independent arms-length organizations may extend the credibility of the positions held by special interests. Our paper argues that one has to be careful in assessing the information provided by these apparently independent organizations when this information comes in close proximity to monetary transfers from firms. Such transfers, often in the form of charitable grants, are virtually undetectable by private citizens and civil servants without access to detailed tax information. These transfers represent potential distortion to policymaking.

In order to provide a quantitative and systematic perspective to this issue, this paper studies the interaction of non-profit organizations and large corporations within the United States federal regulatory environment. The paper presents evidence that corporate foundations' charitable grants reach targeted non-profits just before those same non-profits engage in public commentary. The availability of a large set of public comments by non-profits and by corporations on a diverse set of rules and regulations, ranging from banking to environmental regulation, makes for a rich and virtually untapped empirical environment.

The content of the comments simultaneously communicated by non-profits and by corporations appears systematically closer (in terms of textual similarity) in presence of a charitable contribution provided immediately before those comments are filed. While circumstantial, the evidence seems to point to potential concerns in the assessment of this *prima facie* independent information by targeted regulators, who may be unaware of the philanthropic grants that realize in the backdrop and may interpret similar comments stemming from different segment of the public spectrum as independent.

The paper also tries to address the issue of the benefits to large business interests in enlisting allied advocates who may be perceived as more balanced and less biased. We focus on textual similarity between the commenting firm and final rule discussion to gauge influence of comments over regulation. It appears that the co-commenting patterns of firms and non-profits can offer additional visibility to the messages sent by the firms themselves, measured in terms of comment similarity to the final rule or likelihood of citation of a donor firm. However, the economic returns to political and regulatory influence activities remain extremely complex to measure. This is an area of empirical investigation that is open for future research.

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Table 1: Annual firm comment count distribution by commenting relationship

	Annual firm comment counts (rules per firm/year)[1]							
	Mean	Std. Dev.	Min	Max	P50	P90	P99	Total[2]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Annual comments from each firm on:								
Any rule	1.9	4.9	0.1	108.4	0.6	4.4	20.1	1457.8
Rules where at least one grantee also comments	1.3	2.2	0	18.9	0.6	3.4	12.3	1051.0
Rules where at least one grantee who receives a donation from the firm at any time also comments	0.3	1.0	0	12.3	0	0.7	4.9	229.9
Rules where at least one grantee who has received a recent[3] donation from the firm also comments	0.2	0.7	0	10.9	0	0.3	3.3	136.3

Notes: This table summarizes the number of comments submitted by each firm in a representative year (computed as the average across years 2008-2014, the period during which where our data are most complete).
[1] Each firm-rule-year observation is counted as one comment. Firms that submit multiple documents (or multiple form letters as part of a coordinated campaign) on the same rule in the same calendar year are counted as submitting one comment on that rule.
[2] Total comment count for all firms in our sample.
[3] We use the term "recent" to refer to any donation which occurs in the same or previous calendar year relative to the comment year.

Table 2: Annual grantee comment count distribution by commenting relationship

	Annual grantee comment counts (rules per grantee/year)[1]							
	Mean	Std. Dev.	Min	Max	P50	P90	P99	Total[2]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Annual comments from each grantee on:								
Any rule	0.6	1.9	0.1	71.6	0.1	1.0	6.1	5073.0
Rules where at least one firm also comments	0.3	1.1	0	32.6	0.1	0.6	4.0	3040.0
Rules where at least one firm who donates to the grantee at any time also comments	0.1	0.8	0	33.1	0	0.3	2.9	1255.6
Rules where at least one firm who has recently[3] donated to the grantee also comments	0.1	0.5	0	31.4	0	.1	1.4	645.6

Notes: This table summarizes the number of comments submitted by each grantee in a representative year (computed as the average across years 2008-2014, the period during which our data are most complete).
[1] Each grantee-rule-year observation is counted as one comment. Grantees that submit multiple documents (or multiple form letters as part of a coordinated campaign) on the same rule in the same calendar year are counted as submitting one comment on that rule.
[2] Total comment count for all grantees in our sample.
[3] We use the term "recent" to refer to any donation which occurs in the same or previous calendar year relative to the comment year.

Table 3: Annual firm donation distribution by commenting relationship

	Annual donations (millions $/year)							
	Mean	Std. Dev.	Min	Max	P50	P90	P99	Total[1]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Annual donations from each firm to:								
All grantees	9.0	29.1	0	407	2.3	18.7	124.9	3430.0
Grantees that comment at least once	2.5	7.5	0	78.4	0.5	5.2	39.5	936.1
Grantees that ever submit a comment to the same agency as the firm	1.4	5.9	0	77.4	0.1	2.5	30.3	544.3
Grantees that ever comment on the same rule as the firm	0.7	4.3	0	75.4	0	.9	12.8	247.4

Notes: This table summarizes the distribution of annual firm donations for a representative year for our sample of firms that comment at least once (computed by averaging across years 2008-2014, the period during which our data are most complete).

[1] Total donations for all firms in our sample.

Table 4: Co-commenting - Recent donation

Dependent variable	Firm f and grantee g commented on the same rule in year $t(\times 100)$			
Mean	0.175			
	(1)	(2)	(3)	(4)
Firm f contributed to grantee g in year t or $t-1$	1.167***	0.727***	0.133***	0.080**
	(0.038)	(0.035)	(0.038)	(0.036)
Fixed effects				
Year	Y	Y	Y	
Grantee		Y		
Firm		Y		
Grantee-Firm Pair			Y	Y
Grantee-Year				Y
Firm-Year				Y
Observations	122,287,230	122,287,230	122,232,220	122,232,220

Notes: The dependent variable is equal to 100 if grantee g and firm f comment on the same rule r in year t. The independent variable is equal to one if grantee g received a donation from firm f at year t or $t-1$. Standard errors are clustered at the grantee-firm pair level. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Commenting on rules

Dependent variable	Grantee g commented on rule $r \times 100$			
Mean	0.043			
	(1)	(2)	(3)	(4)
Grantee g received donation	0.237***	0.177***	0.209***	0.142***
from any firm commenting on r	(0.022)	(0.018)	(0.022)	(0.016)
Fixed effects				
Grantee		Y		Y
Regulation			Y	Y
Observations	117,545,368	117,545,368	117,545,368	117,545,368

Notes: The dependent variable is equal to 100 if grantee g comments on rule r. The independent variable is equal to one if grantee g received in any year 2003-2016 a donation from a firm that commented on r. Standard errors are two-way clustered at the rule and grantee level. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Heterogeneity in the grant-co-comment relationship

Dependent variable	Firm f and grantee g commented on the same rule in year $t\times100$			
	(1)	(2)	(3)	(4)
Grantee g received donation	0.966***	0.220***	0.220***	0.190***
from firm f at t or $t-1$	(0.043)	(0.045)	(0.045)	(0.042)
log(Income)	0.026***			
	(0.000)			
Research	0.007***			
	(0.002)			
Advocacy	0.142***			
	(0.005)			
Grantee×Research		-0.213*		
		(0.118)		
Grantee			-0.226*	
×Research University			(0.125)	
Grantee			-0.136	
×Research non Uni.			(0.304)	
Grantee×Advocacy				-0.418
				(0.288)
Fixed Effects				
Year	Y	Y	Y	Y
Firm-Grantee		Y	Y	Y
Observations	65,733,360	75,163,302	75,163,302	75,163,302
R-Squared	0.004	0.131	0.131	0.131

Notes: The dependent variable is equal to 100 if grantee g and firm f comment on the same rule in year t. The independent variable is equal to one if grantee g received a donation from firm f at year t or $t-1$. Standard errors are clustered at the firm-grantee pair level in all columns. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Similarity of comments - Recent donation

Dependent variable	Similarity of comments by grantee g and firm f on same rule					
	(1)	(2)	(3)	(4)	(5)	(6)
Grantee g received donation	0.047***	0.061*	0.032*	0.057***	0.065*	0.040*
from firm f at t or $t-1$	(0.016)	(0.035)	(0.020)	(0.017)	(0.039)	(0.022)
Fixed Effects						
Rule	Y	Y	Y	Y	Y	Y
Firm	Y			Y		
Grantee	Y			Y		
Firm-Grantee Pair		Y			Y	
Agency$\times$NAICS$\times$NTEEC			Y			Y
Comment style control				Y	Y	Y
Observations	168,347	71,195	81,851	168,347	71,195	81,851

Notes: The dependent variable is a similarity index between the comment of firm f and the comment of grantee g in the same rule r, scaled to have a standard deviation of one. The independent variable is equal to one if grantee g received a donation from firm f in the year when the comment appears or the year before. Standard errors use two-way clustering by rule and firm-grantee pair. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Comment sentiment alignment - Recent donation

Dependent variable	Sentiment alignment of comments by grantee g and firm f on same rule-year					
	(1)	(2)	(3)	(4)	(5)	(6)
Grantee g received donation	0.015	0.004	-0.022	0.031	-0.012	-0.024
from firm f at t or $t-1$	(0.021)	(0.041)	(0.019)	(0.027)	(0.044)	(0.022)
Fixed Effects						
Rule	Y	Y	Y	Y	Y	Y
Firm	Y			Y		
Grantee	Y			Y		
Firm-Grantee Pair		Y			Y	
Agency×NAICS×NTEEC			Y			Y
Commenter style control				Y	Y	Y
Observations	166,470	70,276	80,806	166,470	70,276	80,806

Notes: The dependent variable is the negative difference between the sentiment score assigned to the comment of firm f and the comment of grantee g in the same rule-year rt, as described in section 4, scaled to have a standard deviation of one. The independent variable is equal to one if grantee g received a donation from firm f in the year when the comment appears or the year before. Standard errors use two-way clustering by rule and firm-grantee pair. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Rule outcomes - Recent donation

Dependent variable	Similarity between comment submitted by firm f and discussion text in rule r				Log citation count		Any citation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
At least one grantee g co-commenting and receiving donation from firm f in year t or $t-1$	0.156***	0.155***	0.110**	0.107**	0.051*	0.052*	0.021	0.022
	(0.051)	(0.051)	(0.049)	(0.049)	(0.027)	(0.027)	(0.016)	(0.016)
Log expenditure lobbying agency in t and $t-1$		0.002		0.007**		-0.002		-0.002
		(0.004)		(0.004)		(0.002)		(0.001)
Fixed Effects								
Rule	Y	Y	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y	Y	Y
Commenter Style Control			Y	Y	*	*	*	*
Observations	4,375	4,375	4,365	4,365	4,365	4,365	4,365	4,365

Notes: The dependent variables are several measures of the relationship between firm comments and the discussion of comments in subsequent rules. For columns 1-4 the outcome is the overall similarity of the text, for columns 5 and 6, the outcome is log of the number of detected occurrences of the firm's name in the discussion text, and for columns 7 and 8 the outcome is an indicator for the presence of at least one occurrence of the firm's name in the discussion text. Note that many rules do not cite commenters by name, so this is an imprecise measure of attention paid to comments. The independent variable is equal to one if there is at least one grantee g co-commenting on regulation r and receiving a grant from firm f in year t or $t-1$. The asterisks (*) for Commenter Style Control in the citation columns indicates that the outcome measure is not adjusted, but the comment similarity with style control is used to find best matched rule for each comment. Standard errors use two-way clustering by rule and firm. *** p<0.01, ** p<0.05, * p<0.1

Table 10: Hush money

Dependent variable	Grantee g commented on rule $r \times 100$					
Mean	0.043					
	(1)	(2)	(3)	(4)	(5)	(6)
$DonorComment_{gr}$	0.101***	0.072***	0.100***	0.030	0.006	0.031*
	(0.017)	(0.007)	(0.016)	(0.019)	(0.011)	(0.018)
$DonorComment_{gr}$	0.183***			0.183***		
$\times NumberComments_{ga}$	(0.033)			(0.035)		
$DonorComment_{gr}$		2.789***			2.747***	
$\times$Share g comments to a		(0.167)			(0.268)	
$100 * DonorComment_{gr}$			5.617***			5.618***
$\times$Share a comments from g			(0.891)			(0.924)
Fixed effects						
Grantee	Y	Y	Y	Y	Y	Y
Rule				Y	Y	Y
Observations	117,545,368	117,545,368	117,545,368	117,545,368	117,545,368	117,545,368

Notes: The dependent variable is equal to 100 if grantee r comments on rule r. The $DonorComment_{gr}$ is equal to one if grantee g received in any year 2003-2016 a donation from firm f that also commented on rule r. a indicates the agency receiving the comments. Standard errors use two-way clustering by grantee and rule. *** p<0.01, ** p<0.05, * p<0.1

A Appendix: Regulation comments

A.1 Overview

Our data on regulatory comments come from regulations.gov. Under the Administrative Procedures Act (APA), federal agencies must provide a means for the public to submit comments on proposed rules and other regulatory changes. Regulations.gov is a shared platform that is now used by most federal agencies to facilitate submission and public review of comments. Information about submitted comments, including the original text and attachments, can be viewed through a web browser. The site also provides an API that allows more efficient data access, particularly for collecting simple comment metadata such as the title of the comment and posted date.

Our sample starts with the the complete collection of metadata for all comments posted to regulations.gov in the years 2003-2017 (inclusive), yielding a total of 6,871,697 unique documents. From these, we identify 981,232 comments that appear to be authored by organizations rather than private individuals (org comments). We download the complete text for all org comments using common file formats, giving us about 90% of comment text for the org comment sample.

Before moving to a more detailed description of the comment and rule text collection it is worth describing the time dimension of the data. In the early period we are limited by the availability of comment data. Regulations.gov went online in 2003, but it was initially used by only a handful of agencies. Figure D.1 shows the number of proposals published in the Federal Register that direct commenters to regulations.gov. Proposals without a regulations.gov link would have provided alternate contact information such as an agency email address or internal comment management system, and comments submitted on these proposals are not available in our data. The plot shows that the fraction of proposals with a regulations.gov link increased gradually over time, reaching about 80% in 2008. The fraction rose to nearly 90% by 2018, but we have only limited comment data for the 2003-2008 period. In more recent years we are limited by the fact that FoundationSearch may take several years to post data on each firm. Overall, these constraints mean that we have only partial data for 2003-2007 and 2014-2015, and our best coverage is in the 2008-2014 period. This pattern is presented graphically in Figure D.2 which plots the number of co-comments with financial ties by year. The clear hump shape is driven by data availability. In our regressions we generally include the whole 2003-2016 sample, but drop firm-year observations with missing donation data and use year or other year-interacted fixed effects to control for time-varying comment coverage (and other time trends). Finally, when linking comments to rules, we use all rules published in the Federal Register in any year up to 2017. We include this extra year of data because it often takes a long time for agencies to develop the final rule after receiving comments, and some comments from 2016 could be linked to a rule published in 2017.

A.2 Collecting metadata

The regulations.gov API provides a search function for document metadata. We retrieved the metadata for all public submission documents posted since the site came online in 2003, and include all years up to and including 2017. Some agencies have begun digitizing older comments and posting them to regulations.gov retroactively. But an EPA spokesperson stated (in personal email correspondence) that this work is currently incomplete, and that the text of some older comments will never be released digitally since the submitters were not aware of this possibility at the time. Thus we consider data on pre-2003 comments on regulations.gov unreliable and do not include them.

A.3 Identifying org comments

Authorship information can appear in three different metadata fields: "title", "organization", or "submitterName". Comments appear to fall into two main types: those that contain "organization" and/or "submitterName" information, and those that only contain authorship information in the title. First, we drop all comments that have "submitterName" information, but no organization. These appear to be written by private individuals. For the remaining comments, we look for an organization name in either the organization field or the title (if the organization field is blank). We use a custom neural network-based classifier to extract organization names from the selected field (classification is necessary for the organization field because it contains many false positives such as "self" or "none"). The classifier converts each title string to ASCII characters and predicts whether each character is part of an organization string. Contiguous chunks of characters with predicted probability greater than 0.5 are counted as organization names. The classifier is multi-layer bi-directional Gated Recurrent Unit (GRU), implemented in *PyTorch*[43]. Code is available on the Brad Hackinen's github page[44]. The classifier is trained on almost 9000 manually constructed training examples. This training set was constructed iteratively by starting with easy to parse titles, fitting the neural network, estimating the classifier's uncertainty from the total entropy of the character-level predicted probabilities, reviewing a sample of high-entropy titles, adding them to the training set, and repeating until the error rate was acceptably low. We also manually classified an additional set of 1000 random titles as a test set. The results of the test are shown below. 93% of titles are classified without error. 83% of titles with an organization are extracted exactly correctly, while 98.5% of titles with no org are extracted correctly (in other words, the classifier avoids 98.5% of false positives).

[43] https://pytorch.org/
[44] https://github.com/bradhackinen/subex

A.4 Collecting comment text

Comments on regulations.gov can have comment text in two locations: a "text" field in the comment metadata, or in one or more attachments. The "text" field contains text that submitters have entered on a web form. It is often as brief as "see attached". Most substantial text is contained in the comment attachments where submitters can upload PDFs, word documents, other other file formats. We download all attachments of the following formats: PDF, MS Word 8, MS Word 12, and simple .txt files. The majority of attachments are in PDF format.

We use the XpdfReader *pdftotext* [45] command-line utility to extract text from most PDFs. Some PDFs contain only images of each page. In this case we must fall back on Optical Character Recognition (OCR), which we implement with a combination of *GhostScript*[46] (to render page images) and *Tesseract-OCR*[47]. We use *Apache Tika*[48] to extract text from MS Word formats, and the *chardet*[49] Python package to detect formatting of simple text files. All the tools are open source.

A.5 Linking comments to rules

This section discusses the link between comments and final rule discussion, which forms the basis of the analysis in section 5. A practical challenge for this analysis is that regulators do not provide clear direction regarding which comments are addressed in which rule. We use a variety of document identifiers to link comments to rules, in most cases narrowing the set of possibilities to a one or two rules for each comment. We describe the procedure in three steps:

i. Comments have two pieces of information to facilitate the link to a rule: a docket identifier and a submission date (the date that the comment is posted by the agency to regulations.gov). Unfortunately, many rules have a different docket identifier than the preceding document which called for comments. As a result we first need to link Federal Register documents together to determine which comments could potentially be cited. This is a surprisingly difficult task, as agencies are quite inconsistent in how they use dockets and other identifiers. The federalregister.gov API provides a variety of useful information about Federal Register documents including publication date, associated dockets identified by the agency, affected sections of the Code of Federal Regulations (CFR), regulation identifier numbers, title, action description, and topic keywords. Our script uses fuzzy matching techniques to find documents that are linked by keywords and other identifiers which are associated with a

[45] https://www.xpdfreader.com/pdftotext-man.html
[46] https://www.ghostscript.com/
[47] https://github.com/tesseract-ocr
[48] http://tika.apache.org/
[49] https://pypi.org/project/chardet/

small number of Federal Register documents (ideally, only two). For example, one proposal document might be linked to a rule document because they share the same title. Another pair of documents might be linked because they share a docket number and affect the same CFR sections. Some documents share unusual identifiers with a relatively large number of other documents, and the script attempts to reduce the number of large linked clusters by down-weighting documents that have many potential matches.

ii. Once we have linked Federal Register documents to each other, we link comments to Federal Register documents by docket, and assume that the comment could be discussed by any rule that is a) connected to the original call for comments by a chain of linked documents, and b) published after the comment was submitted.

iii. Given this imperfect matching, we take an additional step before running each regression: when comments are potentially linked to multiple rules, we match the comment to the rule discussion with the highest similarity to the comment content (according to whichever version of the similarity measure is in use). Thus, S_{fr} can be also be interpreted as the maximum similarity with any subsequent rule linked to the comment. In this context, we define a grantee as co-commenting with a firm if they commented on the same docket and in the same year as the firm comment which was linked to the rule.

Table A.1: Organization name extraction accuracy

Sample	Count	Character Accuracy	String Accuracy
All test titles	1000	0.970	0.928
Test titles containing org	371	0.935	0.830
Test titles with no org	629	0.991	0.985

Notes: Character accuracy is the average fraction of characters classifier correctly in each title. *String accuracy* is the fraction of titles with every character correctly classified

B Appendix: Construction of comment similarity measures

In sections 4 and 5 of the paper we compare the content of firm comments with grantee comments and regulator discussion text. In the first case, our goal is to capture similarities between in the policies advocated for (or against) in by different commenters. In the second, it is to measure how much attention the regulator has paid to different comments. Complete solutions to these problems (in the sense of replicating what a literate and informed human could deduce from reading the text) are currently beyond the frontier of natural language processing (NLP) technology. Instead, we approximate these notions with a simple and robust method of text analysis called Latent Semantic Analysis (LSA, or sometimes called Latent Semantic Indexing) with bag-of-words features. We also introduce a small but novel adjustment to the LSA algorithm which controls for each author's average commenting style, to reduce the possibility that our results are driven by spurious correlations between fixed aspects of the text like writing style or document formatting.

The basic recipe is as follows: After collecting and cleaning the comment text (to remove headers, page numbers, and so forth), we convert each comment into a vector of word counts. We drop very rare and very common words and weight the remaining counts using a standard term-frequency-inverse-document-frequency (tf-idf) function to emphasize the words that are most useful in distinguishing between documents. These weighted word counts are combined into a large, sparse term-document matrix, which is then factored using singular value decomposition to generate vectors representing each document. Finally, the pairwise document similarity is computed as the cosine similarity between the document vectors. The rest of this section explains these steps in greater detail, and describes a docket classification test we conducted to verify the effectiveness of the approach and choose the dimensionatity of the document vectors.

B.1 Sample construction

Both comments and rules contain text that is not relevant for our desired similarity measure. Comments are usually formatted as letters with addresses at the top, page headers and footers, and sometimes additional contact information at the end. Optical character recognition also sometimes generates "junk" text when it encounters images with text, or poor quality scans. We use regular expressions to detect common opening and closing phrases such as "To Whom It May Concern," and "Sincerely," that occur near the beginning and end of the document, and trim away text that comes before or after these phrases. We drop any line that has less than 50% alphanumeric characters (after removing white-space), and also search for lines that occur multiple times (allowing for changes to numbers and punctuation characters) at the beginning and end of each page to filter out headers and footers. Altogether, some amount of irrelevant text remains in the sample, but it is significantly reduced relative to the raw extracted text.

Rule documents published in the Federal Register are much cleaner than comments. We use bulk XML files provided by the Government Print Office which identify individual individual paragraphs and headers. We start by dropping certain sections that appear in many rules but do not include discussion of comments (Agency, Action, Dates, Summary, Addresses, Contact sections, as well as all appendices and tables of contents). We then search for the key words "comment" and "letter" (also allowing matches to any words such as "commenters" or "commented" that contain those words) to identify paragraphs, footnotes and headers that are likely to contain discussion text. For headers containing these terms, we add all paragraphs under that header to the discussion text for that rule. For paragraphs containing these terms, we select all adjacent paragraphs that fall under the same header and add them to the discussion text. Finally, we check that the agency uses at least one of the words "commenter," "commented," "response," or "received" somewhere in the selected text. This step is useful for dropping the rules that mention "comment" or "letter" but do not actually discuss comments that have been received (for example, this sometimes occurs when the document includes a call for new comments to be submitted).

Once we have selected the text for each comment and rule, we compile all of the text files into a single corpus. Some comments have multiple attachments, and commenters occasionally submit multiple times to a single docket (though this is quite rare). We concatenate all text submitted by each organization to a single docket within a calendar year and treat each of these concatenated texts as a single document. We drop any comments that are highly repetitive (in which the set of unique lines that are more than 25 characters long is less than a third of the total number of lines that are more than 25 characters long). This step drops a small number of comments in which the agency combined many form-letter submissions into one very long file. Then we clean the text by removing all punctuation except that which occurs inside words as a part of acronyms like "U.S.", or hyphenated terms. Finally, we convert all mixed-case words to lower-case, and keep all-uppercase words as is (so that "US" is not converted to "us" for example).

B.2 Generating document vectors

Given the size of our dataset, both in terms of the number and the length of documents, it was important for us to identify an algorithm that is computationally very efficient. Some algorithms require independent comparisons of each document pair, thus making them very costly for our problem (for example, recent methods involving optimal transport distance measures, or older set-based measures like the Jaccard Index). We focused instead on algorithms that generate dense vector representations of each document. These document vectors can then be used to quickly compute cosine similarity measures between many pairs of documents in parallel. We initially considered three candidate algorithms: Latent Semantic Analysis (LSA), Latent Dirchlet Allocation (LDA), and doc2vec. We quickly dropped LDA because it was computationally slow and very difficult to implement on our large corpus. LSA and doc2vec were both able to efficiently generate large document vectors in a reasonable amount of time, so we ran a systematic test to examine the performance of both algorithms for our data.

B.2.1 LSA implementation

Our LSA implementation is standard. We load the corpus, split the text on whitespace to break it into discrete tokens, count the number of times each token occurs in each document, and the number of documents in which each token occurs. We drop all tokens that occur in only one document (they cannot provide any information about similarity), and all tokens that appear in more than 80% of documents (these are also not very informative). Then we convert each count c_{ij} of token i in document j into a feature weight w_{ij} using a common form of term-frequency inverse-document-frequency (TF-IDF) weighting:

$$w_{ij} = c_{ij} ln(\frac{N}{n_i})$$

where n_i is the number of documents containing at least one occurrence of token i, and N is the total number of documents in the corpus. We then stack these weights into a large, sparse, feature-document matrix M and apply a truncated singular value decomposition (SVD) to compute a rank D approximation of M:

$$M \approx A_D \Sigma_D B_D^T$$

where Σ_D is a diagonal matrix containing the D largest singular values of M. We discard A_D and take the singular value-scaled matrix $V := B_D \Sigma_D$ as our set of LSA document vectors. The word "latent" in "Latent Semantic Analysis" refers to the idea that compressing the full feature-document matrix to a lower-dimensional approximation often squeezes synonyms and other co-occuring words into the same singular vectors, improving the quality of the document model. The amount of compression is determined by the parameter D, which we choose using an empirical test described below.

B.2.2 Doc2Vec implementation

Doc2vec is an algorithm for constructing vector representations of documents by learning to predict word occurrences in the text (Le and Mikolov, 2014). It is attractive because it is computationally efficient and scales well for large corpus sizes. We rely on the gensim implementation (Řehůřek and Sojka, 2010). We train the model for 10 epochs, using the negative sampling version of the algorithm with 10 negative samples, a window size of 10, and minimum word count of 5. As with LSA, we experiment with different values for the vector size D.

B.3 Similarity measures

B.3.1 Cosine similarity

For any given document vectors v_i and v_j, our standard measure of document similarity is the cosine of the two vectors:

$$\theta_{ij} = \frac{v_i \cdot v_j}{\|v_i\| \, \|v_j\|}$$

B.3.2 Controlling for commenting style

One of the major challenges in working with the comment data is that the free-form nature of the comment documents makes it difficult to distinguish between substantive content and superfluous text. In our sample construction step, we remove as much extraneous material as possible. But some superfluous text is harder to detect. For example, many organizations spend the first paragraph or two describing themselves – how large they are, where they operate, what products they provide, how many workers they employ. Superficially, these paragraphs do not look any different from later paragraphs which describe the organization's positions on the regulation under discussion, so it is hard to remove them without a deep understanding of the text. But similarities between these paragraphs and other text are not what we wish to capture in our similarity measure. For example, we would not want our co-commenting similarity results to be driven by firms donating to grantees with similar self-description paragraphs. Another concern relates to the very diverse set of organizations that submit comments. When reading through comments, it quickly becomes apparent that some organizations use complex scientific and legal jargon, while others write in plain, even casual, language. We do not want our comment similarity measure to be biased by firms preferentially donating to grantees with a similar level of linguistic complexity.

One improvement we can make is to ensure that our similarity measure focuses on content and linguistic patterns that are not part of a recurring pattern for a particular organization. The solution is analogous to fixed effects in panel data. We often believe that individuals have a specific average outcome that is separate from the variation we aim to measure. Including individual fixed effects in the regression controls for this average outcome, and the resulting estimates depend only on within-individual variation. In the case of comments, we can think of each commenter has having an average commenting style that incorporates the boilerplate text, self-description content, and tendency to use more or less sophisticated language. If we "subtract" each organization's average comment, we control for these stylistic dimensions and ensure that our measure depends only on within-commenter variation. Depending on how text is represented, it might not be clear how to subtract one comment from another, or take an average across documents. Fortunately, one advantage of our document vector-based approach is that linear operations on these vectors are simple and conceptually clear. Suppose that v_{it} is the document vector corresponding to organization i's comment in docket-year t. Then we control for commenting style of organization i by constructing the de-meaned vector

$$\tilde{v}_{it} = v_{it} - \frac{1}{|T_i|} \sum_{t \in T_i} v_{it}$$

where T_i is the set of periods when i submitted a comment. For both LSA and doc2vec document vectors, this operation is roughly equivalent to subtracting the average number of occurrences of each token across documents by the same organization before computing the vectors (but much more computationally efficient). We then compute our new similarity measure that controls for comment style as the cosine similarity between de-meaned vectors:

$$\tilde{\theta}_{ijt} = \frac{\tilde{v}_{it} \cdot \tilde{v}_{jt}}{\|\tilde{v}_{it}\| \, \|\tilde{v}_{jt}\|}$$

At this point, the analogy with fixed effects breaks down somewhat since cosine similarity is a non-linear operation. However, we believe the intuition holds: de-meaning the comments within each organization prior to estimating the relationship between comment similarity and donations prevents many spurious correlations that could be driven by similarities between the average comment style of firms and grantees or between firms and regulators, and instead focuses the similarity measure on aspects of the text that change from comment to comment.

It is worth noting that this procedure for controlling for comment style is different from including separate firm and grantee fixed effects in the similarity regressions. Separate firm and grantee fixed effects can only control for the average similarity of a particular firm or grantee to all organizations with which it co-comments. However, because co-commenting is not random, this average similarity could equally be driven by variation in similarity over time within firm-grantee pair (what we aim to measure), or cross-sectional correlations between the commenting style of firms and grantees who co-comment (what we want to avoid). On the other hand, firm-grantee pair fixed effects do eliminate the same cross-sectional variation in comment similarity (as well as cross-sectional variation in donations). However, these pair fixed effects are only identified for a small portion of our firm-grantee pairs, and so are necessarily limited in precision. Controlling for comment style by de-meaning vectors within organization offers an intermediate level of control between separate firm and grantee fixed effects and pair fixed effects specifications, and it can be estimated even when organizations co-comment only once.

B.4 Docket-match prediction test

There are many ways to construct a similarity measure between documents and this flexibility introduces extra degrees of freedom into our analysis of comments and rules. At the same time, it seems reasonable to expect that some approaches to measuring similarity will work better than others by some objective metric. The trouble is that selecting the similarity measure based on our regression results would surely introduce bias. To solve this problem, we decided to select our similarity measure according to performance on a completely separate benchmark task.

We evaluate similarity measures according to how useful they are in predicting whether two randomly chosen comments come from the same docket. We feel this is a good choice of benchmark for two reasons. First, it can be computed using our actual data. The performance of different similarity measures can vary wildly across datasets (for example, see the performance comparisons in Yurochkin et al., 2019), so it is important that we do not need to extrapolate from some other data that may have different properties. Second, all comments have docket information, and these labels are among the most reliable pieces of information about the comment. We may thus run the test at large scale, without worrying about additional noise introduced by imperfect linking or missing data. A similarity measure that provides good predictive information about whether comments come from the same docket must necessarily be capturing whether comments are discussing the same narrow topics. This is not exactly the same as our goal of detecting parallel arguments between comments, but we believe it is a close enough analogy to be a useful benchmark for comparing similarity measures.

To construct the sample for the test, we select one pair of comments from every unique docket-year (after dropping both docket-years and commenters with only one comment). These become our "matched" observations. We then sample an equal number of random comment pairs in which the two comments come from different dockets. These become our "unmatched" observations. We run two versions of the test: "random pairs" and "same-agency pairs." In one version of the test, the unmatched comments can come from any other docket in our data. In a harder version of the test, the unmatched comment pairs are restricted so that both comments were submitted to the same agency. For example, one comment might have been submitted to the EPA regarding an air quality regulation, and the other submitted to the EPA regarding a water quality regulation. These comments are likely to be more similar to each other than to a comments submitted to the FDA regarding medical device testing, or the FAA regarding the maintenance of a specific airplane part. Thus, the "same-agency" version of the test emphasizes distinctions between comments that are already relatively similar, potentially making it a better match for our co-comment analysis.

To measure the accuracy of a given similarity measure, we first construct document vectors using the entire corpus as our training data, then compute the cosine similarity between the document vectors for the comment pairs in the test sample. We score each similarity measure based on how well a fitted logistic regression can predict out-of-sample pairs, using the cosine similarity measure as the only feature. We use a 5-fold hold-out strategy, fitting the model on 80% of the data and predicting the remaining 20% to generate one prediction for each observation. Observations are predicted to be a "match" if the predicted probability given the similarity is greater than 0.5, and our reported accuracy score is the fraction of pairs for which the predicted match value is equal to the true match value. Given our balanced sample, a completely uninformed guess would obtain 50% accuracy. This measure essentially asks how well the comment pairs can be sorted into matched and unmatched pairs by choosing a single threshold similarity and classifying all pairs with similarity higher than the threshold as matched, and lower than the threshold as unmatched. It would be very surprising if comments in a given docket are so similar to each other and so different from comments in other dockets that the classifier could achieve 100% prediction accuracy using only a one-dimensional similarity measure.

We test two algorithms, LSA and doc2vec, with 5 logarithmically spaced values for D ranging from 64 to 1024. This parameter effectively controls the amount of information that can be contained in the document vectors, and setting D appropriately has a large effect on the accuracy. Intuitively, there is potentially a trade-off between the benefits of compressing the data to reduce noise (low D) and allowing the vectors to capture enough detail to discern between similar documents (high D). For each algorithm and D, we compare the performance of both the random pairs and same-agency pairs, with and without organization de-meaning.

Figure D.3 shows the results of the test. We observe several interesting patterns. First, LSA always performs better than doc2vec, unless D is very small. Second, the performance of LSA is highest when D is large. Given the slope of the curve, it seems possible that even larger vectors would further improve performance. However, $D = 1024$ was the largest LSA vector size we were able to compute on a fairly capable computer with 128 GB RAM. LSA with $D = 1024$ achieves an 93% accuracy on the basic docket-match prediction task with random unmatched comments. We find this quite reassuring, as it suggests that LSA is very good at detecting systematic similarities and differences in the content of comments. As expected, the task is harder when unmatched comments come from the same agency. Here LSA achieves 78% accuracy. De-meaning the document vectors by organization also consistently makes the task harder. Fortunately, LSA with $D = 1024$ achieves the best accuracy on every version of the test, making it a clear choice to use for our analysis.

B.5 Constructing co-comment and rule-comment similarities

Based on our results from the docket-match prediction test, we use LSA document vectors with $D = 1024$ to construct all of our similarity measures. Constructing the co-comment similarity measures is straightforward. We build a corpus as described above using all organization comments for the largest possible sample such that all commenters and dockets have at least two comments (where a single "comment" is actually all the text submitted by a particular organization to a specific docket in one calendar year), and construct document vectors for each comment. From these comment vectors we produce an additional set that are de-meaned by organization. We then compute the cosine similarity for every co-comment pair.

Estimating the similarity between the rule discussion and an organization's comment(s) is only slightly more complicated. We start by compiling a slightly larger corpus that contains all comments and all rule discussions. We construct a new set of LSA vectors with $D = 1024$, and then compute the cosine similarity between every linked firm-rule pair. In the case that there are multiple rules linked to a comment, we compute all possible similarities, and then select the observation with the highest similarity to include in the regression. This step is an (admittedly imperfect) solution to dealing with cases in which the correct match is unclear. There are several reasons why comments might be linked to multiple rules. First, it is possible that the comment-rule linking algorithm generated one or more false positive matches. However, even when the matching is perfect, it is possible to have multiple rules linked to a comment. For example, agencies occasionally publish a short rule that delays implementation of the new regulation without a full discussion of the comments. It is also possible for agencies to publish corrections after the main rule is published. We omit minor corrections from our data, but larger corrections, adjustments, or interpretative guidance may motivate the agency to publish another version of the rule without discussing the prior comments. In each of these examples, only one of the rules actually discusses the linked comment leading to a meaningful similarity measure, while the other only adds noise. Selecting the rule with the highest similarity for each comment should (on average) identify the rule where that comment is actually being discussed. Even when this criterion fails to identify the correct match, there is no obvious reason that it would generate a spurious relationship between document similarity and donations.

C Appendix - Proof of Proposition 1

We start by showing that both conditions $U''_a > U'_a$ and $U'_a > U_a$ are equivalent to requiring that:

$$l_g + l'_g - 2\delta_g > 0. \tag{7}$$

It is similarly possible to simplify the other inequalities as follows. Condition $U'_f > U_f$ is satisfied if and only if:

$$2\delta_f - \delta_g - 1 + 3l_g + 3l'_g > 0 \tag{8}$$

Condition $U'_g > U_g$ is satisfied if and only if:

$$1 + 4\delta_g - 3l_g - l'_g > 0 \tag{9}$$

Condition $U''_f > U_f$ is satisfied if and only if:

$$2l_g + 6l'_g - 1 - 8\delta_g > 0 \tag{10}$$

Finally condition $U''_g > U_g$ is satisfied if and only if:

$$1 - 2l_g - 2l'_g > 0 \tag{11}$$

It is now straightforward to prove the result by contradiction. By contradiction, assume that inequality (7) is violated and $l_g + l'_g < 2\delta_g$. Inequality (11) implies that $l_g + l'_g < \frac{1}{2}$. So we must distinguish between two cases according to whether δ_g is smaller or larger than $\frac{1}{4}$.

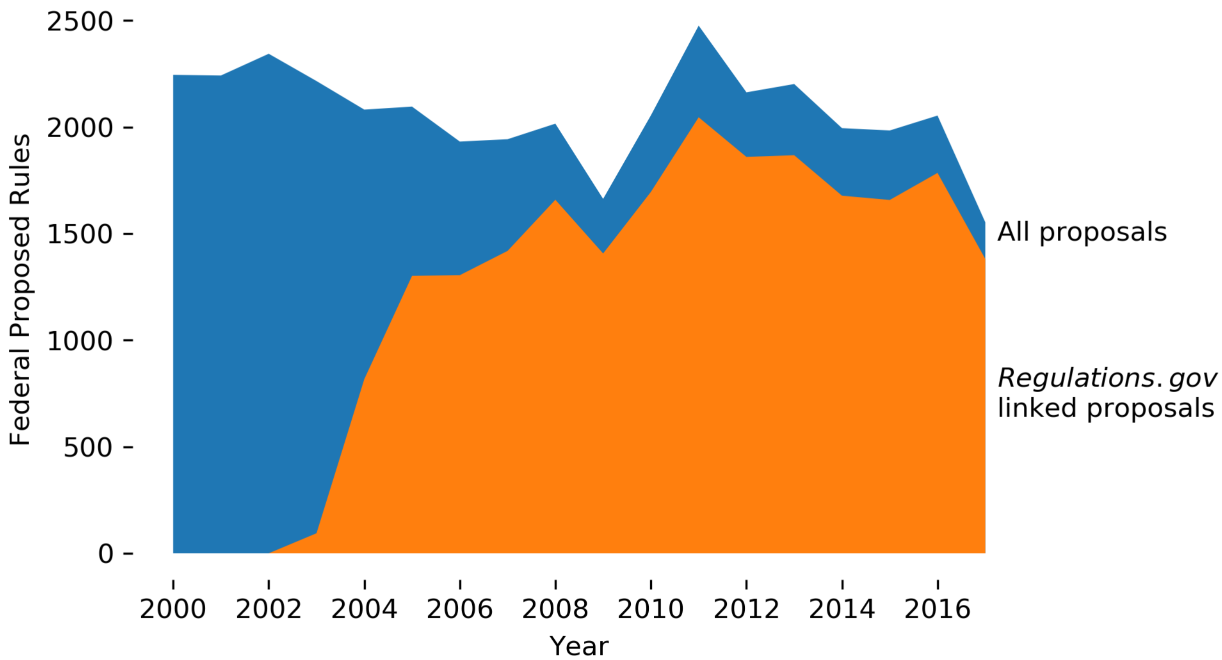
If $\delta_g < \frac{1}{4}$ then $l_g + l'_g < 2\delta_g$ is binding. We now show that the following manipulated inequalities lead to a contradiction when $\delta_g < \frac{1}{4}$: $l_g < 2\delta_g - l'_g$ and condition $10 l_g > \frac{1}{2}\left(1 - 8\delta_g - 6l'_g\right)$. In fact, together, they imply that $1 + 8\delta_g - 6l'_g < 4\delta_g - 2l'_g$, or simplifying, that $l'_g > \frac{1}{4} + \delta_g$. This condition, together with the assumption that (7) is violated leads to the condition $l_g < \delta_g - \frac{1}{4}$ which, under the current case of $\delta_g < \frac{1}{4}$ leads to a contradiction, because l_g is positive.

If $\delta_g > \frac{1}{4}$ then (11) is binding. Manipulating (11) and (10) leads to the following two conditions: $l_g < \frac{1}{2} - l'_g$ and $l_g > \frac{1}{2}\left(1 + 8\delta_g - 6l'_g\right)$ which imply that $l'_g > 2\delta_g$. This condition, together with (11) implies that $l_g < \frac{1}{2} - 2\delta_g$ which is again a contradiction under the case of $\delta_g > \frac{1}{4}$ because l_g is assumed to be positive. QED.

D Appendix: Additional tables and figures

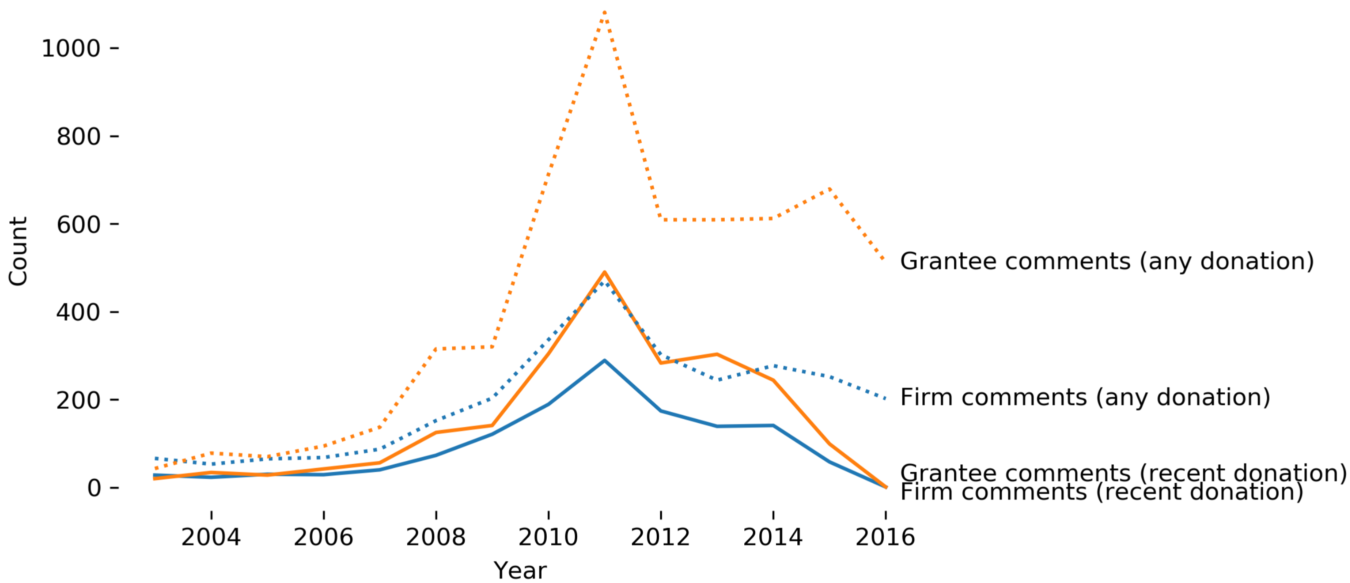
We report here various additional figures and tables mentioned in the text.

Figure D.1: Regulations.gov comment coverage



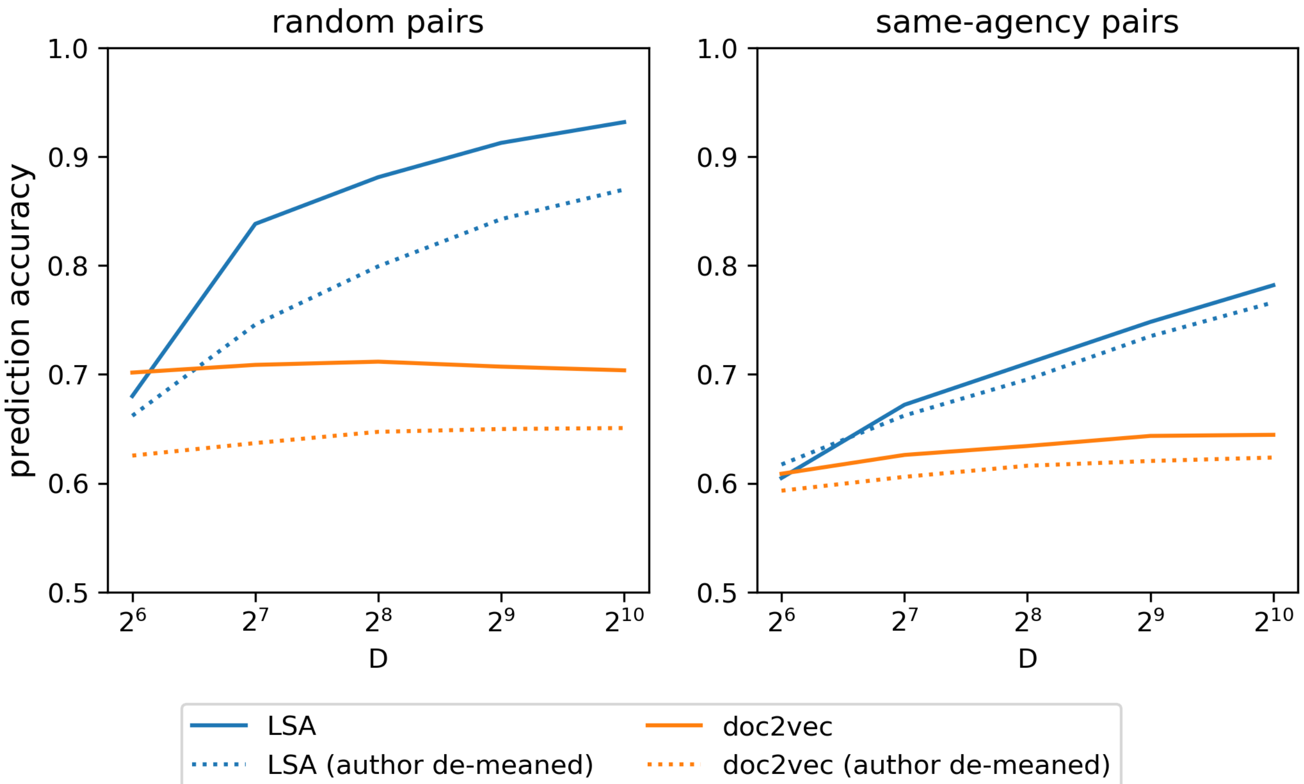
Notes: This figure shows the number of proposed regulations published on regulations.gov each year in blue. The portion that have a regulations.gov link are in orange. Those proposals that do not a have a regulations.gov link represent rulemaking activity that is omitted from our data.

Figure D.2: Annual Donation Co-Comment Counts



Notes: This figure shows the number of donation co-comment events (when a firm donates to a grantee and then both comment on the same rule) by comment year. Dotted lines indicate co-comments that are associated with a donation at any point in the sample, while solid lines indicate co-comments that occur in the same year or the year following a donation. The hump shape is driven by data availability: early in the sample we are missing comment data, and late in the sample we are missing donation data.

Figure D.3: Docket-match Detection Test Results



Notes: This figure shows the results of the docket-match prediction test, in which the goal is to predict whether a given pair of comments come from the same docket using a logistic classifier with cosine similarity between the two document vectors as the only feature. The accuracy of each algorithm is plotted as a function of D, where accuracy is defined as the fraction of correct predictions made when fitting on 80% of the sample and making predictions on the remaining 20%. Results for LSA are in blue, doc2vec in orange. Solid lines indicate the results for unmodified document vectors, while the results using organization-demeaned vectors are plotted as dotted lines. The left panel shows results for the test where unmatched pairs are completely random, and the right panel shows results for the harder task where unmatched pairs were still submitted to the same agency.

Table D.1: Annual firm comment count distribution by commenting relationship (Significant rules only)

	Annual firm comment counts (rules per firm/year)[1]							
	Mean	Std. Dev.	Min	Max	P50	P90	P99	Total[2]
Annual comments from each firm on:								
Any rule	0.8	1.3	0	11.6	0.3	2.0	6.6	596.9
Rules where at least one grantee also comments	0.7	1.1	0	10.0	0.3	1.7	5.7	549.3
Rules where at least one grantee who receives a donation from the firm at any time also comments	0.2	0.6	0	6.6	0	0.4	2.6	134.3
Rules where at least one grantee who has received a recent[3] donation from the firm also comments	0.1	0.4	0	5.7	0	0.3	2.0	84.7

Notes: This table summarizes the number of comments submitted by each firm in a representative year on rules that are deemed "significant" under EO 12866 (computed as the average across years 2008-2014 where our data is most complete).
[1] Each firm-rule-year observation is counted as one comment. Firms that submit multiple documents (or multiple form letters as part of a coordinated campaign) on the same rule in the same calendar year are counted as submitting one comment on that rule.
[2] Total comment count for all firms in our sample.
[3] We use the term "recent" to refer to any donation which occurs in the same or previous calendar year relative to the comment year.

Table D.2: Annual grantee comment count distribution by commenting relationship (Significant rules only)

	Annual grantee comment counts (rules per grantee/year)[1]							
	Mean	Std. Dev.	Min	Max	P50	P90	P99	Total[2]
Annual comments from each grantee on:								
Any rule	0.3	0.7	0	22.7	0.1	0.6	2.7	2401.7
Rules where at least one firm also comments	0.2	0.5	0	17.9	0.1	0.4	2.0	1670.3
Rules where at least one firm who donates to the grantee at any time also comments	0.1	0.3	0	8.1	0	0.1	1.1	553.4
Rules where at least one firm who has recently[3] donated to the grantee also comments	0	0.2	0	7.4	0	0	0.7	265.3

Notes: This table summarizes the number of comments submitted by each grantee in a representative year on rules that are deemed "significant" under EO 12866 (computed as the average across years 2008-2014 where our data is most complete).
[1] Each grantee-rule-year observation is counted as one comment. Grantees that submit multiple documents (or multiple form letters as part of a coordinated campaign) on the same rule in the same calendar year are counted as submitting one comment on that rule.
[2] Total comment count for all grantees in our sample.
[3] We use the term "recent" to refer to any donation which occurs in the same or previous calendar year relative to the comment year.

Table D.3: Top Agencies by Number of Comments

Top 30 agencies in firms' comments	Number of comments	Top 30 agencies in grantees' comments	Number of comments
EPA	8099	FWS	76404
FAA	3870	NOAA	69171
FDA	1942	HHS	60969
OSHA	1245	CMS	47215
PHMSA	745	EPA	13556
NHTSA	724	ED	5105
CMS	721	FDA	4773
EERE	709	FAA	3485
DOT	541	FNS	2821
OCC	466	FSIS	2436
FMCSA	451	APHIS	2232
IRS	444	HUD	1910
NLRB	366	IRS	1733
USTR	336	CFPB	1361
CFPB	328	AMS	1310
EBSA	302	OSHA	1192
HHS	276	FHWA	1095
USCG	222	SSA	1064
FWS	208	NHTSA	1001
AMS	181	EERE	936
HUD	163	DOT	925
APHIS	152	BOEM	909
FSIS	144	ICEB	861
TSA	129	DOJ	824
FRA	109	USCG	750
FHWA	108	OMB	748
LMSO	102	FMCSA	708
BOEM	95	DOS	667
BIS	94	OPM	649
EIB	91	NLRB	616

Notes: This table reports the 30 top agencies as ranked by the number of comments they receive by firms (first two columns) or by grantees (last two columns).

Table D.4: Co-commenting and donations - Future, contemporaneous and lagged donations

Dependent variable	Firm f and grantee g commented on the same rule in year $t \times 100$			
Mean	0.175			
	(1)	(2)	(3)	(4)
Firm f contributed to grantee g in year $t+1$	0.572***	0.341***	-0.018	-0.028
	(0.042)	(0.041)	(0.046)	(0.045)
Firm f contributed to grantee g in year t	0.488***	0.276***	-0.029	-0.048
	(0.042)	(0.042)	(0.045)	(0.043)
Firm f contributed to grantee g in year $t-1$	0.801***	0.534***	0.180***	0.142***
	(0.047)	(0.046)	(0.049)	(0.047)
Fixed effects				
Year	Y	Y	Y	
Grantee		Y		
Firm		Y		
Grantee-Firm Pair			Y	Y
Grantee-Year				Y
Firm-Year				Y
Observations	102,714,672	102,714,672	102,637,658	102,637,658

Notes: Standard errors are clustered at the grantee×firm level. *** p<0.01, ** p<0.05, * p<0.1

Table D.5: Comment similarity - Recent and future Donations

Dependent variable	Similarity of comments by grantee g and firm f on same rule					
	(1)	(2)	(3)	(4)	(5)	(6)
Grantee g received donation from firm f at t or $t-1$	0.029	0.037	0.022	0.036*	0.032	0.027
	(0.018)	(0.040)	(0.022)	(0.019)	(0.044)	(0.025)
Grantee g received donation from firm f at $t+1$	0.004	0.002	-0.010	0.007	-0.011	0.003
	(0.021)	(0.043)	(0.022)	(0.022)	(0.046)	(0.024)
Fixed Effects						
Rule	Y	Y	Y	Y	Y	Y
Firm	Y			Y		
Grantee	Y			Y		
Firm-Grantee Pair		Y			Y	
Agency×NAICS×NTEEC			Y			Y
Commenter style control				Y	Y	Y
Observations	156,263	63,496	75,205	156,263	63,496	75,205

Notes: The dependent variable is a similarity index between the comment of firm f and the comment of grantee g on in the same rule r, scaled to have a standard deviation of one. The independent variables are equal to one if grantee g received a donation from firm f in the year when the comment appears or the year before (a recent donation), or the year after the comment appears (a future donation). Standard errors use two-way clustering by rule and firm-grantee pair. *** p<0.01, ** p<0.05, * p<0.1.
*** p<0.01, ** p<0.05, * p<0.1

Table D.6: Rule outcomes - Recent and future donations

Dependent variable	Similarity between comment submitted by firm f and discussion text in rule r				Log citation count		Any citation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
At least one grantee g co-commenting and receiving donation from firm f in year t or $t-1$	0.148**	0.148**	0.129**	0.129**	0.057	0.057*	0.017	0.017
	(0.063)	(0.063)	(0.057)	(0.058)	(0.035)	(0.035)	(0.017)	(0.017)
At least one grantee g co-commenting and receiving donation from firm f in year $t+1$	0.018	0.017	-0.033	-0.037	0.016	0.017	0.013	0.013
	(0.054)	(0.054)	(0.055)	(0.055)	(0.030)	(0.030)	(0.013)	(0.013)
Log expenditure lobbying agency in t and $t-1$		0.005		0.009***		-0.002		-0.001
		(0.004)		(0.003)		(0.002)		(0.001)
Fixed Effects								
Rule	Y	Y	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y	Y	Y
Commenter Style Control			Y	Y	*	*	*	*
Observations	4,375	4,375	4,365	4,365	4,365	4,365	4,365	4,365

Notes: The dependent variables are several measures of the relationship between firm comments and the discussion of comments in subsequent rules. For columns 1-4 the outcome is the overall similarity of the text, for columns 5 and 6, the outcome is log of the number of detected occurrences of the firm's name in the discussion text, for columns 7 and 8 the outcome is an indicator for the presence of at least one occurrence of the firm's name in the discussion text. Note many rules do not cite commenters by name, so this is an imprecise measure of attention paid to comments. The independent variables are equal to one if grantee g received a donation from firm f in the year when the comment appears or the year before (a recent donation), or the year after the comment appears (a future donation). The asterisks (*) for Commenter Style Control in the citation columns indicates that the outcome measure is not adjusted, but the comment similarity with style control is used to find best matched rule for each comment. Standard errors use two-way clustering by rule and firm. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table D.7: List of Agencies on regulations.gov (A-F)

ACF	Children and Families Administration	DOI	Interior Department
AHRQ	Agency for Healthcare Research and Quality	DOJ	Justice Department
AID	Agency for International Development	DOL	Employment Standards Administration
AMS	Agricultural Marketing Service	DOS	State Department
AOA	Aging Administration	DOT	Transportation Department
APHIS	Animal and Plant Health Inspection Service	EAB	Economic Analysis Bureau
ARS	Agricultural Research Service	EAC	Election Assistance Commission
ASC	Appraisal Subcommittee	EBSA	Employee Benefits Security Administration
ATBCB	Archit. and Transportation Barriers Compliance Board	ED	Education Department
ATF	Alcohol, Tobacco, Firearms, and Explosives Bureau	EDA	Economic Development Administration
ATSDR	Agency for Toxic Substances and Disease Registry	EEOC	Equal Employment Opportunity Commission
BIA	Indian Affairs Bureau	EERE	Off. Energy Efficiency and Renewable Energy
BIS	Industry and Security Bureau	EIB	Import Export Bank of the United States
BLM	Land Management Bureau	EOIR	Executive Office for Immigration Review
BOEM	Ocean Energy Management Bureau	EPA	Environmental Protection Agency
BOP	Prisons Bureau	ESA	Employment Standards Administration
BOR	Reclamation Bureau	ETA	Employment and Training Administration
BPD	Public Debt Bureau	FAA	Federal Aviation Administration
BSEE	Safety and Environmental Enforcement Bureau	FAR	Federal Acquisition Regulation System
CCC	Commodity Credit Corporation	FBI	Federal Bureau of Investigation
CDC	Centers for Disease Control and Prevention	FCIC	Federal Crop Insurance Corporation
CDFI	Community Development Financial Institutions Fund	FDA	Food and Drug Administration
CFPB	Consumer Financial Protection Bureau	FEMA	Federal Emergency Management Agency
CMS	Centers for Medicare Medicaid Services	FFIEC	Federal Financial Institutions Exam. Council
CNCS	Corporation for National and Security Service	FHWA	Federal Highway Administration
COE	Engineers Corps	FINCEN	Financial Crimes Enforcement Network
COLC	U.S. Copyright Office, Library of Congress	FISCAL	Bureau of the Fiscal Service
CPSC	Consumer Product Safety Commission	FMCSA	Federal Motor Carrier Safety Administration
CSREES	Coop. State Research, Education, and Extension Service	FNS	Food and Nutrition Service
DARS	Defense Acquisition Regulations System	FRA	Federal Railroad Administration
DEA	Drug Enforcement Administration	FS	Fiscal Service
DHS	Homeland Security Department	FSA	Farm Service Agency
DOC	Commerce Department	FSIS	Food Safety and Inspection Service
DOD	Defense Department	FSOC	Financial Stability Oversight Council
DOE	Energy Department	FTA	Federal Transit Administration

Table D.8: List of Agencies on regulations.gov (F-Z)

FTC	Federal Trade Commission	OJP	Justice Programs Office
FWS	Fish and Wildlife Service	OMB	Management and Budget Office
GIPSA	Grain Inspection, Packers and Stockyards Adm.	ONRR	Natural Resources Revenue Office
GSA	General Services Administration	OPM	Personnel Management Office
HHS	Health and Human Services Department	OPPM	Procurement and Property Management, Office of
HHSIG	Inspector General, Health and Human Serv Dept	OSHA	Occupational Safety and Health Administration
HRSA	Health Resources and Services Administration	OSM	Surface Mining Reclamation and Enforcement Office
HUD	Housing and Urban Development Department	OTS	Thrift Supervision Office
ICEB	Immigration and Customs Enforcement Bureau	PBGC	Pension Benefit Guaranty Corporation
IHS	Indian Health Service	PCLOB	Privacy and Civil Liberties Oversight Board
IRS	Internal Revenue Service	PHMSA	Pipeline and Hazardous Materials Safety Adm.
ITA	International Trade Administration	PTO	Patent and Trademark Office
LMSO	Labor-Management Standards Office	RBS	Rural Business-Cooperative Service
MARAD	Maritime Administration	RHS	Rural Housing Service
MMS	Minerals Management Service	RITA	Research and Innovative Technology Administration
MSHA	Mine Safety and Health Administration	RUS	Rural Utilities Service
NHTSA	National Highway Traffic Safety Administration	SAMHSA	Substance Abuse and Mental Health Services Adm.
NIFA	National Institute of Food and Agriculture	SBA	Small Business Administration
NIGC	National Indian Gaming Commission	SLSDC	Saint Lawrence Seaway Development Corporation
NIH	National Institutes of Health	SSA	Social Security Administration
NIST	National Institute of Standards and Technology	TREAS	Treasury Department
NLRB	National Labor Relations Board	TSA	Transportation Security Administration
NOAA	National Oceanic and Atmospheric Administration	TTB	Alcohol and Tobacco Tax and Trade Bureau
NPS	National Park Service	USC	United States Courts
NRC	Nuclear Regulatory Commission	USCBP	U.S. Customs and Border Protection
NRCS	Natural Resources Conservation Service	USCG	Coast Guard
NSF	National Science Foundation	USCIS	U.S. Citizenship and Immigration Services
NTIA	National Telecommunications and Information Adm.	USDA	Agriculture Department
NTSB	National Transportation Safety Board	USPC	Parole Commission
OCC	Comptroller of the Currency	USTR	Trade Representative, Office of United States
OFAC	Foreign Assets Control Office	VA	Veterans Affairs Department
OFCCP	Federal Contract Compliance Programs Office	VETS	Veterans Employment and Training Service
OFPP	Federal Procurement Policy Office	WCPO	Workers Compensation Programs Office
OJJDP	Juvenile Justice and Delinquency Prevention Office	WHD	Wage and Hour Division