Teaming Up Across Political Divides: Evidence from Climate Regulations*

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Why do interest groups with contrasting interests and policy goals work together? I present a theory of collaborative policy production and show that interest groups prioritize high-quality implementation of policies even when it means compromising on their policy preferences. To test theoretical results, I introduce original measurement strategies that reveal systematic patterns in which firms and environmental groups invest in joint efforts to improve fine-grained details of policy to achieve greenhouse gas emissions targets. The analysis, using public comments spanning 2010-2020, demonstrates that comments written jointly by environmental groups and firms contain more information that can contribute to the quality of policy implementation than individual efforts alone, despite compromises on policy preferences. These findings highlight the hidden dynamics of regulatory politics, wherein divergent political goals are reconciled for high-quality policy implementation.

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1. Introduction

Why do political actors collaborate despite having competing interests and policy goals? The question of how political actors influence a policy is a long-standing central topic in political science. During the prior several decades, much progress has been made in understanding the process of developing policy when political actors with vested interests compete in varying institutional contexts (e.g., Hirsch and Shotts 2015, 2012; Baron and Ferejohn 1989; Krehbiel 2010; Crawford and Sobel 1982; Gilligan and Krehbiel 1989). One prominent argument is that actors use *policy-specific* expertise to effectively achieve a particular political goal. However, there are no clear explanations as to why and how political actors compromise their contrasting policy preferences "within a team," despite abundant empirical evidence pointing to the formation of "interest-diverse" coalitions (e.g., Nelson and Yackee 2012; Baumgartner et al. 2009; Dwidar 2022a; Heaney and Leifeld 2018; Lorenz 2020; Phinney 2017).

This paper is motivated by several consistent empirical patterns in climate politics that classical accounts in the policymaking literature do not explain. For example, although the U.S. Chamber of Commerce opposed passing cap-and-trade legislation during the 111th Congress, several Chamber members joined the U.S. Climate Action Partnership (USCAP), a coalition of industry and environmental stakeholders that attempted to hammer out a workable compromise that could attract the necessary votes to become law (Livermore and Revesz 2015).[1] The Environmental Defense Fund (EDF), one of the mainstream nonprofit environmental advocacy groups, explicitly mentions on its website that it saw the need to partner with mainstream businesses since the 1980s. The group is actively partnering with

[1]See U.S. Climate Action Partnership, About U.S., http://www.us-cap.org/about-us/ (declaring USCAP's "pledge to work with the President, the Congress, and all other stakeholders to enact an environmentally effective, economically sustainable, and fair climate change program"); see also Eric Pooley, *The Climate War: The Believers, Power Brokers, and the Fight to Save the Earth* (2010), 34. (quoting Duke Energy executive Jim Rogers, a member of USCAP, responding to criticism of the participation by coal mining executive Robert Murray of Murray Energy: "Legislation is coming. We can help shape it, or we can sit on the sidelines and let others do it.")

Walmart and FedEx.[2] Another example is the American Council for an Energy-Efficient Economy (ACEEE), one of the nonprofit coalitions supporting climate action. More explicitly, its Ally Program includes utilities, manufacturers, and other energy industries as partners, such as the American Chemical Council, and Xcel Energy, as well as a group of environmental and consumer leaders.[3]

These partnerships are puzzling given the contrasting policy preferences of firms and environmental groups. A closer analysis of business strategies in climate change reveals that restrictions on firms' polluting behaviors pose a significant challenge to particular industries. Although some firms (e.g., Shell, BP) have begun to diversify into other energy sources that produce less greenhouse gas emissions, none of these alternative energy sources can provide business opportunities on the same scale as those provided by oil and coal production (Stokes 2020). Contrary to industries' fear of adverse consequences from regulations, previous studies indicate that stringent regulations would primarily benefit environmental groups (Cheon and Urpelainen 2013; Bernauer and Caduff 2004; Aidt 1998). However, despite the divergent effects of regulations leading to different policy preferences, firms and environmental groups collaborate closely.

I argue that concerns over the quality of policy implementation is the reason behind collaborative efforts between interest groups who have contrasting policy preferences. In regulatory politics, the pursuit of *policy preference* is accompanied by concerns for *quality* of policy. By *quality*, I mean fine-grained and technical details of the policy that help achieve the targeted policy goals realistically. In climate policymaking, despite differing preferences for target emission reductions, interest groups share a common interest in developing feasible and sustainable solutions to achieve the given emission standards. For example, they are interested in considering the unexpected consequences of proposed

[2]See the website of Environmental Defense Fund, https://www.edf.org/partnerships/business-and-industry. EDF has collaborated with over 30% of Fortune 100 companies.

[3]See the website of ACEEE for further details. https://www.aceee.org/aceee-ally-program. Allies receive benefits from ACEEE, including public recognition via ACEEE's website, early access to ACEEE research reports, and access to a network of energy efficiency experts, leaders, and decision-makers.

emission control technologies, the economic costs involved, and how environmental groups' technical knowledge of climate mitigation can be used in industrial operations to develop sustainable and long-term practices. Here, the instrumental motive of policy outcomes themselves becomes less significant (Hirsch 2022; McCarty 2020), as long as groups are able to contribute to refining the details of the emission reduction targets. Although the divergent policy goals are reconciled, interest groups prefer a compromise with a high-quality of policy implementation instead of their own preferred policies with a low-quality implementation. And these dynamics can be observed empirically during the notice and comment period in the United States, which is the focus of this article. This process involves an agency attempting to "develop" rules after Congress sets the policy goal.[4]

To analyze why political actors work together despite unaligned preferences, I draw upon the theoretical framework of McCarty (2020) and Alchian and Demsetz (1972) to incorporate rulemaking dynamics for which regulatory officials need quality information to make reasonably good policy decisions. Bureaucrats create most regulations (Warren 2018; Shipan 2004), a process that is particularly true for environmental policymaking by which relatively few environmental laws have been passed (e.g., Rothenberg 2018; Lazarus 2014). On the basis of theoretical results, I provide descriptive evidence that firms and environmental groups, which have competing interests, invest in joint efforts to provide informative texts (defined as abundant analytical evidence and scientific reasoning) so that regulators can make fine-grained and technical judgments (Breyer 1982; Hawkins and Thomas 1989). This empirical pattern is consistent with the qualitative testimony provided by a former chief scientist at the EDF.

My theory also provides micro-foundations for the argument that interest group competition in regulatory policymaking is centered on the provision of expertise (Epstein et al. 2014; Carpenter and Moss 2014; Huber and Shipan 2002; Weingast 1984; Schnaken-

[4]"Learn About the Regulatory Process," Regulation.gov, April 24, 2024., https://www.regulations.gov/learn.

berg 2017). Existing empirical research on interest group politics is focused on financial resources, such as PAC contributions or lobbying expenditures, as a measure of political power. However, the primary resource of power in the regulatory context is information.[5] To provide evidence consistent with theoretical predictions, I describe systematic measurements of information, placing particular emphasis on expertise. This approach contrasts with existing literature on rulemaking, which has been focused primarily on analyzing the frequency of submissions or the types of political actors involved in the notice-and-comment period. I accomplish measurements of information by analyzing 15,883 publicly submitted comments on greenhouse gas emissions standards between 2010 and 2020.

I then provide empirical evidence consistent with the theoretical prediction that interest groups collaborate to improve the quality of a policy, despite compromises in their policy preferences. To quantify compromise, I leverage qualitative evidence indicating that business interests attempt to reframe the climate conversation by focusing on R&D and technological issues, whereas environmental groups emphasize reduction (e.g., Supran and Oreskes 2021; Downie 2017; Grumbach 2015; Schlichting 2013). I incorporate text embedding methods with a *Paragraph Vector* framework to construct the issue dimension, with each end indicating the topic favored by each interest group. My analysis shows that comments from environmental groups with business partners tend to be located in the middle of this issue dimension, indicating a compromise between the two factions. For example, comments from environmental groups with business partners are relatively skewed toward business-friendly topics compared with comments from environmental groups without business partnerships. However, because they represent a compromised outcome, the extent of the issue slant in comments from partnerships is comparatively less pronounced than the slant in comments from business interests alone.

[5]The role of information in the regulatory process has been discussed widely. Magat et al. (2013) elaborates that higher quality information supporting a proposed regulation reduces opponents' ability to modify the regulations. Moreover, the timing of when information is received can influence the rulemaking decisions (Ingram and Ullery 1977).

In trade-offs for policy preferences, both interest groups achieve policy gains from strategic partnerships. To empirically demonstrate this outcome, I use named entity recognition techniques to measure the quantity of expertise. Public comments written by strategic partnerships of firms and environmental groups contain more specific evidence and analytical reasoning compared with comments composed individually by each group, which is consistent with my theoretical predictions. Specifically, a collaboration with business partners substantially augmented the volume of information present in the comments associated with environmental groups, even after controlling for different group characteristics. Lastly, I employ information theory to quantify the political influence of strategic partnerships on finalized policy outcomes. I find that comments produced by collaboration between firms and environmental groups show a closer statistical distance to the finalized policy relative to comments composed by single entities. As a robustness check, I examine the citation patterns among Environmental Protection Agency (EPA) officials. The results reveal that EPA officials tend to cite comments written by strategic partnerships more frequently than they cite other types of comments. These findings provide further support for my argument on why political actors with conflicting interests engage in collaboration, and how the enhanced quality of information that results from strategic partnerships is translated into political influence.

This article makes both theoretical and empirical contributions to the study of coalition lobbying in policymaking (e.g., Bertrand et al. 2020; Dwidar 2022a; Heaney and Lorenz 2013; Hula 1999). My argument differs from a signaling model that suggests that regulators tend to seek broad indications of support (Esterling 2009) and that identifies the conditions under which interest groups benefit from signaling the diversity of their coalition to policymakers (Junk 2019; Mahoney 2007; Nelson and Yackee 2012; Phinney 2017). Although it is well-known that bureaucrats have diverse considerations, including their political or career interests, the formation of a coalition among interest groups in regulatory policymaking is not explained solely by the need to signal diversity of membership. During the stage

whereby technical judgment is required for designing the major operations to achieve the given policy goals, regulators have a significant incentive to invest in expertise and obtain technical information to refine the fine-grained details (Stephenson 2007; Gailmard and Patty 2012; Carpenter and Ting 2007; Huber 2007; McCarty 2017). In this regard, I offer a new perspective that cooperative policy production among interest groups can help regulators refine the details of a policy once a target policy objective is defined. By examining the coalition of polluting firms and environmental groups and its impact on climate regulations, I also contribute to the empirical literature on the influence of interest groups on climate politics (e.g., Cory et al. 2021; Colgan et al. 2021; Culhane et al. 2021; Brulle and Downie 2022; Lerner and Osgood 2022; Sautner et al. 2020; Urpelainen and Van de Graaf 2018).

2. Interest Groups Working Together in Regulatory Politics

Scholars have emphasized the influence that interest groups have over regulatory policy-making. Regulators have significant discretion in formulating regulations (McCarty 2017), and interest groups engage in various activities to influence regulators' policy choices that are in their favor. Such activities include direct lobbying of bureaucrats (You 2017), participation in federal advisory committees (Balla and Wright 2001; Moffitt 2014), lobbying of legislators who oversee bureaucrats (Hall and Miler 2008; Epstein and O'halloran 1995; McCubbins and Schwartz 1984), and involvement in the notice and comment process (Gordon and Rashin 2021; Carpenter et al. 2020; Libgober et al. 2020; Haeder and Yackee 2015; McKay and Yackee 2007; Furlong and Kerwin 2005).

Interest groups frequently engage in these political activities via formal partnerships or ad-hoc coalitions (Nelson and Yackee 2012; Baumgartner et al. 2009; Hula 1999; Heinz et al. 1993). They invest as teams in any coordinated efforts, with the objective of advancing their interests. To explain why lobbying together is a more advantageous strategy compared to lobbying alone, scholars have analyzed the size of coalitions (Nelson and Yackee 2012)

or the types of their interests (e.g., broad versus narrow) represented in the coalition (Mahoney 2007). A growing body of work relates lobbying success to the effect of the composition of coalition such as organization types (e.g., trade association and sectoral firms), partisan identities, or interest diversity (e.g., organizations representing diverse industries) (Dwidar 2022a; Heaney and Leifeld 2018; Lorenz 2020; Phinney 2017). However, the dynamics of how competing interests compromise a policy "within a team" and what incentivizes them to work together despite such compromises are rarely addressed. To bridge the gap, I propose a theoretical prediction wherein compromises between political actors emerge endogenously due to interest groups' concern for high-quality policy.

3. Theory: Investing in Team Efforts for Improving the Quality of Policy

Regulators use notice-and-comment periods to "develop" rules (Potter 2019; Balla 1998; Libgober 2020; Baumgartner et al. 2009; Yackee and Yackee 2006; Baumgartner and Jones 2010) after the policy goal is outlined by Congress.[6] Thus, the stage requires fine-grained, technical judgment concerning how major operations should be designed. Therefore, information, namely expertise, plays a vital role in regulatory politics (Libgober et al. 2020; Breyer 1982; Hawkins and Thomas 1989), and interest groups with specialized knowledge of the complex policy arena have an advantage in this competition (Epstein et al. 2014). Given the nature of regulatory policymaking, I present a theoretic model to generate predictions concerning the demand for high-quality policy by a coalition of groups whose preferences may diverge significantly.[7]

I analyze the behavior of interest groups under the following scenario. Let there be

[6] Under the Administrative Procedure Act (APA) of 1946, agencies typically must provide the notice and comment period in which a proposed policy is open for public review. During this stage, all interested parties are invited to provide written comments regarding the content of the proposed rule posted by agencies.

[7] The closest model is McCarty (2020), which examines how policy outcomes under the separation of powers are influenced by the interplay between legislative design and executive branch implementation. Although the contexts differ, the fundamental idea of policymaking as a team effort among relevant agents remains consistent.

two interest groups i =1,2 and a regulator. Group 1 holds an ideal policy position of 0, and Group 2's ideal policy position is represented by ϕ, where $0 < \phi \leq 1$. Both groups possess preferences for the policy outcome, denoted as p, and the quality of the policy χ. For simplicity, we assume that the cost associated with developing a compromised policy is zero and a regulator is concerned only about the quality χ. This setting reflects the context of agency policymaking when the target policy is already determined by Congress, and the agency is responsible for developing the details of the mandate. The utility function of interest groups follows the following setup proposed by McCarty (2020):

$$U_i(\chi, d(i,\ p)) = \chi(1 - d(Ideal_i,\ p)) - c(e_i) \tag{1}$$

, where *Ideal* is an ideal policy of groups, 0 or ϕ. d(.) is the Euclidean distance $(Ideal_i - p)^2$, and U is an increasing function of policy quality χ and a decreasing function of d(.). In contrast to the common assumption made in models of policymaking that the level of quality is determined by the efforts of a single agent, quality here is defined as an increasing function of the groups' joint efforts, $\chi = f(\alpha_1 e_1, \alpha_2 e_2)$ where e_i indicates the effort, and α_i indicates the impact of efforts of group i.

The game progresses through two stages. In the first stage, groups engage in bargaining over the policy outcome p. If bargaining is successful, both groups make simultaneous decisions about the amount of effort to invest in relation to the negotiated policy outcome p, and then submit a joint proposal. However, if bargaining fails, each group independently and simultaneously decides on their own p and individual effort levels. Next, if the interest groups submit a joint proposal, the regulator accepts it as long as its quality is higher than the regulator's reservation value. However, if groups submit separate proposals, the regulator evaluates the quality and accepts the proposal with the higher value.

To capture the notion that the impact of interest groups' efforts are asymmetric, I assume that $\alpha_2 > \alpha_1$. This setup reflects the reality through which interest groups with

varying expertise and resources might affect regulators differently (Berry and Wilcox 2015; Yackee and Yackee 2006). I also define $R \equiv \frac{\alpha_2}{\alpha_1} > 1$ to represent the relative capacity of the groups. $c(e_1)$ is defined as $\frac{1}{2}ke_i^2$ to produce closed form solutions. Because interest groups have various resources and information that will be in joint demand, I consider efforts as perfect complements and the production function is represented as $\chi = min\{\alpha_1 e_1, \alpha_2 e_2\}$. I then characterize the optimal policy and effort in the game.

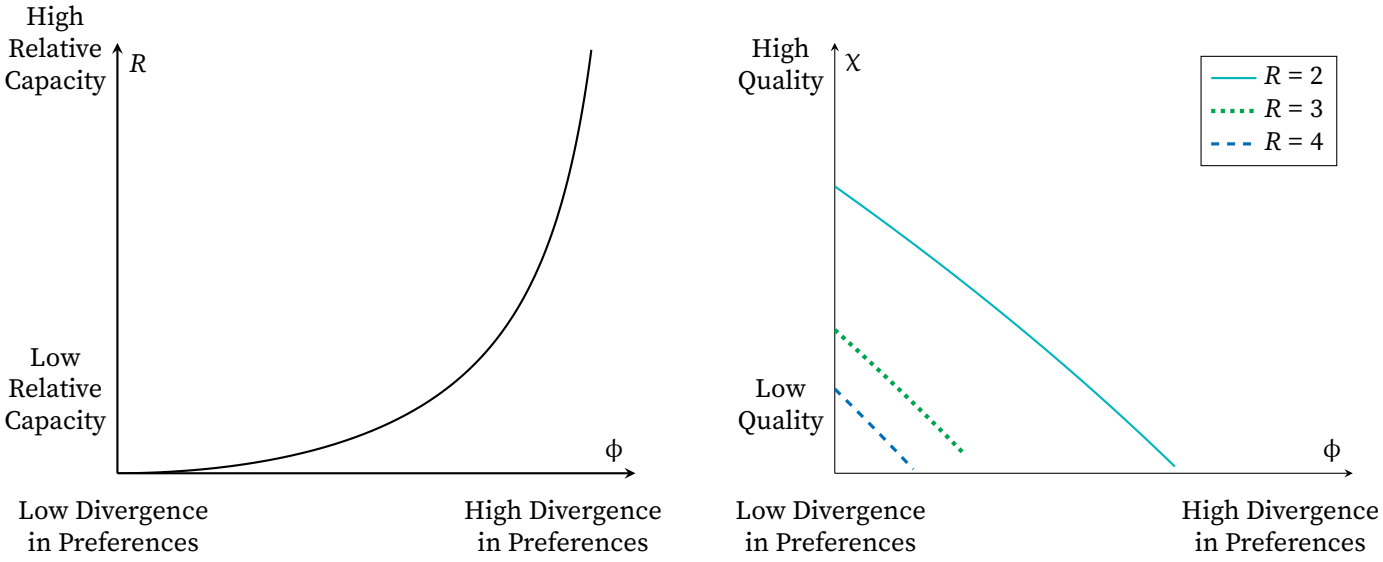


FIGURE 1. Conditions for Interest Groups to Invest in Collaborative Efforts

Note: This figure presents a simulation result regarding the conditions under which interest groups can benefit from collaboration. For simplicity, k is assumed to be 1, and α_1 is also assumed to be 1. The plot on the right illustrates the quality that can be achieved when interest groups agree to pursue a quality-maximizing policy.

PROPOSITION 1. *Suppose that χ_1 is low enough or that $d(\phi, p)$ is sufficiently high such that player 1 is the low contributor. Groups invest in team efforts if $\frac{1}{R^2} > (1 - \phi^2)$ and their joint proposal is accepted by a regulator. The optimal policy p^c is in the interval $(\hat{p}, \frac{\phi}{2})$, where $\hat{p}$ is the quality-maximizing policy, $\frac{1-\phi^2}{\frac{1}{R^2}+1-2\phi}$, located between the ideal policy positions of two groups.*

The proof and specific functional forms are in the Appendix. Proposition 1 shows several important results. First, the competing political goals of interest groups are reconciled

to the extent that groups maintain incentives to contribute to joint products to improve the quality of policy. The equilibrium efforts of both interest groups are decreasing in ϕ, implying that preferences should not be too extreme to motivate groups to invest in efforts. When R is high or ϕ is low, meaning Group 2 has relatively high capacity or preferences are less polarized, the optimum policy favors Group 1's ideal policy. However, when Group 1 has higher relative capacity or preferences are more polarized, the quality-maximizing policy leans toward Group 2's ideal policy. In either scenario, interest groups compromise on their ideal policy positions to collaborate.

Second, despite compromise in policy preferences, interest groups produce higher quality that cannot be achieved when working separately. Given that the efforts are perfect complements and quality is defined as a function of the groups' joint efforts, the groups always benefit from cooperative policy production.[8] The condition for $\hat{p} > 0$ shows that the ideological distance or preference polarization captured by ϕ is instrumental, as long as groups obtain higher policy gains by inducing efforts from their partner. In the complementary efforts setting with $\alpha_1 < \alpha_2$, the quality of the policy is determined by Group 1's willingness to exert effort, therefore α_2 has no direct impact on the policy quality, as shown in the plot on the right of Figure 1. But when α_2 is higher, Group 2 wants a greater increase in quality and is willing to make concessions to achieve this, even with a high divergence in preferences, as illustrated in the plot on the left. Although divergence in preferences and relative capacity introduce variation in the degree of policy quality that groups can achieve through joint efforts, collaboration still brings more policy gains compared to working separately.

[8] By the definition of a perfect complement, the utility of groups if they decide not to work together is 0 due to its negative cross elasticity of demand; if one agent decides not to invest, another agent's efforts will not be demanded. Therefore, none of the agents would invest in efforts when working separately and independently.

3.1. Discussion of Theoretic Model

The model of collaborative policy production is distinct from the conventional signaling mechanism. The signaling model suggests that coalitions are successful because the formation of a coalition itself signals credibility or broad support to regulators (Junk 2019; Nelson and Yackee 2012; Lorenz 2020; Phinney 2017; Mahoney 2007), regardless of the quality of policy it contributes to. However, signals derived from ideological positioning or diversity of interests are rarely the sole factor influencing regulators' decisions. Although regulators may have various considerations, such as career incentives or political preferences, they are primarily motivated to acquire the necessary expertise and fulfill their roles as technical experts (e.g., Brierley et al. 2023; Huber 2007; Carpenter and Moss 2014).[9] Therefore, sophisticated public comments that contain a wide range of policy and legal expertise tend to attract more attention from regulators (Dwidar 2022b), because these comments provide opportunities for regulators to obtain subject-area expertise. Although I do not model idiosyncratic concerns, such as a regulator's political bias or responsiveness to the degree of diversity, I emphasize that, in a regulatory context for which fine-grained policymaking demands technical expertise, collaboration among interest groups with diverse interests is not solely determined by reputational concerns or incentives to signal diversity to regulators. The empirical analysis in Section 4.4 offers evidence supporting this claim, while also accounting for the diversity of interests among groups.

This perspective also aligns with the qualitative witness of Michael Oppenheimer, who served for more than two decades as a senior scientist and director of the Climate and Air Program at the Environmental Defense Fund. He pointed out that, although environmental groups may have numerous researchers and scientists, they need information from industries to develop sustainable and feasible environmental practices. [10] Furthermore,

[9] For detailed explanations on relevant studies highlighting bureaucratic expertise, see Brierley et al. (2023).

[10] The interviews were conducted on June 6, 2023, and September 13, 2023. Dr. Michael Oppenheimer has graciously agreed to contribute his insights to this article. His perspective on the various resources and inputs provided by environmental groups and industry aligns with the underlying assumption of the model that efforts are complementary.

he noted that collaboration between companies and environmental groups can yield "new information" by pooling their resources, a synergy that continues to mutually benefit both parties. This perspective offers an alternative notion to the commonly held preconception of greenwashing regarding the collaboration between firms and environmental groups. Should partnerships significantly favor one party, they may become singular events, thereby reducing environmental groups' incentives to build lasting relationships with industries. Nonetheless, it is worth noting that the history of such partnerships spans the past twenty-five years. [11]

The model can undoubtedly accommodate various extensions. The assumption of complementary efforts reflects the diverse resources and inputs that environmental groups and firms contribute. For example, environmental groups offer expertise in climate mitigation, and firms provide information about their pollution levels or the processes of producing polluting chemicals in their facilities. However, another scenario of interest might still arise when efforts are perfect substitutes, with the quality function χ being $\frac{1}{2}\chi_1 e_1 + \frac{1}{2}\chi_2 e_2$.[12] In such a case, the compromise favors an interest group with a higher impact of efforts, and the optimal policy becomes more sensitive to the polarization of interest groups' ideal policy. However, both groups still obtain policy gains when they collaborate. As this does not present a substantial difference from the key results obtained under the original assumption, I opt not to address it to economize space.

4. Evidence: Partnerships between Firms and Environmental Groups

The dynamics of partnerships between firms and environmental groups provide evidence consistent with theoretical predictions: interest groups can achieve policy gains by collaborative efforts, even if it means compromising on their ideal policy preferences. On the basis of theoretical results, I present three hypotheses that will be tested empirically.

[11] To obtain further details regarding the history of collaborations between companies and environmental groups, refer to this website.

[12] This function is derived from the constant elasticity of the substitution production function.

First, I examine the compromise between firms and environmental groups. To demonstrate this compromise in policy preferences, I leverage the fact that polluting firms have strategically highlighted R&D and technological issues in climate debates. Abundant qualitative evidence suggests that business actors strategically discuss R&D and technological issues to attempt to reframe climate policy and weaken EPA's justification for emission cuts (e.g., Supran and Oreskes 2021; Downie 2017; Grumbach 2015; Schlichting 2013).[13] To give an example, ExxonMobil highlights its contributions to climate actions with advertorials citing "our industry-leading investments in research and development," such as the Global Climate and Energy Project at Stanford University, which implies that current solar or wind technologies are inadequate (Supran and Oreskes 2021). According to related witnesses and testimonies, business interests strategically use scientific research and technology to undermine efforts aimed at reducing emissions or to emphasize the uncertain costs associated with climate policies (Schlichting 2013).[14] This use of science to weaken antipollution efforts leads to my first hypothesis, namely, that comments written by strategic partnerships would emphasize R&D and technological issues more than comments written by environmental groups alone. However, the extent of the slant toward R&D topics in the comments would be less pronounced than what is observed in comments authored solely by business interests because comments written as an outcome of strategic partnerships are a compromise between the two groups.

HYPOTHESIS 1. *(Compromise) Comments from strategic partnerships between firms and environmental groups would fall in the middle of the issue dimension, with one end representing a business-friendly topic (R&D) and the other end representing an environmental group-friendly topic (reduction).*

[13] Still, large firms have not provided emissions reduction targets despite saying they want to reduce their impact on climate change. They have made R&D and technology commitments but have struggled to cut emissions. Eavis, P., & Krauss, C. (2021, May 12). What's Really Behind Corporate Promises on Climate Change? The New York Times. https://www.nytimes.com/2021/02/22/business/energy-environment/corporations-climate-change.html

[14] I empirically test the qualitative evidence in Appendix C.1 through granular analysis of Granger causality, using R&D coverage and CO2 data. The analysis reveals a strong correlation between CO2 measurements and R&D coverage, indicating that an increase in emissions is followed by an increase in R&D coverage.

Despite compromises in policy preferences, both interest groups achieve policy gains by collaboration. I have not explicitly measured policy quality, because the consequences of environmental regulations can be long-term and the definition of what constitutes a "good" policy can be highly subjective and controversial. However, we can still make some inferences about how comments from partnerships connect to policymaking. Specifically, if partnerships produce more informative comments that are more likely to be accepted by regulators for developing policy details, we can conclude that, by providing rich information to regulators, collaboratively crafted proposals contribute to a more sophisticated policy design.

Based on this inference, the second hypothesis focuses on whether the collaborative efforts of firms and environmental groups can convey more expertise to regulators. Firms can better frame their private information in conjunction with environmental groups' expertise in climate mitigation strategies, community-level knowledge (Bolden et al. 2018), or scientific research presented by environmental groups that concern the likely impact of further pollution (Bromley-Trujillo et al. 2014). And environmental groups can access private information that firms hold concerning the types of pollutants firms produce or the processes of generating those pollutants. Based on this reasoning, I posit that comments formulated by collaborative efforts between firms and environmental groups contain the comprehensive scientific reasoning and specific information sought by regulators to develop technical aspects of a policy, as compared to other forms of comments written separately by each group. The nature of collaborative comments leads to my second hypothesis:

HYPOTHESIS 2. *(Augmented Expertise): Comments crafted by collaborative efforts between firms and environmental groups contain a greater amount of scientific evidence and specific information compared with comments written separately by either environmental groups or business interests.*

Lastly, regulators who implement environmental regulations require an understanding

of various solutions to reducing pollutants and greenhouse gas or the unexpected consequences of alternative regulatory standards (Coglianese 2007). Therefore, expertise is a key factor in policy design and regulators value the specialized knowledge that reveals the intricacies of the policy landscape. Given that comments arising from the joint efforts of firms and environmental groups are more informative than other types of comments, I hypothesize that the comments produced by the collaboration of firms and environmental groups will have a greater impact on the policy outcome compared with comments written independently by either business interests or environmental groups. Hence, my final hypothesis is the following:

HYPOTHESIS 3. *(Political Influence): Comments from joint efforts are more likely to influence policy amendments than other types of comments, among comparably resourced comments.*

4.1. Data and Stylized Facts

I use an original dataset containing 15,883 comments officially submitted on *Greenhouse Gas Emissions Standards* from 2011 to 2020; the dataset does not have duplicates.[15] The policy comments were submitted for the EPA's regulatory review of the Greenhouse Gas Emissions Standards under sections 111 and 112 of the Clean Air Act, for which the EPA opened notice-and-comment periods seven times.[16] The year 2011 was chosen as a starting point because it immediately follows the new rules in which the EPA expanded emission regulations to a wide range of industries. The 10-year time period ensures that I am able to observe how both Republican and Democratic administrations respond to policy comments. As noted on the website of the Environmental Defense Fund,[17] the history of strategic partnerships with

[15] Regulations.gov includes data including the proposed policy, finalized amendments, and the comments associated with them. All rules and associated comments are linked by a docket number. A docket number is a unique identifier created by agencies that follow a regulation throughout its rulemaking process. The specific docket IDs used to collect public comments includes "EPA-HQ-OAR-2010-0505" and "EPA-HQ-OAR-2014-0827".

[16] Following is the list of starting dates the EPA posted for each notice and comment period: 1) November 30, 2011, 2) May 13, 2013 , 3) July 22, 2014, 4) January 5, 2015, 5) November 17, 2015, 6) April 1, 2016, and 7) August 9,2017.

[17] Refer to Figure B.3, which displays a screenshot of the Environmental Defense Fund's website.

business interests traces back to the 1980s. Between 2011 and 2020, these partnerships have remained unchanged in terms of temporal variation between firms and environmental groups. Comments from individuals without organizational affiliations tend to be simple endorsements focused on support for or opposition to a proposed policy. To compare comments that provide substantive information, comments from individuals who lack any association with entities or organizations are dropped from the main analysis. Ultimately, using company/organization identifiers and automated text analysis, I filter 903 comments submitted by companies, entities, or organizations and I use these filtered comments as the basis of my analysis.[18]

Comments are classified into five categories: 1) environmental groups with business partnerships, 2) environmental groups without business partnerships, 3) business associations (e.g., trade associations), 4) single businesses, and 5) others such as universities or government agencies.[19] One interesting pattern to note about this collection of comments is that recognizable polluting firms (e.g., Exxon, BP, Ford, or General Motors) submitted relatively few comments by themselves. Most of the single firms that participated in the rulemaking process by themselves are "green firms" or small local businesses. The classification is operated by two measurement strategies. First, I provide the conservative measure of strategic partnerships between firms and environmental groups based on explicitly visible evidence. I retrieve the history of environmental groups' websites for the prior decade using the Wayback Machine, and code if environmental groups have explicitly posted polluting firms as partners.[20] Next, I reference the classification framework of

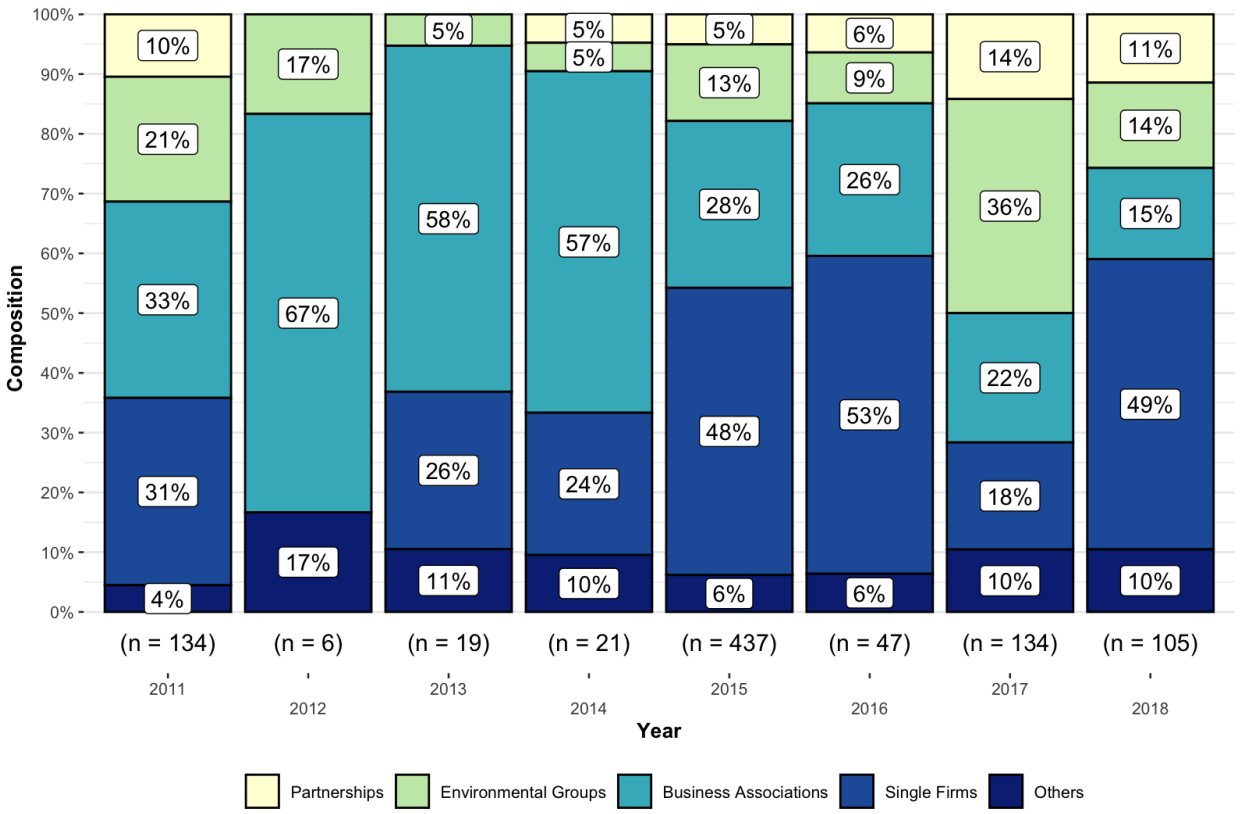
[18]There is no systematic correlation between the number of comments by type and participation year.

[19]I used three criteria to identify environmental groups. First, I required that these groups had a mission primarily relating to climate change and public policy. Second, the groups were membership-based organizations. Finally, the group's membership included diverse categories of political actors, such as citizens, consumers, and environmentalists. For instance, although it is introduced as a pro-climate coalition in the press, the group is categorized as a business association if the membership is limited to firms. The detailed codebook providing justification for the classifications is available under separate cover.

[20]The measurement strategy focuses solely on partnerships between environmental groups and firms operating within polluting industries such as energy, transportation, oil, or coal. It does not consider partnerships between environmental groups and green firms within renewable energy or green technology industries. Although there are a few instances of environmental groups collaborating with green firms,

Cory et al. (2021) to double-check the validity of the memberships lists that I collected from other sources.[21] The main analysis presented in this paper is based on the most conservative measure of partnerships between polluting firms and environmental groups constructed from explicit evidence- environmental groups' websites. In total, I have 541 unique entities in my data. The summary statistics are provided in the Appendix,[22] and the codebook is available separately.

FIGURE 2. Comment Participation With Time



No comments were submitted by organizations in 2019 and 2020. EPA did not open the notice-and-comment period in 2012 and 2013 but comments were still submitted by individuals.

Figure 2 presents the composition of the comments across time. On the whole, policy

partnerships with polluting firms are more widespread.

[21] Unfortunately, Cory et al. (2021) classification covers approximately one hundred firm-centered climate coalitions. So it was not enough to fully validate the strategic partnerships of firms and environmental groups examined in this analysis.

[22] See Table B.3 in Appendix.

comments by business associations and single firms represent the plurality of comments most of the time.[23] With time, there has been a gradual decrease in the percentage of comments from business associations and a stable trend in the percentage of comments from the partnerships between firms and environmental groups. The increase in the percentage of comments from single firms might mean an increase in participation from "green" firms. Although the frequency of joint coalitions' participation in rulemaking seems to be smaller than that based on other types of comments, the information conveyed by joint coalitions to regulators tends to be richer than the information from other types of comments. The next section substantiates this statement empirically. I also construct a variable to control for group characteristics, such as staff size. Data for this variable are collected from various sources, including *InfluenceWatch*, which provides descriptions of political actors involved in public policy issues, and from firms' websites, LinkedIn, Indeed, Buzzfile, Rocketreach, or Glassdoor to control for group characteristics such as staff size.[24]

4.2. Hypothesis 1: Compromised Policy Preferences

In this section, I test Hypothesis 1. To empirically demonstrate a compromise, I construct two measures to capture the prevalence of the topics favorable to business interests: 1) a count-based metric and 2) an embedding-based metric of R&D and technology coverage. The main analysis focuses on the second measure and the analysis using the count-based metric is provided in the Appendix. If comments from partnerships are positioned in the middle of the issue dimension, with each end representing the topic favored by respective interest groups, we can infer that there is a compromise in policy preferences.

[23] This observation is consistent with Golden (1998)'s finding that a huge percentage of comments are from business interests.

[24] When employment size is indicated in ranges, the upper bound is coded as the staffing size of the group.

Measuring issue slant towards R&D and Technology

As a count-based metric conveys little information about the context in which words are used, I apply a text embedding method that enables words to encode meaningful information about analogies. Political science research has used *Word2Vec* which embeds words in a low-dimensional vector space using neural network structure (e.g., Rodriguez and Spirling 2022). This method results in a set of vectors whereby proximity in vector spaces implies similar meaning context-wise, and vectors distant from each other have different meanings. For instance, “diligent" and “industrious" would be close together, whereas “diligent" and “lazy" would be relatively distant from each other. On the basis of embedding methods, I allow the algorithm to assign each word to a vector in a shared space during the training stage, and these assignments create clusters of words that are semantically connected. As a result, the more similar the context, the closer two words are located in geometric space.

Built on this advance in modern natural language processing technique, I use *Paragraph Vector* proposed by Le and Mikolov (2014), an unsupervised framework that learns continuously distributed vector representations at the comment level. In the *Paragraph Vector* framework, each document is mapped to a unique vector while each token is also mapped to another unique vector. They are then averaged to predict the next words in each sentence. Similar to Word2Vec’s continuous-bag-of-words model, this approach is based on a distributed memory model whereby document vectors can be acquired by the task of predicting a word based on an average in consideration of context and full document levels.[25] I construct a model with a window size of five, and I do not consider words that are observed less than five times in the entire corpus.[26]

As explained earlier, a key feature of word embeddings is that the difference between word vectors in the geometric space conveys meaning. For instance, the difference between

[25]See Figure C.2 for further details about the paragraph vector framework.

[26]The analysis reported in this paper was implemented by Doc2Vec Gensim and python3 on December 29, 2022. The parameters epoch is specified as 200. Typically epochs are set to be between 50 and 200.

the two vectors, $\overrightarrow{R\&D} - \overrightarrow{Reductions}$, identifies an issue dimension in the space by taking the difference between the normalized vector across a set of research words and the average normalized vector across a set of emission words: [27]

$$\overrightarrow{R\&D} - \overrightarrow{Reduction} = \frac{\sum_n \overrightarrow{R\&D_n}}{|N_{R\&D}|} - \frac{\sum_n \overrightarrow{Reduction_n}}{|N_{Reduction}|}$$

Therefore, the vector difference corresponds to the issue slant towards the R&D direction and can be substantively interpreted as a degree to which a proposal is leaning towards the issue of R&D instead of emission cuts. Note that word vectors and document vectors live in the same space by the way that *Paragraph vector* is constructed. By the geometry of vector space, I measure the cosine of the angle between the inferred vectors of the issue slant and each document vector.[28] This approach represents an integration of supervised and unsupervised learning techniques, combining text embeddings with a set of topics selected by researchers based on substantive concerns. The details of the analysis are also provided in Appendix C.2.

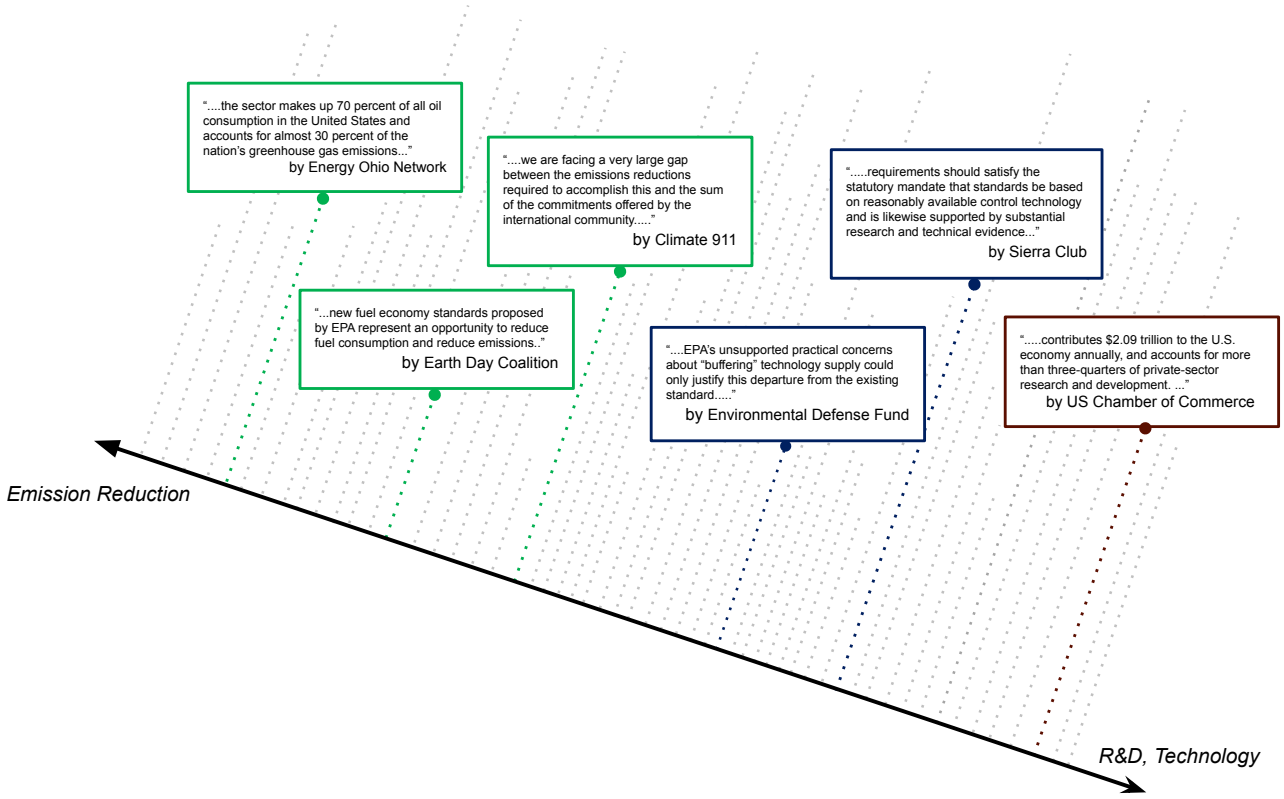
The cosine similarity metric enables a substantive interpretation of each comment's inclination towards emphasizing the topic of R&D and technology. Ranging from -1 to 1, the score indicates the emphasis in a document on R&D compared with the emphasis on reductions. A score close to 1 suggests a tendency to emphasize R&D, whereas a negative score implies a skew toward emission reductions.[29] Figure 3 depicts a schematic representation of the vector projection used in this method. It is evident that comments submitted by environmental groups in collaboration with business partners, such as the Sierra Club or Environmental Defense Fund, exhibit a tendency towards *R&D* and technology-related aspects compared with comments from environmental groups that lack business partner-

[27] The vocabularies are geometrically close vocabularies in the embedding spaces trained on comments. See the Appendix for more details concerning R&D and Technology vocabularies and emission reduction vocabularies. The vector dimensionality of the analysis presented in the paper is 200, and the Appendix provides a robustness check using models with the dimensionality of 1,000, and 10,000.

[28] See the Equation C.3 for the mathematical formula.

[29] See Appendix C.3 for further discussions on the interpretation of cosine similarity.

FIGURE 3. Schematic illustration of vector projection



ships. However, comments from partnerships are relatively less skewed compared with comments from business interests alone, which demonstrates a notable bias toward *R&D* directions. I use the similarity score for each comment i submitted by k in a time period t as a dependent variable and run an ordinary least squares regression.[30] Specifically, I estimate the following model:

$$\text{Similarity Score}_{ikt} = \alpha + \beta_1 \text{Strategic Partnership}_i + \delta Z_k + \tau_t + \epsilon_{ikt} \quad (2)$$

, where Z denotes the group-level control variable and τ are year-fixed effects. The specifica-

[30]The cosine similarity score used in Table 1 is measured with 6 vocabularies. For robustness checks, the same analyses are repeated using different numbers of vocabularies: 1, 2, 3, and 9. Further details can be found in the Appendix.

tion controls for group-level characteristics because there might be a systematic difference in research capacities due to staff size.[31] The error term is ϵ_{ikt}.

TABLE 1. Regression Models Examining the Issue Slant toward R&D versus Greenhouse Gas Reductions

Baseline	Environmental Groups	Business Association	Environmental Groups
Sample	Partnerships + Environmental Groups	Partnerships + Business Association + Single Firms	Whole Sample
	(1)	(2)	(3)
Partnership	0.128**	−0.062***	0.016**
	(0.049)	(0.016)	(0.008)
Single firms		0.008	0.028***
		(0.013)	(0.005)
Business associations			0.042***
			(0.009)
Others			0.031***
			(0.007)
Staff Size	✓	✓	✓
Year FE	✓	✓	✓
Commenter FE	✓	✓	✓
Mean Outcome	0.06	0.092	0.085
Observations	225	683	903
R2 Adj.	0.318	0.456	0.066

*p < .1; **p < .05; ***p < .01. In the first column, the reference category is *environmental groups*, while in the second column, it is *business associations*. For the third column, the reference category remains *environmental groups*. Standard errors are clustered by notice and comment periods in parentheses.

The first column of Table 1 examines comments from environmental groups, both with and without business partners, and the second column is focused on comments from environmental groups with business partners, business associations, and individual firms. The reference category for the second column is business associations. The last column identifies a correlation between the slant towards *R&D* and technology and the types of comments in the entire dataset. Comments from environmental groups without business partners serve as the reference category. The full results, including all control variables and fixed effects, are presented in Table C.5. Overall, comments from business associations tend to be slanted most towards the topic of *R&D*. Comments from the "others"

[31]The summary statistics are given in the Appendix.

category also tend to be skewed towards *R&D* topics because a substantial number of comments in this category are from universities. This empirical evidence lends support to the *Compromised Policy Outcome* hypothesis; the policy goals of firms and environmental groups are reconciled when jointly working together. For robustness check, I construct another measure to capture the prevalence of the topic, a frequency-based metric of *R&D* and technology coverage. The results are presented in Section C.5 of the Appendix.

4.3. Hypothesis 2: Achieving a Higher-quality Proposal for a Higher-quality Policy

In this section, I investigate the effect of strategic partnerships between firms and environmental groups by the amount of technical and analytical information in the comments.

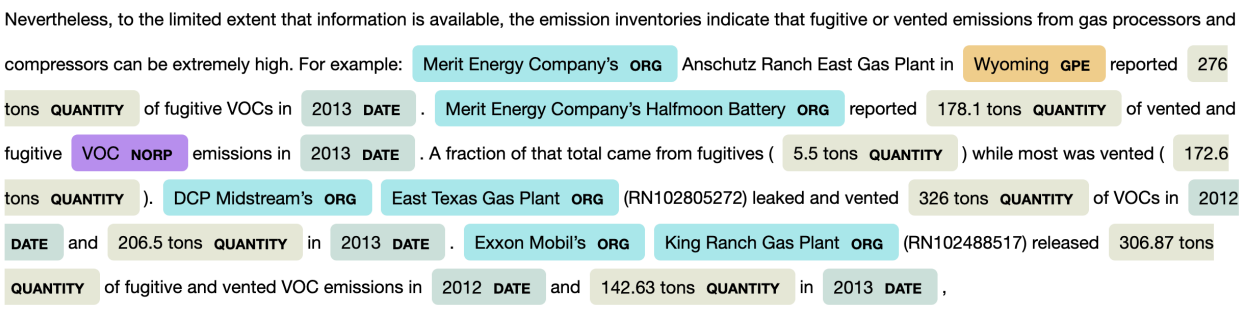
To construct a measure of information quality, I use an information retrieval technique to extract technical and informative chunks from unstructured raw text documents. The primary problem to be tackled when measuring information is the identification of scientific entities or languages that convey specific information. Although crowdsourcing is one method for performing manual, human-oriented tasks, the expertise required to extract scientific evidence or analytical facts makes crowd-sourcing impractical (Bonney et al. 2014, 2009). Therefore entity recognition techniques have been widely used in academic disciplines to quantify information (e.g., Liu et al. 2021; Hong et al. 2020). This technique operates by locating and classifying proper nouns into categories, such as organizations (e.g., companies, government organizations, committees), local-level knowledge (e.g., cities, countries, rivers) or measurement.[32] In total, eighteen categories are used to measure the amount of scientific information.[33]

Figure 4 illustrates the application of the information retrieval technique to comments.

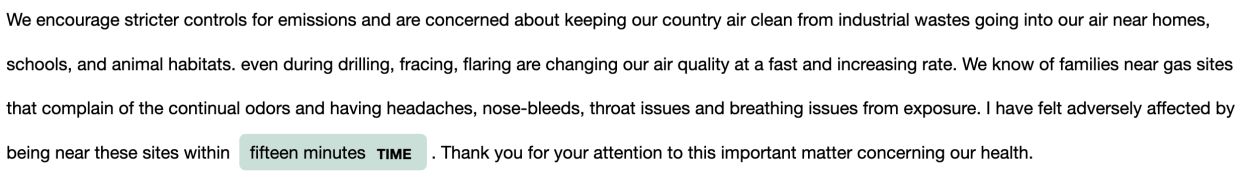
[32]The analysis presented in the paper is implemented by SpaCy v3.0, an open-source library for advanced language processing, on December 27, 2022. This transformer-based pipeline has an accuracy of 89.8.

[33]Eighteen classes include PERSON, NORP, FAC, ORG, GPE, LOC, PRODUCT, EVENT (Named hurricanes, wars, natural disasters, and so on), WORK OF ART (titles of books and so on), LAW (Named documents made into laws), LANGUAGE (any named language), DATE (absolute or relative dates or periods), TIME (times smaller than a day), PERCENT(percentage, including "%"), MONEY (monetary values, including unit), QUANTITY (measurements, as of weight or distance), ORDINAL("first", "second", etc.), CARDINAL (numerals that do not fall under another type). See the Appendix for further details.

FIGURE 4. Illustration of Information Retrieval Techniques for Public Comments



A. Comment Submitted by Clean Air Council



B. Comment Submitted by Citizens For Clean Water

The colored boxes represent the technical details identified by this approach. Each box is marked to display the named entities identified by the technique. For instance, the example demonstrates that the named entity recognition technique successfully captures organizations discussed in the comment submitted by the Clean Air Council, such as Merit Energy Company or Exxon Mobile, as well as various locations such as King Ranch Gas Plant, East Texas Gas Plant, or Wyoming. Furthermore, the technique identifies quantities of emissions (e.g., 326 tons) and specific dates. However, in the comment submitted by Citizens for Clean Water, there are only a few colored boxes because the comment does not include any specific or scientific evidence. During the validation process, the frequency of false-positive identifications is noticeably smaller than the frequency of false-negative identifications, suggesting that the named entity recognition provides a conservative measure of expertise. Additional details regarding human validations are presented in Appendix D.1. I use the number of all the colored boxes in each comment as a measure of expertise and estimate the effect of a strategic partnership on it. Formally, the dependent

variable is a count variable that represents the number of detected named entities in each comment. Negative binomial models are presented in the main analysis, considering the count data. Quasi-Poisson models are used as a robustness check, and the analysis is presented in Tables D.3 and D.4.

TABLE 2. Negative binomial model estimating the quantity of information

Baseline	Environmental Groups		Business Association		Environmental Groups	Business Association
Sample	Partnerships + Environmental Groups		Partnerships + Business Association + Single Firm		Whole Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Partnership	0.705***	2.670***	0.760***	1.878***	0.864***	0.730***
	(0.149)	(0.366)	(0.141)	(0.582)	(0.148)	(0.135)
Single Firm			−0.355***	−0.033	−0.200*	−0.334***
			(0.090)	(0.538)	(0.117)	(0.089)
Business associations					0.134	
					(0.123)	
Environmental groups						−0.134
						(0.123)
Others					0.167	0.033
					(0.167)	(0.152)
Issue Slant	1.301	−0.123	−0.429	0.069	−0.237	−0.237
(*R&D* and Technology)	(0.791)	(1.426)	(0.530)	(1.479)	(0.462)	(0.462)
Staff Size	✓	✓	✓	✓	✓	✓
Commenter FE		✓		✓		
Year FE	✓	✓	✓	✓	✓	✓
Observations	225	225	683	683	903	903

*p < .1; **p < .05; ***p < .01. Standard errors are clustered by notice and comment periods in parentheses. In the fifth column, the reference category is environmental groups, while in the sixth column, it is business associations.

The negative binomial model controls the issue slant toward R&D and technology constructed in the previous section because that topic is likely to be accompanied by technical details. Table 2 suggests that comments from strategic partnerships generally have more technical information than comments from other entities. Across all models, *Partnership* consistently shows a positive and statistically significant relationship at the 0.01 level. Overall, we observe that the magnitude of the partnership effect is significantly larger when the reference category is environmental groups. These findings lend confidence to the theoretical expectations that both firms and environmental groups derive advantages from investing in joint efforts. Table D.1 in the Appendix presents the full results.

4.4. Hypothesis 3: Political Influence of Strategic Partnerships on Regulatory Outcome

I investigate the political influence of strategic partnerships on environmental regulations by examining whether comments from the joint efforts of firms and environmental groups affect policy amendments during the notice and comment period. Specifically, I estimate the effects of *Partnerships* on two dependent variables: (1) the divergence scores from information theory and (2) a binary variable that indicates whether a comment was cited by EPA officials in the final rule after the notice and comment period.

Quantifying Political Influence Using Information Theory

In this section, I examine whether the increased quantity of knowledge translates into political power in regulatory politics by capturing distribution similarity. The intuition of this analysis is to examine how likely it is that a comment and a policy amendment come from the same probability distribution. I particularly use divergence scores from information theory because relative entropy captured via divergence score denotes how close two samples are to each other. Given that the vectors in this context indicate probability distributions, the cosine angle is inappropriate because it fits for vector space modeling. Therefore, I use Jensen-Shannon (JS) divergence score as a metric of statistical distance.[34] JS divergences have been widely used in social science research as a similarity measure of sparse data.[35] Divergence scores close to 0 indicate a closer statistical distance, implying that two samples are likely to be from the same probabilistic distribution.[36]

A finalized rule is generally a hundred-page document, whereas policy comments tend to focus on a few provisions of a proposed policy. Capturing the statistical distance between each comment and a huge corpus of the entire policy would underestimate the influence

[34]The Kullback-Leibler (KL) measure is inappropriate in this context as it is an asymmetric measure, leading to different scores for A to B and B to A. The algebraic reason is that $D(P||O) - D(O||P)$ is equal to $\sum_i^n ln(\frac{P_i}{O_i})(P_i + O_i)$ and there is no reason for this to be 0. Refer to the Appendix for further details.

[35]See Section E.2 in the Appendix for the mathematical proofs justifying the use of JS divergence as a test statistic and the detailed procedure of this analysis.

[36]See Appendix E for further details of the analysis.

of each comment on rulemaking, because a finalized rule is sparse, and particular provisions are supposed to be examined during the notice-and-comment process. Therefore, I construct a set of clauses updated after the notice-and-comment period and use the set as a basis of analysis to quantify the influence of comments on finalized policy outcome. If a policy amendment is likely to be from the same distribution of comments by partnerships of environmental groups and firms, we can infer that the joint efforts of firms and environmental groups exercise political leverage over climate regulations. There might be some concerns that this analysis would capture linguistic similarity or legal formalism between comments and policies, instead of the influence of comments on policy changes. To address this concern, I control the JS divergence score to a proposed policy posted by EPA officials before the notice and comment period. The model specification is similar to the one estimated in the previous section, with the exception that I include administration fixed effects because Republican politicians are generally considered business-friendly and prioritize policies that put business interests over environmental concerns.

Although the primary focus of the analysis centers on the provision of information, the decision of firms and environmental groups to collaborate could result from a multifaceted strategic interaction. To account for the signaling mechanism whereby regulators may find the diversity within partnerships more appealing (Lorenz 2020; Phinney 2017; Mahoney 2007), [37] I combine a dataset of public comments with interest group ideal point estimates, referred to as "IGscore," introduced by Crosson et al. (2020). Then, I estimate the preference gap by calculating the absolute difference between the highest IGscore of firms and the lowest IGscore of environmental groups.[38] For single entities, the absolute difference is 0.

[37] Most literature on coalition lobbying is based on a signaling model which suggests policymakers find diverse coalitions' signal more credible for the following reasons. Interest-diverse coalitions can synergize their advocacy tactics and network, and they send a more heterogeneous signal to legislators about the quality of a legislative proposal. Third, diverse coalitions are harder to maintain, making their legislative signals costlier. Thus, legislators have reason to believe that bills favored by diverse coalitions are more deserving of their attention and support than those favored by homogeneous coalitions, all else equal. However, it is worth pointing out that the canonical signaling models including Crawford and Sobel (1982) do not lead to policy bias but only to the reduction of uncertainty.

[38] Environmental groups tend to work with multiple business partners.

Capturing Political Influence Using Citations by EPA officials

Alternatively, I measure the political influence of comments by examining citations made by EPA officials. After the notice and comment period, EPA officials consider the comments submitted on a proposed policy and decide whether to revise the regulations accordingly when issuing a final rule.[39] When posting the finalized amendments, EPA officials add supplementary information; they provide a broad executive summary and explain the regulatory background of final standards. In addition, EPA officials summarize the significant comments, and they respond to those comments in a document that announces a final rule.

To estimate the influence of strategic partnerships on regulatory outcomes, I specifically focus on a final rule that was posted on March 12, 2018. The finalized policies posted by EPA officials take various inconsistent forms. In most cases, EPA officials make broad and generic statements that summarize the collection of comments without referencing specific commenters or comment IDs. However, for the March 2018 rule, the officials explicitly included comment IDs or commenters that regulators considered to update a proposed policy. Using this final rule as the basis for analysis, I construct a binary indicator that is coded as 1 if a comment is specifically cited by EPA officials in their response.[40] The “others" category is dropped from the analysis because there were few comments in that category on the rule on March 12, 2018.

TABLE 3. Regression Models Estimating JS Divergence Scores and Citation by EPA Officials

	JS Divergence Scores (OLS)		*Citation By EPA Officials* (Probit)	
	(1)	(2)	(3)	(4)
Partnership	−0.031***	−0.015*	0.512	1.737**
	(0.003)	(0.009)	(0.679)	(0.720)
Environmental groups	−0.015**		−1.225***	
	(0.007)		(0.396)	
Single firm	−0.001	0.014***	−0.445	0.779*
	(0.003)	(0.004)	(0.346)	(0.426)
Business associations		0.015**		1.225***
		(0.007)		(0.396)
Absolute difference between IGscores	0.002	0.002	0.207	0.207
	(0.004)	(0.004)	(0.497)	(0.497)
Staff Size	✓	✓	✓	✓
Administration FE	✓	✓		
JS Divergence to a proposed policy	✓	✓		
Observations	903	903	181	181

*p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered by notice and comment periods in parentheses (columns 1 and 2). Since our analysis focuses on single notice and comment periods that overlap both the Obama and Trump administrations, we do not have control over the years of submission. Therefore, the analysis using citation patterns by EPA officials (Columns 3 and 4) does not consider the years of submission as a controlled factor. In the first and third columns, the reference category is business associations, while in the second and fourth columns, it is environmental groups.

Results

Table 3 reports the coefficients of the probit model using citation patterns by EPA officials and the ordinary least squares model estimating JS divergence scores. The full results are presented in Table E.1. In all models, *Partnership* decreases the statistical distance and its effect is statistically significant (Columns 1 and 2). A finalized policy outcome tends to have

[39] Sometimes the agency extends or reopens a comment period because it has not received enough comments. Similarly, the agency may find that people have raised new issues in their comments that were not previously considered in the initial proposed policy. As new issues or additional complexity arises, the agency may publish a series of proposed rules in the Federal Register.

[40] The purpose of opening the notice and comment period in 2017 and 208 was to make amendments to two specific provisions related to the requirements for the collection of emission components at well sites. In the final rule, the agency announced the removal of the requirement for the repair of a component within 30 days of the detection of fugitive emissions. See Appendix E.5 for further details concerning the rule posted in March 2018.

a closer statistical distance to comments from joint efforts, namely more informative comments that contain a larger amount of scientific reasoning and specific evidence. Columns 3 and 4 further show that comments from joint efforts by firms and environmental groups are more likely to be cited by EPA officials when the reference category is environmental groups, while their confidence intervals overlap with zero when the reference category is business associations. However, the effect of partnerships is more pronounced than in any other category across the models. If the signaling perspective holds true, a higher absolute difference between IGscores would lead to a reduced statistical distance to a finalized policy or more citations by EPA officials. However, we do not find any effect of IG scores on the JS divergence scores and citations by EPA officials.[41] This demonstrates that enhanced expertise as a result of joint efforts by firms and environmental groups translates into political power in the rulemaking process, controlling the difference between IGscores.

4.5. Discussion of Empirical Analysis

This analysis tackles complex empirical tasks. The quantification of information provision by interest groups is particularly challenging because of the inherently subjective and elusive nature of information, and the lack of necessary data. Although this article could benefit from recent advancements in machine learning to measure key concepts, acknowledging the assumptions and limitations opens up avenues for further research.

First, while the analysis focuses on information exchange between firms and environmental groups, there may be valid concerns that financial and information exchanges are not mutually exclusive. Interestingly, some environmental groups have very strict corporate giving policies, which explicitly state that they do not accept donations from entities with expected conflicting interests. Specifically, Figure F.1 illustrates the EDF's policy, which prohibits receiving money from firms whose environmental performance conflicts with the organization's mission or introduces potential conflicts of interest. Addi-

[41] In the Appendix, I conduct analyses without considering commenter types and observe a negative relationship between the absolute difference of IGscores and JS divergence scores. See Table E.2.

tionally, following the approach taken by Bertrand et al. (2020) on charitable donations by interest groups to non-governmental organizations, I identified environmental groups that received corporate funding and found no significant overlap with those involved in the strategic partnership.

Second, although the analysis focuses on expertise defined by hard and quantitative information, it does not deny the importance of soft information, such as individual experience or anecdotal evidence. Soft information can indeed be helpful for policymakers to broadly gauge public sentiment or endorsement of a policy. However, it is worth highlighting that the notice and comment period is intended to collect technical, subject-area domain expertise for the specific details of the policy. For example, the notice and comment periods announced on November 1, 2017, for *the Emission Standards for New, Reconstructed, and Modified Sources* included topics such as implementing the fugitive emissions requirements, well site pneumatic pump standards, and the requirements for certification of closed vent systems by a professional engineer. [42]

Lastly, the analysis does not consider whether a high-quality policy necessarily means a "good" policy empirically. The definition of a good policy can be contested, given the multi-dimensional consequences of regulations that entail societal or economic impacts despite the primary goal of reducing pollution. Moreover, although a policy may be meticulously designed to address a specific issue, the implementing agency might lack the necessary capacity or resources to translate the policy design into reality. However, since the quality of implementation also depends on the quality of what is being implemented, this article implicitly assumes that a policy crafted with subject-area expertise and comprehensive information will significantly contribute to reducing noise in policy outcomes. Further investigating the complexities involved in assessing what constitutes a "good" policy would be an interesting direction for future research.

[42]When opening a notice and comment period, the agency proposes the topics of discussion in the announcement. See the details of the notice and comment periods from this website.

5. Conclusion

Interest groups play a crucial role in policymaking. Canonical models of policymaking focus primarily on how interest groups compete using their policy-relevant information to realize their political interests. Conversely, empirical evidence points to interest-diverse coalitions in which interest groups with divergent interests cooperate. What motivates them to collaborate despite their differing policy goals and how does the outcome of their collaborative efforts empirically manifest?

In this paper, I tackle this question by focusing on the dynamics of regulatory policymaking. Drawing upon a model of collaborative team policy production, I expect that compromise arises endogenously because the involved parties have incentives to produce high-quality details of the target policy. Using public comments on greenhouse gas emission standards and employing automated text analysis, I empirically demonstrate that environmental groups and polluting firms, despite their conflicting interests, craft public comments that incorporate a greater amount of scientific evidence and analytical information compared with other types of comments. On the basis of information theory and citation patterns by EPA officials, I further show that the enhanced expertise of strategic partnerships between firms and environmental groups has the greatest leverage on the final policy, even when controlling for the difference in ideology scores of the partnered interest groups.

I have not excluded the possibility that, in certain cases, regulators and interest groups may prioritize political interests, concerns about reputations or interest diversity. Instead, I argue that, despite such idiosyncrasies at the interest group or regulator level, there are strong reasons for both groups and regulators to be concerned about implementing high-quality policy, given the nature of regulatory policymaking where fine-grained and technical details of a policy are designed. This argument aligns with long-standing patterns in which partnerships between firms and environmental groups focus on research

programs to create mutually beneficial solutions that can improve the details of the policy (Rondinelli and London 2003; Stadtler and Lin 2019; Hartman and Stafford 1997).

The theoretical and empirical results are primarily focused on the stage after the coalition is formed, and this article is agnostic to the process by which interest groups select their partners from multiple options. Groups might prefer to collaborate with others who have greater resources or more influence. Alternatively, groups might be more willing to work with partners with a variety of political instruments. [43] Although these two mechanisms may not be mutually exclusive, the dynamics of how interest groups select partners and navigate complex relationships are an interesting avenue for future research.

In this article, I present a theory of cooperative policy production and offer evidence that the motives behind investing in joint efforts amid political rivalry are not solely a product of political interests or an incentive to signal credibility or diversity. Although I focus on interest group lobbying in environmental policymaking as an example, there are numerous opportunities to use this theory to understand generic phenomena whereby different political interests among members cannot be perfectly aligned, as is often the case in a "diverse" coalition. For example, in 1995, the National Governors Association represented a coalition of Republican Governors Association and Democratic Governors Association, with contrasting partisan orientations of its members. While its members had to negotiate their political interests, they produced a joint proposal that reframed welfare reform into a block grant, relaxing some of the work requirements and illegitimacy provisions and allocating more resources for child care (Haskins 2007). There are many possibilities for expanding the theory to encompass such broader contexts to consider when competing political goals can be reconciled and under what conditions they do so.

[43] See Pulkkinen, Levi. (2021, March 12). Washington climate activists disagree about how to cut carbon, https://crosscut.com/environment/2021/03/washington-climate-activists-disagree-about-how-cut-carbon. There has been ongoing disagreement among environmentalists regarding strategies to reduce carbon emissions, and some environmental groups may find it more beneficial to collaborate with business interests, rather than working solely with other climate activists.

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Supporting Information for

Teaming up Across Political Divides: Evidence from Climate Regulations

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A. Proofs for Proposition 1

The game is solved using backward induction, starting from the stage where the regulator implements a policy with a higher value of quality. For simplicity, we also assume that the regulator's reservation quality is 0. When efforts are perfect complements, the quality of the policy is determined by the lowest contribution. The quality function is written as $\chi = min\{\alpha_1 e_1, \alpha_2 e_2\}$. By the definition of a perfect complement, the utility of groups if they decide not to work together is 0 due to its negative cross elasticity of demand; if one agent decides not to invest, another agent's efforts will not be demanded. Therefore, none of the agents would invest in efforts when working separately and independently.

TABLE A.1. Normal Form Representation

Payoffs (Agent 1)	Payoffs (Agent 2)	Policy	Quality (χ)
When groups work together on a compromised policy			
$\alpha_1 e_1(1 - p^2) - ke_1^2$	$\alpha_1 e_1(1 - (\phi - p)^2) - ke_2^2$	p	$\alpha_1 e_1$
When groups work independently and separately			
0	0		0

Table A.1 represents the normal form representation of the game, assuming that α_1 is low enough or that $d(\phi, p)$ is sufficiently high such that Group 1 is the low contributor. As long as $\alpha_1 e_1$ is weakly bigger than 0, groups always work together for a compromised policy and the rest of the process is identical to McCarty (2020).

Intuitively, the optimal amount of effort that Group 1 is willing to invest $e_1^c = \frac{\alpha_1(1-p^2)}{2k}$ and e_2^c becomes $\frac{\alpha_1^2}{\alpha_2}\frac{1-p^2}{2k}$. In the alternative case where Group 2 is the low contributor, e_1^c is $\frac{\alpha_2^2}{\alpha_1}\frac{1-(\phi-p)^2}{2k}$ and e_2^c becomes $\frac{\alpha_2(1-(\phi-p)^2)}{2k}$. Note that the first condition only works for one of the groups, considering that the kink exists.

And there is a critical value $\hat{p}$ above which Group1 1 is a low contributor if p is bigger than $\hat{p}$. Agent 1's effort is decreasing in p but Group 2's effort is increasing therefore policy quality is maximized at $\hat{p}$. This critical value $\hat{p}$ is the maximum of 0 or the solution to

$(1-p^2) = R^2(1-(\phi-p)^2)$. As we assume that $\alpha_1 < \alpha_2$, R is bigger than 1, therefore, $(1-(\phi-p)^2)$ should be smaller than $1-\hat{p}^2$, that is $\hat{p} < \frac{\phi}{2}$.

LEMMA A1. *(Quality-Maximizing Policy) The quality-maximizing policy, $\hat{p}$ satisfies the condition that $1-\hat{p}^2 = R^2(\phi-\hat{p})^2$. $\hat{p}$ is greater than 0 if $\frac{1}{R^2} > 1-\phi^2$, and increasing in ϕ.*

However, the process may not produce the quality-maximizing outcome. To illustrate, I analyze the joint maximization between two groups. In this setting, groups choose efforts to maximize,

$$\Pi(p) = \sum_{i=1,2} [\chi^c(1-d(i,\ p)) - ke_i^{c2}] \tag{A1}$$

I consider two cases to figure out the optimal policy: 1) when $p \geq \hat{p}$ and 2) when $p \leq \hat{p}$. When p is greater than $\hat{p}$,

$$\Pi(p) = \sum_{i=1,2} [\alpha_1 e_1(1-d(i,\ p))] - ke_1^2 - ke_2^2 \tag{A2}$$

And the partial derivative with respect to p can be written as

$$[\alpha_1(1-d(o,\ p)) - ke_1]e_1\,p + [\alpha_1(1-d(\phi,\ p)) - k\frac{1}{R^2}e_1]e_1\,p - 2\alpha_1 e_1[2\,p-\phi] \tag{A3}$$

, where the first term is 0.

If p is smaller than $\hat{p}$, the partial can be written as

$$[\alpha_2(1-d(\phi,\ p)) - ke_2]e_2\,p + [\alpha_2(1-d(0,\ p)) - k\frac{1}{R^2}e_2]e_2\,p - 2\alpha_2 e_2[2\,p-\phi] \tag{A4}$$

, where the first term is 0 as it is the first condition for the optimal effort of Group 2.

Because $\frac{\phi}{2}$ should be greater than $\hat{p}$, the first case is relevant. The bracketed second term of Equation A3 indicates Group2's marginal gains from investing in efforts. The terms

is positive as Group 2 prefers more effort level than Group 1. Therefore, the second term of Equation A3 is negative as Group 1 decreases its efforts as p increases. Since the second term is negative, the third term should be positive. Therefore, we end up with the following lemma.

LEMMA A2. *The policy optimum $\hat{c}$ must be smaller than $\frac{\phi}{2}$.*

Next, we examine how $\Pi(p)$ operates in p. What's worth noting is that Π is increasing in $p \leq \hat{p}$ and decreasing in $p \in (\hat{p}, \frac{\phi}{2})$. Proofs are provided below.

First, we demonstrate that $\Pi(p)$ is decreasing in $p \in (\hat{p}, \frac{\phi}{2})$. This pertains to the scenario when p is greater than or equal to $\hat{p}$. Then the last term of Equation A3 is decreasing in $p < \frac{\phi}{2}$. Then, the partial derivative of the second term of it can be written as

$$\alpha_1[1-(\phi-p)^2-\frac{1}{R^2}(1-p^2)]e_1 p^2 + 2\alpha_1[\phi - p + \frac{1}{R^2}p]e_1 p \tag{A5}$$

Because p is greater than $\hat{p}$, the bracketed term of the first term is positive and the whole first term is negative. By the assumption that $\phi > p$, the second bracketed term is positive. Therefore, the whole second term is negative because $e_1 p$ is smaller than 0. As the equation above is negative, we can say that $\Pi(p)$ is decreasing in $p \in (\hat{p}, \frac{\phi}{2})$.

Second, we demonstrate that $\Pi(p)$ is increasing in p smaller than $\hat{p}$. Note that a kink exists; therefore, we examine whether the derivatives are positive from both the left and right. The different condition for $\hat{p}$ can be written as

$$\frac{1}{R^2} = \frac{1-(\phi-p)^2}{1-p^2} \tag{A6}$$

Then the last term of Equation A3 is positive therefore we establish that derivatives are positive on the right derivative. Next, we consider Equation A4 to examine the left derivative. Then, $\hat{p}$ can be re-written as

$$R^2 = \frac{1 - p^2}{1 - (\phi - p)^2} \tag{A7}$$

After plugging in the value, the second term of Equation A4 is zero at $\hat{p}$ and the last term is positive. Note that the bracketed term of the second term of Equation A4 is the marginal benefit of extra efforts, therefore it should be positive as Group 1 prefers more efforts than Group 2 if p is smaller than $\hat{p}$. Therefore, the second term of Equation A4 is positive. Because the last term is also positive when p is smaller than $\hat{p}$, we can conclude that the joint utility is increasing if $p \leq \hat{p}$.

B. Summary Statistics

Table B.1 presents the summary statistics of entity/organization comments submitted for the Greenhouse Gas Emissions Standards from 2010 to 2020. There were no entity comments submitted in 2019 and 2020. I extracted this information from *Regulations.gov*.[1] There is no observable correlation between comment types and the year of submission.

TABLE B.1. Frequency of Comments By Year×Types

	2011	2012	2013	2014	2015	2016	2017	2018
Partnerships	14	0	0	1	22	3	19	12
Environmental Groups	28	1	1	1	56	4	48	15
Business Associations	44	4	11	12	122	12	29	16
Single Firms	42	0	5	5	210	25	24	51
Others	6	1	2	2	27	3	14	11

Table B.2 shows the summary statistics of key variables measured and constructed in the empirical analysis.

TABLE B.2. Descriptive Statistics on Key Variables

	mean	sd	median	min	max	range
Staff Size	6570.66	38276.32	141.00	1.00	543000.00	542999.00
NER score	153.61	169.51	79.00	0.00	1461.00	1461.00
Environmental Groups' IGscore	-0.88	0.75	-1.06	-2.65	1.82	4.47
Firms' IGscore	0.55	0.41	0.57	-1.20	1.78	2.98
difference between IGscores	0.10	0.37	0.00	0.00	2.25	2.25
Issue Slant to R&D	0.09	0.08	0.09	-0.20	0.33	0.53

[1] docket IDs include EPA-HQ-OAR-2014-0827 and EPA-HQ-OAR-2010-0505

ACEEE
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To:
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Docket Management Facility, M–30,
U.S. Department of Transportation,
West Building, Ground Floor, Rm. W12–140,
1200 New Jersey Avenue S.E., Washington, DC 20590

From:
Therese Langer and Siddiq Khan, American Council for an Energy-Efficient Economy (ACEEE)

Re: Docket ID Nos. NHTSA-2014-0132 and EPA-HQ-OAR-2014-0827

Date: October 1, 2015

Attached please find the comments of the American Council for an Energy-Efficient Economy (ACEEE) on EPA and NHTSA's Proposed Greenhouse Gas Emissions and Fuel Efficiency Standards for Medium- and Heavy-Duty Engines and Vehicles; Phase 2.

ACEEE, a nonprofit, 501(c)(3) organization, acts as a catalyst to advance energy efficiency policies, programs, technologies, investments, and behaviors. We believe that the United States can harness the full potential of energy efficiency to achieve greater economic prosperity, energy security, and environmental protection for all its people. ACEEE carries out its mission by:

- Conducting in-depth technical and policy analyses
- Advising policymakers and program managers
- Working collaboratively with businesses, government officials, public interest groups, and other organizations
- Convening conferences and workshops, primarily for energy efficiency professionals
- Assisting and encouraging traditional and new media to cover energy efficiency policy and technology issues
- Educating consumers and businesses through our reports, books, conference proceedings, press activities, and websites

ACEEE was founded in 1980 by leading researchers in the energy field.

We appreciate this opportunity to provide comment on the agencies' proposal. Unless otherwise indicated, page references in the comments that follow refer to the proposed rule as it appeared in the Federal Register on July 13, 2015 (FR Vol. 80, No. 133).

FIGURE B.1. A Proposal submitted by Siddiq Khan, Senior Researcher and Lead, Heavy-Duty Vehicle Work, American Council for an Energy-Efficient Economy (ACEEE)

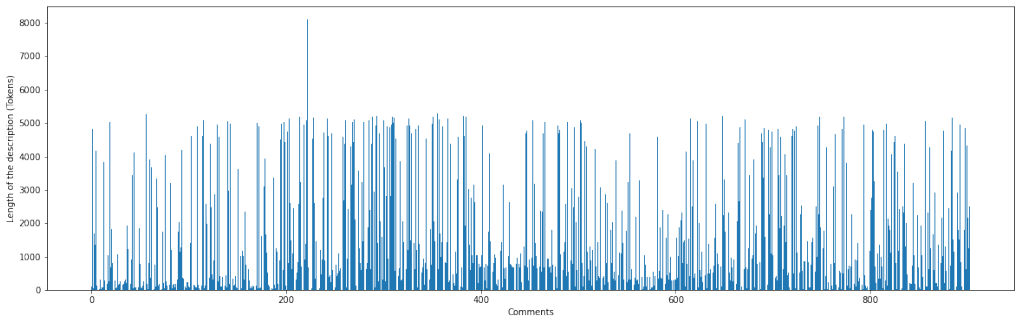


FIGURE B.2. Length of comments in the company/organization sample

TABLE B.3. Examples of Commenters in the Parternship Category

	partner1	partner2
1	Sierra Club	Amazon, Google, Patagonia, The North Face
2	Chesapeake Bay Foundation	Lockheed Martin
3	National Wildlife Federation	General Motors Company
4	Environmental Defense Fund	FedEx Corporation, Walmart, Lyft
5	Trout Unlimited	The Coca-Cola Company, Con Edison
6	Institute for Energy Research	koch
7	Clean Air Task Force	Caterpillar
8	FreedomWorks Foundation	Koch foundations
9	Resources for the Future	ConocoPhillips
10	Diesel Emissions Reduction Act (DERA) coalition	Caterpillar Inc
11	American Council for an Energy-Efficient Economy	Dow Chemical Co
12	Clean Fuels Ohio	American Electric Power

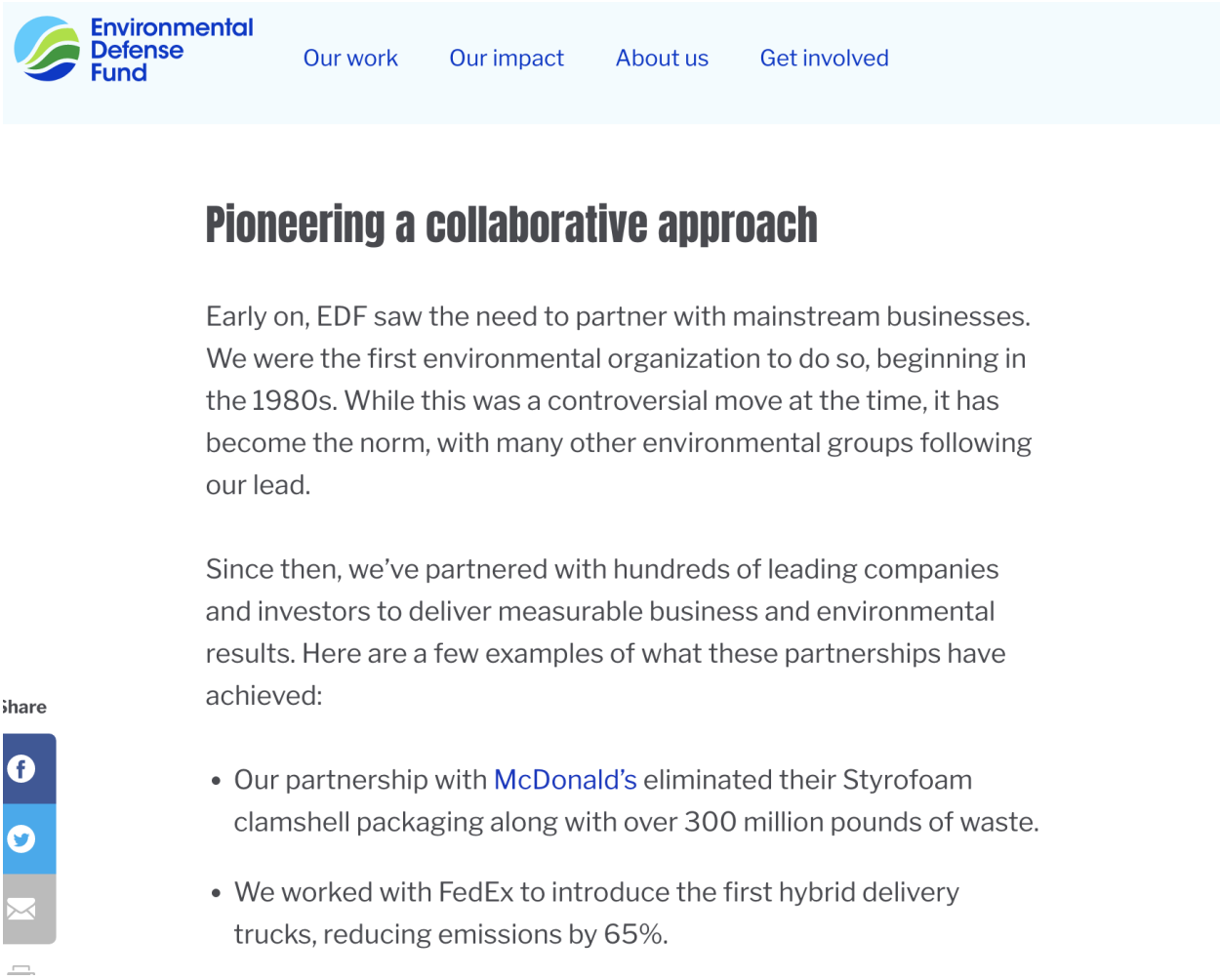


FIGURE B.3. Environmental Defense Fund's Website- Business Partnership

C. Compromised Policy Outcome Biased Towards Polluting Firms

C.1. Strategic use of the topic of R&D and technology by business interests

Correlation

In this section, I empirically test the qualitative evidence suggesting that business actors strategically emphasize R&D and technology to divert attention from emission standards. I compare the prominence of issues related to research and development with indicators reflecting firms' demand for regulatory intensity. I test the hypothesis that the deliberate emphasis on research and development serves as a distraction from stringent emission reductions. I start by conducting an initial and simplistic examination of this agenda-setting strategy. I define 'R&D' coverage in line with the comparative agendas project and include specific conditions that require mentioning research and development at least twice. The proportion of comments discussing 'R&D' is illustrated in Figure C.1. I identify a strong positive correlation (γ_1 = 0.8722452 for Carbon Dioxide emissions, γ_2 = 0.913333 for Methane emissions). This suggests that mentions of research and development increase as emissions increase. Such a positive correlation indicates the potential use of agenda-setting strategies by business interests.

Next, I expand upon these preliminary results in various ways. Firstly, I redefine the concept of 'R&D' coverage using two metrics: at the comment level, the count of comments that mention research, development, or technology at least twice, normalized by the total number of comments within the time slice; and at the word level, the frequency of occurrences of research and development topics normalized by the total word count within the time slice. Following that, I enhance the temporal resolution by conducting analyses at both the yearly and monthly levels. For the monthly analysis, I utilize average monthly emission data measured by the ESRL Global Monitoring Laboratory.

Table C.1 describes the correlation between metrics of R&D coverages and climate

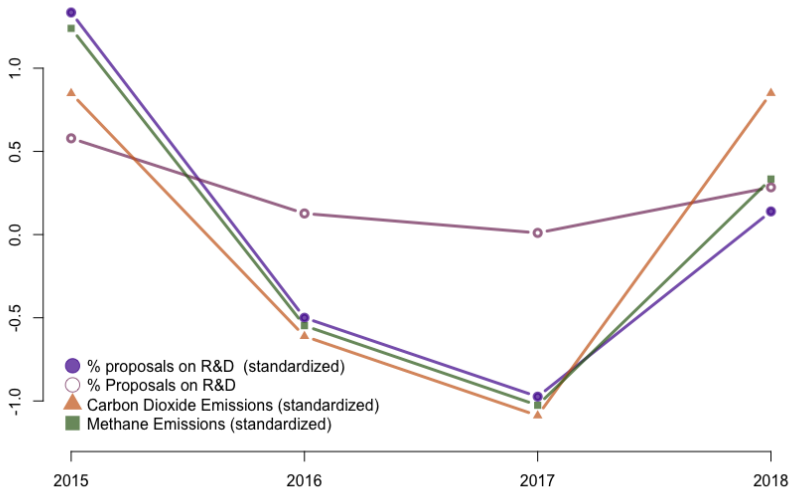


FIGURE C.1. Proportion of regulatory proposals by business interests groups that mention research, technology, and development at least twice and emission (Yearly emission data is from EPA)

change indicators at year and month levels. At all levels, there exist correlations between the proportion of agenda focused on research and development and CO2 emissions.

Granular Analysis of Granger Causality

Next, I hypothesize that these correlations are directed in fact: Greenhouse gas emissions are followed by business interests' coverage of research and development. To scrutinize this conjecture, I combine Granger Causality test with measures based on textual analysis. The crux of Granger causality is that we can identify if cause precedes effects. Therefore, a time series X is said to Granger-cause a time series value Y if past values x_{t-i} are a statistically significant indicator in predicting y_i.

The analysis for Granger Causality proceeds as follows: 1) I calculate the metrics at both the proposal and word levels, enabling a granular weekly analysis from 2015 to 2018. I utilize U.S. weekly mean CO2 data from the Global Monitoring Laboratory. Next, I assess Granger causality between the word-metric and CO2 molfrac (ppm) by fitting a linear

Levels	Comment-level	Word-level
U.S. Atmospheric CO2 (Global Monitoring Laboratory, Monthly Averages)*	0.3723696	0.3364334
CO2 Emissions (EPA, Yearly)**	0.3328969	0.4501426

CO2 measurements from flask-air samples scaled by National Oceanic and Atmospheric Administration (NOAA)

Emissions are expressed in million metric tons of carbon dioxide equivalents.

TABLE C.1. Pearson's correlation between proposal coverage of the Research and Development and emission indicators

regression model with m-lag and n-lag. CO2 emissions Granger-cause the coverage of 'RD' if the analysis identifies β as different from zero.with statistical significance.

$$\text{Word-level metric}_t = \sum_{i=1}^{m} \alpha_i(\text{Word-level metric}_{t-1}) + \sum_{j=1}^{n} \beta_j(\text{CO2 molfrac (ppm)}_{t-1})$$

Table C.2 indicates the analysis results. I found 1-lag mean Carbon Dioxide values Granger-cause coverage of *R&D* agenda at both proposal-level and word-level metrics. Remarkably, the coefficients for Greenhouse gas emission are positive, which indicates that the increase in the emission is followed by an increase in R&D coverage. In the 2-lag analysis, the p-value at the proposal-level is less than 0.1 but it is not statistically significant at the word-level. To rule out the likelihood of reverse causality, I compute Grange causality in the opposite direction, and the analysis does not return statistically meaningful results. The Granger Causality Tests in the reverse direction are presented below (Table C.3). These findings imply that corporate actors discuss the topic of R&D when air pollution increases.

	Comment-level		Word-level	
	1-Lag	**2-Lag**	**1-Lag**	**2-Lag**
R&D Coverage$_{t-1}$	0.800**	0.202***	0.003	0.002
	(0.353)	(0.073)	(0.072)	(0.072)
R&D Coverage$_{t-2}$		−0.073		0.051
		(0.072)		(0.072)
Mean carbon dioxide$_{t-1}$	0.115***	0.044	0.00002***	−0.001
	(0.036)	(0.038)	(0.00000)	(0.001)
Mean carbon dioxide$_{t-2}$		0.070*		0.001
		(0.038)		(0.001)
N	190	190	190	190
Adj. R-squared	0.1079	0.117	0.127	0.122

***p < .01; **p < .05; *p < .1

TABLE C.2. Granger Causality between CO2 molfrac (ppm) and the coverage of *R&D*

	Comment-level		Word-level	
	1-Lag	**2-Lag**	**1-Lag**	**2-Lag**
Mean carbon dioxide$_{t-1}$	1.000***	0.728***	0.002***	0.001***
	(0.0002)	(0.069)	(0.084)	(0.092)
Mean carbon dioxide$_{t-2}$		0.272***		0.089***
		(0.069)		(0.071)
R&D Coverage$_{t-1}$	1.767	1.601	1.0004	1.001
	(3.804)	(3.677)	(0.509)	(0.704)
R&D Coverage$_{t-2}$		1.602		0.007
		(3.681)		(2.001)
N	190	190	190	190
Adj. R-squared	0.1079	0.117	0.137	0.112

***p < .01; **p < .05; *p < .1

TABLE C.3. Granger Causality between CO2 molfrac (ppm) and the coverage of *R&D* (Reverse Direction)

C.2. Paragraph Vector Framework

Figure C.2 is from Le and Mikolov (2014). In this schematic framework, context of three words ("the," "cat," and "sat") is used to predict the fourth word. The input words are mapped to columns of the matrix W to predict the output word. And the additional paragraph token that is mapped to a vector via matrix D. Next the concatenation or average of this vector with a context of three words is used to predict the fourth word. The paragraph vector represents the missing information from the current context and can act as a memory of the topic of the paragraph. The paragraph vectors and word vectors are trained using stochastic gradient descent and the gradient is obtained via backpropagation. At every step of stochastic gradient descent, one can sample a fixed-length context from a random paragraph, compute the error gradient from the network and use the gradient to update the parameters in the model.

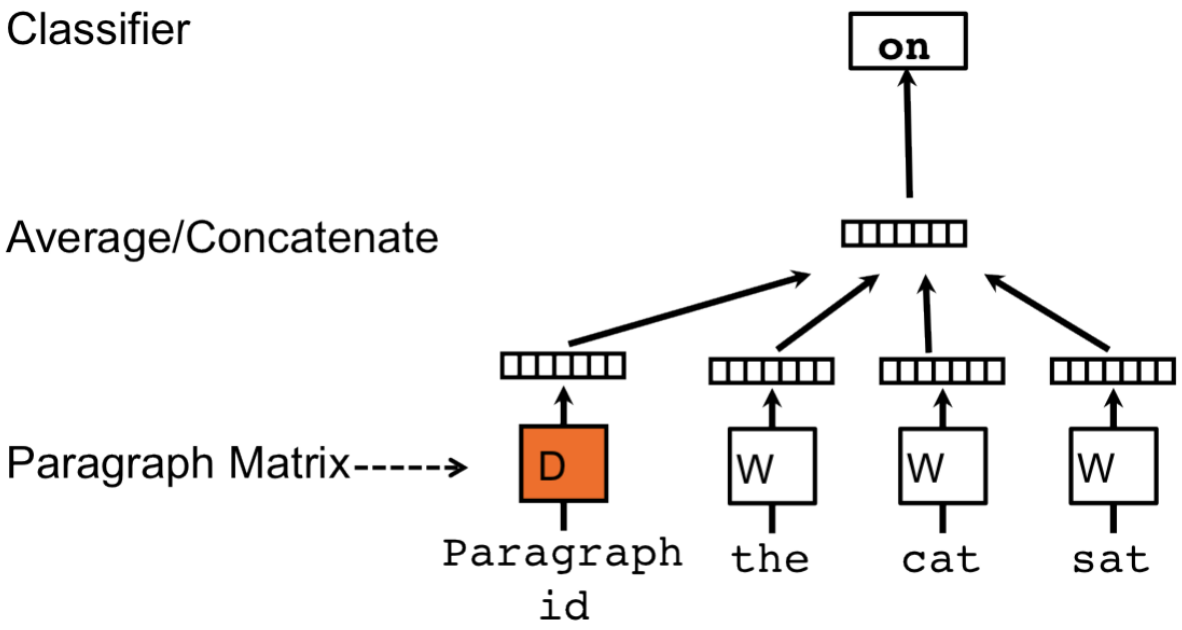


FIGURE C.2. A Framework for Learning Paragraph Vectors in Le and Mikolov (2014)

C.3. Cosine Similarity

Figure C.3 below illustrates the intuition of using cosine similarity as a measure of issue slant toward R&D and technology. The positive score implies that a comment is slanted in the RD and technology direction while the negative score indicates that a comment is slanted in the reduction direction. A score of 0 means a comment is balanced between the two.

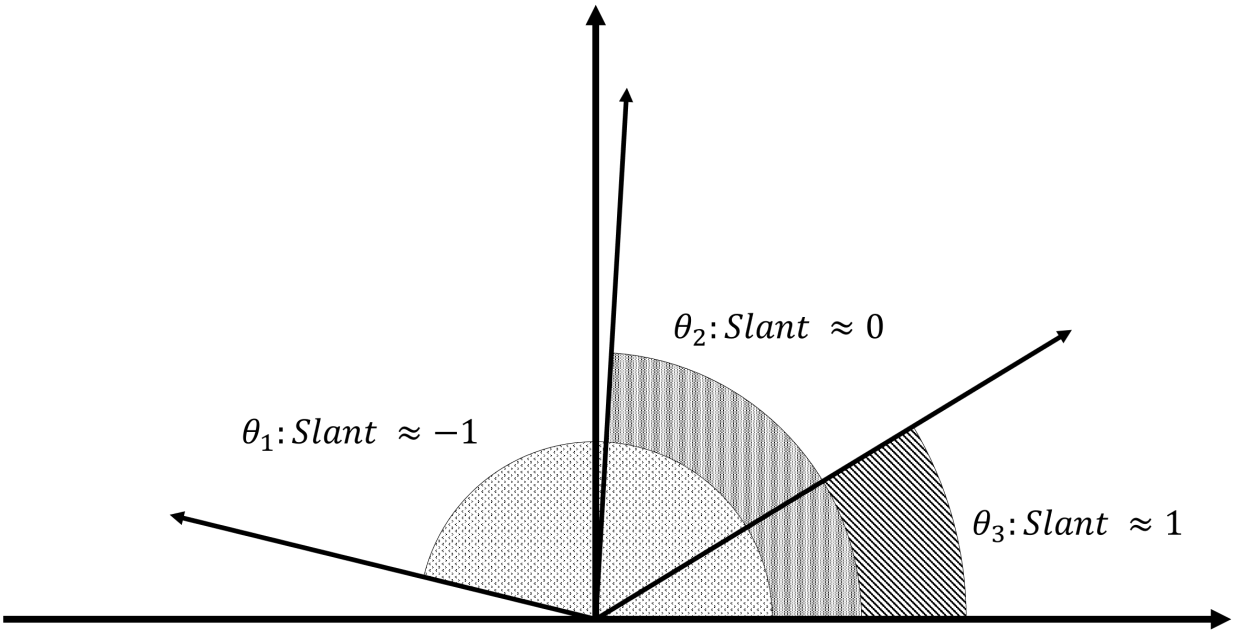


FIGURE C.3. Cosine Similarity as a measure of issue slant towards R&D and Technology

For simplicity, I denote $\overrightarrow{R\&D}-\overrightarrow{Reduction}$ as $\vec{x}$ and paragraphs vectors for each document as $\vec{y}$. This metric for non-zero vectors, $\vec{x}$ and $\vec{y}$, is defined as

$$similarity(\vec{x}, \vec{y}) = cos(\theta) = \frac{\vec{x} * \vec{y}}{||\vec{x}||||\vec{y}||} = \frac{\sum x_i y_i}{\sqrt{\sum {x_i}^2}\sqrt{\sum {y_i}^2}} \quad \text{(A8)}$$

where θ denotes the angle between vectors and $||*||$ indicates the 2-norm. The similarity score ranges from -1 to 1 and, a score close to 1 indicates that a document tends to emphasize R&D compared to reductions. If the score is negative, it implies that the issue is slanted in

the direction of emissions.

C.4. Word Embeddings Evaluations

There is no real evaluation possible except to test how Paragraph Vectors performs on the downstream task as it is an unsupervised model. Alternatively, I implemented human-based validation by examining the closest words to the words; research, development, technology and reductions to make sure that training a neural network makes sense substantively. The table below indicates the words used for constructing a global issue slant vector. For robustness check, I adjust the number of words 3,5 and 9 for each topic and the results are still consistent.

TABLE C.4. Vocabularies Associated with Each Topic

	Related Vocabularies
R& D Technology	research, development, technology, alternatives, strategies, solutions, innovations, drilling, sector, extraction
Emission Reductions	limit, address, mitigate, curb, prevent, minimize reducing, decrease, restrict, cut

TABLE C.5. Regression Models Examining the Issue Slant toward R&D versus Greenhouse Gas Reductions (Vocabulary size 6)

Sample	Partnerships + Environmental Groups	Partnerships + Business Association + Single Firms	Whole Sample
	(1)	(2)	(3)
Partnership	0.128**	–0.062***	0.016**
	(0.049)	0.016)	(0.008)
Single firms		0.008	0.028***
		(0.013)	(0.005)
Business associations			0.042***
			(0.009)
Others			0.031***
			(0.007)
Staff Size	–0.00004	–0.00000	0.00000
	(0.00003)	(0.00000)	(0.00000)
Constant	0.034	0.163***	0.044***
	(0.031)	(0.016)	(0.004)
Year FE	✓	✓	✓

*p < .1; **p < .05; ***p < .01. In the first column, the reference category is *environmental groups*, while in the second column, it is *business associations*. For the third column, the reference category remains *environmental groups*.

TABLE C.6. Regression Models Examining the Issue Slant toward R&D versus Greenhouse Gas Reductions (Vocabulary size 9)

Sample	Partnerships + Environmental Groups	Partnerships + Business Association + Single Firms	Whole Sample
	(1)	(2)	(3)
Partnership	0.052	−0.115***	0.012
	(0.054)	(0.014)	(0.008)
Single firms		−0.017	0.040***
		(0.011)	(0.007)
Business associations			0.049***
			(0.011)
Others			0.031***
			(0.009)
Staff Size	−0.00004	−0.00000***	0.00000
	(0.00002)	(0.00000)	(0.00000)
Constant	0.062*	0.197***	0.044***
	(0.032)	(0.014)	(0.005)
Year FE	✓	✓	✓

*p < .1; **p < .05; ***p < .01. In the first column, the reference category is *environmental groups*, while in the second column, it is *business associations*. For the third column, the reference category remains *environmental groups*. Standard errors are clustered by notice and comment periods in parentheses.

C.5. Analysis Using Simple Count-based Metrics for Robustness Check

In this subsection, I examine additional measures that capture the dynamics of a compromise between firms and environmental groups as robustness checks. I construct two measures: 1) a count-based metric that indicates how many times research, development, and technology vocabularies are mentioned, and 2) a binary variable indicating whether a comment has mentioned the vocabularies of research, development, or technologies at least three times.

TABLE C.7. Negative Binomial Model Estimating the Frequency of R&D Vocabularies- Using Count-based Metric

Sample	Partnerships + Environmental Groups	Partnerships + Business Association + Single Firms	Whole Sample
	(1)	(2)	(3)
Partnership	0.639***	1.125***	1.085***
	(0.187)	(0.358)	(0.355)
Single Firms		−0.082	−0.063
		(0.164)	(0.162)
Environmental Groups			0.309
			(0.233)
Others			−0.065
			(0.208)
Staff Size	0.0001	0.00001***	0.00000***
	(0.0003)	(0.00000)	(0.00000)
Constant	1.014***	0.120	0.225*
	(0.095)	(0.098)	(0.119)
Year FE	✓	✓	✓

*p < .1; **p < .05; ***p < .01

*p < .1; **p < .05; ***p < .01. In the first column, the reference category is *environmental groups*, while in the second column, it is *business associations*. For the third column, the reference category remains *business associations*. Standard errors are clustered by notice and comment periods in parentheses.

TABLE C.8. Probit Regression estimating the likelihood that the comment mentions R&D and technological topics

Sample	Partnerships + Environmental Groups	Partnerships + Business Association + Single Firms	Whole Sample
	(1)	(2)	(3)
Partnership	0.533***	1.125***	0.821***
	(0.098)	(0.358)	(0.253)
Single Firms		−0.082	−0.087
		(0.164)	(0.122)
Environmental Groups			0.140
			(0.164)
Others			−0.006
			(0.110)
Staff Size	0.0004	0.00001***	0.00000
	(0.0002)	(0.00000)	(0.00000)
Constant	−0.455***	0.120	−0.913***
	(0.051)	(0.098)	(0.085)
Year FE	Yes	Yes	Yes

*p < .1; **p < .05; ***p < .01. In the first column, the reference category is *environmental groups*, while in the second column, it is *business associations*. For the third column, the reference category remains *business associations*. Standard errors are clustered by notice and comment periods in parentheses.

D. Increased Quantity of Expertise for a Higher-quality Policy Implementation

	busi_coalition (N=250)	env (N=154)	others (N=66)	Partnership (N=71)	single_business (N=362)	Overall (N=903)
Count of Technical Information						
Mean (SD)	165 (173)	134 (157)	161 (167)	299 (248)	124 (136)	154 (170)
Median [Min, Max]	93.5 [0, 1130]	68.5 [0, 720]	78.5 [7.00, 737]	248 [30.0, 1460]	62.0 [0, 573]	79.0 [0, 1460]
Staff Numbers of Group						
Mean (SD)	1280 (10600)	121 (243)	8300 (48700)	430 (314)	13900 (55300)	6570 (38300)
Median [Min, Max]	50.0 [1.00, 160000]	40.0 [1.00, 1510]	245 [4.00, 390000]	600 [10.0, 800]	700 [1.00, 543000]	141 [1.00, 543000]

Note: Entries indicate the statistics for each comment type.

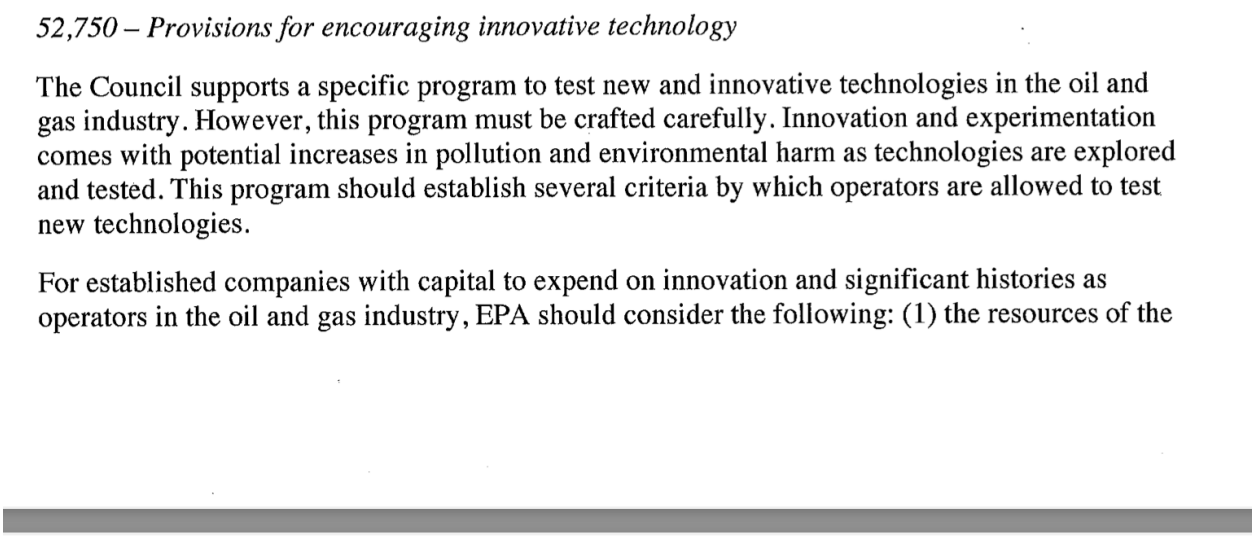
FIGURE D.1. Summary Statistics - A Measure Constructed by Named Entity Recognition

D.1. Validating named entity recognition techniques

As a classification task, the performance of the named entity recognition technique is usually measured in terms of classification metrics (over all the tokens) like precision, recall, F-score, accuracy, etc. I used spaCy v3.0, which introduces a transformer-based pipeline, and the testing accuracy of it is found to be around .89. After training a NER model, I conducted a human validation exercise using public comments submitted by the Clean Air Council. Figure D.2 shows pages 6-7 of the comments written by the Clean Air Council. The specific comment ID that includes the comment is EPA-HQ-OAR-2010-0505-4375, and the link is as follows: 'https://www.regulations.gov/comment/EPA-HQ-OAR-2010-0505-4375.'

The colored boxes in Figure D.3 show the words detected by the entity recognition technique, which includes organizations, geopolitical locations, or cardinality. One interesting pattern to note is that the number of false positives is relatively lower compared to that of false negatives. It is very obvious that all the colored boxes refer to very specific words, such as 'Ohio,' 'Evaporation Pond Facilities,' or '23 tons.' even though named entity recognition sometimes cannot detect *volatile organic compounds (VOCs)* or *Hydraulics*, which convey

scientific implications. Therefore, we can conclude that the expertise captured by entity recognition techniques provides a more conservative estimate than the actual amount of specific evidence and scientific knowledge present in the public comments, despite the challenge that identifying "false negatives" may be less straightforward compared to sorting out "false positives".



52,750 – Provisions for encouraging innovative technology

The Council supports a specific program to test new and innovative technologies in the oil and gas industry. However, this program must be crafted carefully. Innovation and experimentation comes with potential increases in pollution and environmental harm as technologies are explored and tested. This program should establish several criteria by which operators are allowed to test new technologies.

For established companies with capital to expend on innovation and significant histories as operators in the oil and gas industry, EPA should consider the following: (1) the resources of the

Clean Air Council EPA-HQ-OAR-2010-0505 7

company to determine whether it has the capacity to test new technology; (2) the number and seriousness of the violations of environmental laws and regulations in relation to the size of the company to determine its relative level of environmental safety; (3) whether the company is a member of EPA's Natural Gas STAR program; (4) whether the new and innovative technology proposed would significantly reduce potential cumulative pollution relative to the older technology or method the new innovative technology would displace; and (5) whether the technology would significantly reduce the risk of a larger, immediate pollution event relative to the older technology or method the new innovative technology would displace. EPA should also consider collateral or bonding requirements to test these technologies as well, with amounts depending on the scale of the test and the potential environmental impacts.

52,756 – Evaporation Pond Facilities

FIGURE D.2. Public Comment by Clean Air Council

For established companies with capital to expend on innovation and significant histories as operators in the oil and gas industry, EPA ORG should consider the following: (1 CARDINAL) the resources of the company to determine whether it has the capacity to test new technology; (2 CARDINAL) the number and seriousness of the violations of environmental laws and regulations in relation to the size of the company to determine its relative level of environmental safety; (3 CARDINAL) whether the company is a member of EPA ORG 's Natural Gas STAR ORG program; (4 CARDINAL) whether the new and innovative technology proposed would significantly reduce potential cumulative pollution relative to the older technology or method the new innovative technology would displace; and (5 CARDINAL) whether the technology would significantly reduce the risk of a larger, immediate pollution event relative to the older technology or method the new innovative technology would displace. EPA ORG should also consider collateral or bonding requirements to test these technologies as well, with amounts depending on the scale of the test and the potential environmental impacts. 52,756 CARDINAL — Evaporation Pond Facilities ORG The Council does not have firm data on the emissions from evaporation pond facilities. However, anecdotal evidence from Council ORG members living near multiple evaporation ponds suggests these are a significant source of VOCs and HAPs. Members have stated that rashes, allergies, and difficulty breathing coincide with evaporation pit installation, venting, and burn-off operations. EPA ORG should evaluate short-term impacts from these ponds because they may pose a significant threat to human health. Cumulative impacts are largely unknown as well. Should EPA ORG find what the Council ORG and its members suspect—that these ponds represent the types of dangers the NSPS/NESHAP rule revision are meant to guard against—then EPA ORG should consider strict rules on technologies to be used for evaporation ponds, should there even be technology in existence that would make evaporation ponds safer. 52,758 CARDINAL — Reduced Emission Completions The Council supports all efforts by the EPA ORG to require companies to perform emission completions (RECs) of wells. It is estimated that tens of thousands CARDINAL of wells will be drilled in shale deposits in Pennsylvania GPE 's portion of the Marcellus Shale LOC alone. The underlying and nearby Utica Shale ORG suggests that hydraulically fractured well drilling could expand in Ohio GPE and other parts of Pennsylvania GPE . EPA ORG 's estimate of 23 tons QUANTITY of VOCs emitted from uncontrolled hydraulically fractured wells multiplied by the thousands CARDINAL of potential wells that could be drilled and hydraulically fractured indicates the gravity of the pending air quality problem. EPA ORG estimates that many RECs would recover enough methane that would otherwise be lost to provide a net return despite the increased costs. But EPA ORG should also consider health impacts and the broader cost to society that not requiring RECs would cause. Increased VOCs would have a significant, measurable set of impacts on public health, from increased hospital visits to premature death. This is an important part of any economic impact assessment; the EPA ORG should not merely stop with an estimate on the change in profitability that any company doing the REC ORG would undergo.

FIGURE D.3. Applying Entity Recognition Technique to Public Comment by Clean Air Council

TABLE D.1. Negative binomial model estimating the quality of information (Year Fixed Effect)

Sample	Partnerships + Environmental Groups		Partnerships + Business Association + Single Firm		Whole Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Partnership	0.705***	2.670***	0.760***	1.878***	0.864***	0.730***
	(0.149)	(0.366)	(0.141)	(0.582)	(0.148)	(0.135)
Single Firm			–0.355***	–0.033	–0.200*	–0.334***
			(0.090)	(0.538)	(0.117)	(0.089)
Business associations					0.134	
					(0.123)	
Others					0.167	0.033
					(0.167)	(0.152)
Environmental Groups						–0.134
						(0.123)
Issue Slant	1.301	–0.123	–0.429	0.069	–0.237	–0.237
(*R&D* and Technology)	(0.791)	(1.426)	(0.530)	(1.479)	(0.462)	(0.462)
Year FE	✓	✓	✓	✓	✓	✓
Env_staff	0.0002	–0.0001	0.00000*	0.00001	0.00000	0.00000
	(0.0002)	(0.001)	(0.00000)	(0.00001)	(0.00000)	(0.00000)
Constant	4.801***	6.621***	4.801***	3.194***	4.668***	4.802***
	(0.204)	(0.445)	(0.145)	(0.606)	(0.146)	(0.132)

*p < .1; **p < .05; ***p < .01

TABLE D.2. Negative binomial model estimating the quality of information (Administration Fixed Effect)

Sample	Partnerships + Environmental Groups		Partnerships + Business Association + Single Firm		Whole Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Partnership	0.712***	0.284	0.644***	1.378**	0.786***	0.626***
	(0.144)	(0.970)	(0.127)	(0.564)	(0.137)	(0.123)
Single Firm			−0.344***	0.179	−0.158	−0.317***
			(0.090)	(0.554)	(0.112)	(0.089)
Business associations					0.160	
					(0.120)	
Others					0.161	0.001
					(0.161)	(0.147)
Environmental Groups						−0.160
						(0.120)
Administration FE	✓	✓	✓	✓	✓	✓
Staff Size	0.0002	−0.0002	0.00000**	0.00001	0.00000	0.00000
	(0.0002)	(0.001)	(0.00000)	(0.00001)	(0.00000)	(0.00000)
Issue Slant toward R&D	1.225	0.090	−0.276	−0.338	−0.039	−0.039
	(0.814)	(1.333)	(0.547)	(1.508)	(0.468)	(0.468)
Constant	4.766***	6.168***	5.205***	3.735***	4.988***	5.147***
	(0.130)	(0.326)	(0.089)	(0.612)	(0.101)	(0.086)

*p < .1; **p < .05; ***p < .01. In the first and second columns, the reference category is *environmental groups*, while in the third and fourth columns, it is *business associations*. For the fifth column, the reference category remains *environmental groups* while the reference category becomes *business associations*. Standard errors are clustered by notice and comment periods in parentheses.

TABLE D.3. Quasi-Poisson Model Estimating the Quality of Information (Year Fixed Effect)

Sample	Partnerships + Environmental Groups		Partnerships + Business Association + Single Firm		Whole Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Partnership	0.700***	2.757***	0.658***	1.337***	0.822***	0.646***
	(0.148)	(0.383)	(0.127)	(0.475)	(0.139)	(0.086)
Single Firm			−0.321***	−0.110	−0.134	−0.311***
			(0.086)	(0.405)	(0.114)	(0.086)
Business associations					0.176	
					(0.120)	
Others					0.158	−0.018
					(0.163)	(0.146)
Environmental Groups						−0.176
						(0.120)
Year FE	✓	✓	✓	✓	✓	✓
Staff Size	0.0002	−0.0002	0.00000	0.00001	0.00000	0.00000
	(0.0002)	(0.001)	(0.00000)	(0.00001)	(0.00000)	(0.00000)
Issue Slant toward R&D	1.241*	0.109	−0.342	0.054	−0.032	−0.032
	(0.744)	(1.543)	(0.518)	(1.352)	(0.452)	(0.452)
Constant	4.873***	6.565***	4.900***	3.736***	4.701***	4.878***
	(0.181)	(0.476)	(0.142)	(0.488)	(0.145)	(0.130)

*p < .1; **p < .05; ***p < .01. In the first and second columns, the reference category is *environmental groups*, while in the third and fourth columns, it is *business associations*. For the fifth column, the reference category remains *environmental groups* while the reference category becomes *business associations*. Standard errors are clustered by notice and comment periods in parentheses.

TABLE D.4. Quasi-Poisson Model Estimating the Quality of Information (Administration Fixed Effect)

Sample	Partnerships + Environmental Groups		Partnerships + Business Association + Single Firm		Whole Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Partnership	0.720***	0.183	0.645***	1.179***	0.802***	0.632***
	(0.141)	(0.932)	(0.124)	(0.408)	(0.136)	(0.123)
Single Firm			−0.294***	−0.008	−0.116	−0.286***
			(0.090)	(0.400)	(0.112)	(0.089)
Business associations					0.170	
					(0.119)	
Others					0.172	0.002
					(0.160)	(0.146)
Environmental Groups						−0.170
						(0.119)
Administration FE	0.026	−0.143	−0.241**	−0.066	−0.138	−0.138
	(0.140)	(0.208)	(0.107)	(0.174)	(0.086)	(0.086)
Staff Size	0.0002	−0.0003	0.00000	0.00001	0.00000	0.00000
	(0.0002)	(0.001)	(0.00000)	(0.00001)	(0.00000)	(0.00000)
Issue Slant toward R&D	1.303*	−0.142	−0.376	−0.473	−0.005	−0.005
	(0.716)	(1.311)	(0.517)	(1.275)	(0.449)	(0.449)
Constant	4.788***	6.174***	5.179***	3.947***	4.956***	5.126***
	(0.124)	(0.313)	(0.089)	(0.451)	(0.101)	(0.086)

*p < .1; **p < .05; ***p < .01

*p < .1; **p < .05; ***p < .01. In the first and second columns, the reference category is *environmental groups*, while in the third and fourth columns, it is *business associations*. For the fifth column, the reference category remains *environmental groups* while the reference category becomes *business associations*. Standard errors are clustered by notice and comment periods in parentheses.

E. Political Influence of Strategic Partnerships on Regulatory Outcome

E.1. Proof: Comparing Multinomial Distributions and Divergence Scores

The procedure for calculating JS divergence scores is as follows. I collapse the comments of each group and adopt the notion of the bag-of-words model which represents a document as a set of the count. Equivalently, a cluster of proposals is represented as a multinomial probability distribution over words. *P* denotes the proposals submitted by business interests while *O* indicates final amendments. Again, each of them is represented as multinomial distribution. *P* is a multinomial distribution of (p_1, p_2, ..., p_n) and *O* is a multinomial distribution of (o_1, o_2, o_3, ..., o_n). n is the total number of tokens in the entire text. p_i is defined as the $\frac{count(word_i, proposals)}{length(proposals)}$ and o_i is defined as the $\frac{count(word_i, finalizedrule)}{length(finalizedrule)}$.
Let x be a discrete variable, and the set of probability distribution x is parameterized by a vector p where p(x=k)= p_k.

$$p(x|p) = \prod_{k=1}^{K} p_k \tag{A9}$$

where $\delta(x = k)$ is an indicator function. Therefore, the joint probability of N IID samples X can be expressed as

$$p(X|P) = \prod_{k=1} K\, p_k \tag{A10}$$

$$N_k = \sum_{k} \delta(x_k = k) \tag{A11}$$

A conjugate prior for p is the Dirichlet distribution:

$$p(p|\alpha) \sim D(\alpha_1, ..., \alpha_k) = \frac{\Gamma(\sum_k \alpha_k)}{\pi_k \Gamma(\alpha_k)} \prod_k^{k-1} \tag{A12}$$

$$\sum_k p_k = 1 \tag{A13}$$

In above equations, α_k is the hyper-parameter, a virtual count for value k. Large α is equivalent to prior knowledge about the distribution. The Dirichlet distribution has the properties of

$$p(p_1|\alpha) \sim D(\alpha_1, \alpha_2 + ..., +\alpha_k) \tag{A14}$$

$$E[p_1] = \frac{\alpha_1}{\sum_k \alpha_k} \tag{A15}$$

$$E[log\, p_1] = \psi(\alpha_1) - \psi(\sum_k \alpha_k) \tag{A16}$$

, where $\psi(x) = \frac{\Gamma'(x)}{\Gamma(x)}$. The maximum of its density is at $p_k = (\alpha_k - 1)/((\sum_k \alpha_k) - k)$. Given Dirichlet prior, the joint distribution of a set of samples X and p is

$$p(X, p|\alpha) = \frac{\Gamma(\sum_k \alpha_k)}{\prod_k \Gamma(\alpha_k)}{}_k\, p_k^{N_k + \alpha_k - 1} \tag{A17}$$

and the posterior is reduced to $p(p|X, \alpha) \sim D(N_k + \alpha_k)$

Therefore, the probability that data all come from one multinomial distribution can be indicated as;

$$p(X|\alpha) = \int_p p(X, p|\alpha) \tag{A18}$$

$$= \frac{\Gamma_k \alpha_k \prod_k \Gamma(N_k + \alpha_k)}{\prod_k \Gamma(\alpha_k) \Gamma(\sum_k N_k + \alpha_k)} \int_p D(p; N_k + \alpha_k) \tag{A19}$$

$$= \frac{\Gamma(\sum_k \alpha_k)}{\Gamma(N + \sum_k \alpha_k)} \prod_k \frac{\Gamma(N_k + \alpha_k)}{\Gamma(\alpha_k)} \tag{A20}$$

E.2. Proof: Jenson-Shannon divergence as a test statistic

Our primary concern is the probability that finalized rule (= Y) and proposals (=X) are from the same probabilistic distribution. Based on information-theoretic quantity of mutual information, I connect distribution similarity to hypothesis testing. This is a problem related to homogeneity and I examine if two samples X and Y are from the same multinomial distribution or different distribution. Therefore, I am interested in

$$P(same|X, Y) = \frac{P(X|Y|same)\, p(same)}{p(X, Y|same)\, p(same) + p(X, Y|different)\, p(different)} \tag{A21}$$

$$= \frac{1}{1 + \frac{P(X,Y|\text{different}))}{P(X,Y|same)} \frac{P(\text{different})}{P(same)}} \tag{A22}$$

The quantity of $\frac{p(X,Y|different)}{p(X,Y|same)}$ is the ratio in favor of difference as shown below by Wolpert (1995)

$$\frac{p(X|\alpha)\, p(Y|\alpha)}{p(X, Y|\alpha)} = \frac{\Gamma(\sum_k \alpha_k \Gamma(M + N + \sum_k k)}{\Gamma(M + \sum_k \alpha_k) \Gamma(N + \sum_k k)} \prod_k \frac{\Gamma(M_k + \alpha_k) \Gamma(N_k + \alpha_k)}{\Gamma(\alpha_k) \Gamma(M_k + N_k + \alpha_k)} \tag{A23}$$

By entropy approximation, the logarithm of this ratio is equal to

$$log\frac{p(X|\alpha)\,p(Y|\alpha)}{p(X,Y|\alpha)} \approx -MH(\frac{M_k}{M}) - NH(\frac{N_k}{N}) + (M+N)H\frac{M_k+N_k}{M+N}) \tag{A24}$$

$$= MD(\frac{M_k}{M}||\frac{M_k+N_k}{M+N}) + ND(\frac{N_k}{N}||\frac{M_k+N_k}{M+N}) \tag{A25}$$

$$\text{where } D(p||q) = \sum_k p_k log\frac{p_k}{q_k} \tag{A26}$$

The equation A19 is equal to the average divergence to the mean, which is known to be the Jensen-Shannon divergence.

Note: Entropy Approximation

$$\frac{\gamma(K)}{\Gamma(N+K)} \approx \frac{\Gamma(K)}{\Gamma(N+1)N^{K-1}} \approx \frac{1}{\Gamma(N+1)} \tag{A27}$$

$$log\,p(X|\alpha=1) \approx -NlogN + N + \sum_k (N_k logN_k - N_k) \tag{A28}$$

$$= \sum_k N_k log\frac{N_k}{N} \tag{A29}$$

$$= -NH(N_k/N) \tag{A30}$$

E.3. What does the Jensen-Shannon (JS) divergence score capture?

Figure E.1 provides intuition behind the use of the JS divergence score with actual examples. The box at the top shows one paragraph from the policy comments submitted by the Environmental Defense Fund (EDF) and the Sierra Club, both of which are classified as environmental groups with business partners. The box at the bottom represents one paragraph from the EPA's response to the policy announcement. In their comments, EDF and the Sierra Club point out that EPA misunderstood the emission control measure of lower explosive limits (LEL). In response to these concerns, EPA acknowledged learning from the comments and recognized that emission control based on LEL detectors would not work effectively.

The purpose of the analysis using the divergence score in this section is to quantify the influence of policy comments on the policy amendments made by EPA.

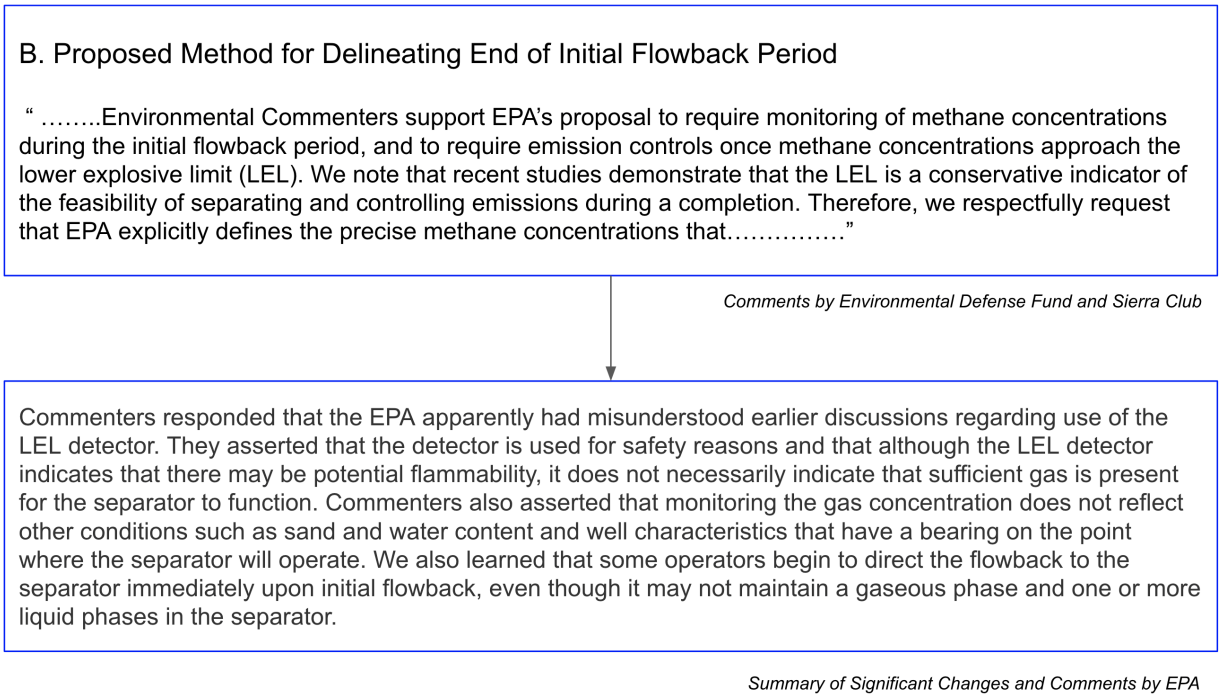


FIGURE E.1. Example: Comments Submitted by the Environmental Defense Fund and EPA's response to the comment

E.4. Analysis Procedure- JS divergence scores

The procedure for calculating the statistical distance is as follows: After adopting the bag of words model, each comment and a set of policy amendments can be represented as a normalized count, or equivalently, as a multinomial probability distribution over words. KL divergence is formally defined as:

$$D(P||O) = \sum_i P_i log(\frac{P_i}{O_i})$$

where P and O are multinomial distributions of the words in comments and policy amendments and the expectation value of the log difference between the two probability distribution is computed with weights of P_i.[2]

However, the KL divergence is an asymmetric measure, resulting in the score for A to B being different from the score for B to A. The algebraic reason is that $D(P||O) - D(O||P)$ is equal to $\sum_i^n ln(\frac{P_i}{O_i})(P_i+O_i)$ and there is no reason for this to be 0. Therefore, the test statistics used in this analysis are inferred from Jensen-Shannon (JS) divergence. JS divergence is defined as

$$J(P||O)) = \frac{1}{2}(D(P||M) + D(O||M))$$

where $M = \frac{1}{2}(P + O)$ is a mean distribution. Figure E.2 represents the density plot of JS divergence scores to a finalized policy.

[2] P_i is equal to $\frac{count(word_i, doc_1)}{length(doc_1)}$. Similarly, O_i is $\frac{count(word_i, doc_2)}{length(doc_2)}$.

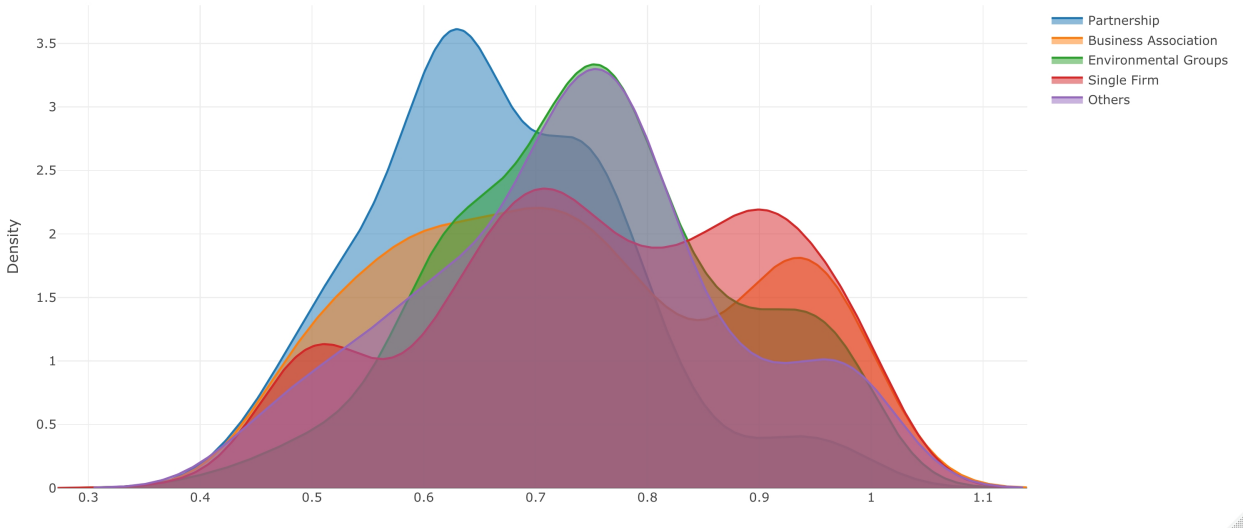


FIGURE E.2. Density Plot: JS Divergence Scores to Policy Amendments

TABLE E.1. Regression Models Estimating JS Divergence Scores and Citation by EPA Officials

	JS Divergence (OLS)		*Citation Counts* (Probit)	
	(1)	(2)	(3)	(4)
Partnership	−0.031***	−0.015*	0.512	1.737**
	(0.003)	(0.009)	(0.679)	(0.720)
Environmental groups	−0.015**		−1.225***	
	(0.007)		(0.396)	
Others	−0.015***	−0.0001	−5.014	−3.789
	(0.006)	(0.001)	(228.534)	(228.534)
Single firm	−0.001	0.014***	−0.445	0.779*
	(0.003)	(0.004)	(0.346)	(0.426)
Business associations		0.015**		1.225***
		(0.007)		(0.396)
Administration FE	−0.001	−0.001	0.869**	0.869**
	(0.001)	(0.001)	(0.380)	(0.380)
Staff Size	−0.00000	−0.00000	−0.00000	−0.00000
	(0.00000)	(0.00000)	(0.00001)	(0.00001)
JS Divergence to a proposed policy	0.917***	0.917***		
	(0.014)	(0.014)		
Parity IGscore	0.002	0.002	0.207	0.207
	(0.004)	(0.004)	(0.497)	(0.497)
Constant	0.083***	0.068***	−1.381***	−2.606***
	(0.012)	(0.010)	(0.387)	(0.494)
Observations	903	903	181	181

*p < .1; **p < .05; ***p < .01

TABLE E.2. Does the signaling mechanism hold without any consideration of partnerships?

	JS Divergence	
	(1)	(2)
Absolute difference between IGscores	−0.015***	−0.015***
	(0.001)	(0.001)
Administration	✓	✓
Staff Size	✓	✓
JS Divergence to a proposed policy	✓	✓
Year FE	✓	

*p < .1; **p < .05; ***p < .01

E.5. The use of rule posted on March 12, 2018, to capture citations patterns

This section further provides visualizations to justify the use of the final rule posted on March 12, 2018, for quantifying the political influence of public comments. Figure E.3 is a part of the final amendment posted by EPA on Sep 23, 2013, after the notice and the comment period [3]. However, while the response by EPA attempts to address the issues raised by commenters, it does not provide specific comment IDs or the names of commenters that were considered by EPA officials to make amendments. Similar to the rule on Sep 23, 2013, other rules were written without references to specific comments, so there have been empirical challenges in clearly identifying whose comments have been considered by EPA officials and what comments have been reflected in the final rule.

Comment: One commenter requested that the final rule specify the date upon which the determination of the potential VOC emission rate should occur for the purpose of determining whether the storage vessel is an affected facility. According to the commenter, since the EPA has stipulated controls to not be cost effective for storage vessels emitting less than 6 tpy of VOC, and emission rates for storage vessels in the oil production segment tend to decrease as production declines, the commenter believes the determination should be made near to the date upon which controls would be required in order to minimize the potential to install controls on storage vessels for which production decline has rendered controls no longer cost effective. The commenter stated that the proposed revisions would require a determination by October 15, 2013, of whether individual Group 1 storage vessels are affected facilities, and thus October 15, 2013, would be an appropriate date upon which determination of the potential VOC emission rate should be based. According to the commenter, this would remain consistent with the requirement for determining the potential VOC emission rate for Group 2 storage vessels by April 15, 2014 or 30 days after startup, whichever comes later.

The commenter appears to suggest that, like Group 2, Group 1 storage vessel affected facilities located in the natural gas processing and natural gas transmission and storage segments should also be required to determine potential VOC emissions as the trigger for installing control instead of tracking events but to do so by April 15, 2015 (instead of April 15, 2014, proposed for Group 2). According to the commenter, control of the relatively low number of Group 1 storage vessel affected facilities in these segments could likely be accommodated by this date.

Another commenter pointed out that the proposed reconsideration rule does not establish the date for a Group 1 storage vessel to determine its potential emissions. The commenter also recommended that notifications are only required for tanks that exceed the 6 tpy threshold on October 15, 2013. Although the publication date of the proposed reconsideration rule was April 12, 2013, the commenter contends that the EPA is not required to, nor should it, establish the emissions determination date for the source category of Group 1 storage vessels on that date. First, given the rapidly declining emissions at storage vessels following initial fracturing, the commenter believes that the expected emissions reduction to be gained from Group 1 storage vessels is likely to be limited. The commenter also states that the proposal date of April 12, 2013, has passed and operators may not be able to accurately back-calculate emissions from that date. Moreover, the commenter contends that emissions from many of these storage vessels will be below the 6 tpy affected source threshold as of October 2013. Given EPA's proposed approach, where storage vessel affected facilities whose emissions drop below 6 tpy remain subject to the standard, the commenter believes that many Group 1 storage vessels will be unnecessarily captured in the source category and required to indefinitely track “events” and perhaps install control devices even if their emissions never again exceed 6 tpy.

FIGURE E.3. A final rule posted on September 23, 2013

[3]The full text is available at https://www.regulations.gov/document/EPA-HQ-OAR-2010-0505-4635

One commenter described configurations at well sites that can lead to an automatic emergency well shut-in and where the rule, if applied as suggested in the preamble, could have unintended consequences. [2] Where well sites have a compressor that collects flash gas from a low pressure separator or a vapor recovery unit that collects flash gas from storage vessels, there are certain safety measures put in place in the event these compressors unexpectedly go offline. Depending on the remoteness of the well site, one safety measure available is to automatically shut in the well to prevent the release of gas from pressure relief valves. In these, and other similar emergency shut-in situations, the equipment is not depressurized so the well can be brought back into production as soon as possible. However, by requiring completion of the delayed repair during such shut-in events, equipment at this well site that have components placed on delayed repair would have to be depressurized and blown down, resulting in emissions that would not have occurred except for the delayed repair requirement and could be higher than the emissions from continuing to delay repair.

A. A Paragraph of a Final Rule

Footnotes

[1] See 40 CFR 60.5397a(h)(2) for delay of repair requirements.

[2] See Docket ID No. EPA-HQ-OAR-2010-0505-12446.

[3] See Docket ID No. EPA-HQ-OAR-2010-0505-12447.

[4] See Docket ID Nos. EPA-HQ-OAR-2010-0505-12421, EPA-HQ-OAR-2010-0505-12424, EPA-HQ-OAR-2010-0505-12430, EPA-HQ-OAR-2010-0505-12436, EPA-HQ-OAR-2010-0505-12446, EPA-HQ-OAR-2010-0505-12447, and EPA-HQ-OAR-2010-0505-12454.

[5] See Docket ID Nos. EPA-HQ-OAR-2010-0505-12430, EPA-HQ-OAR-2010-0505-12436, EPA-HQ-OAR-2010-0505-12446, EPA-HQ-OAR-2010-0505-12447, and EPA-HQ-OAR-2010-0505-12454.

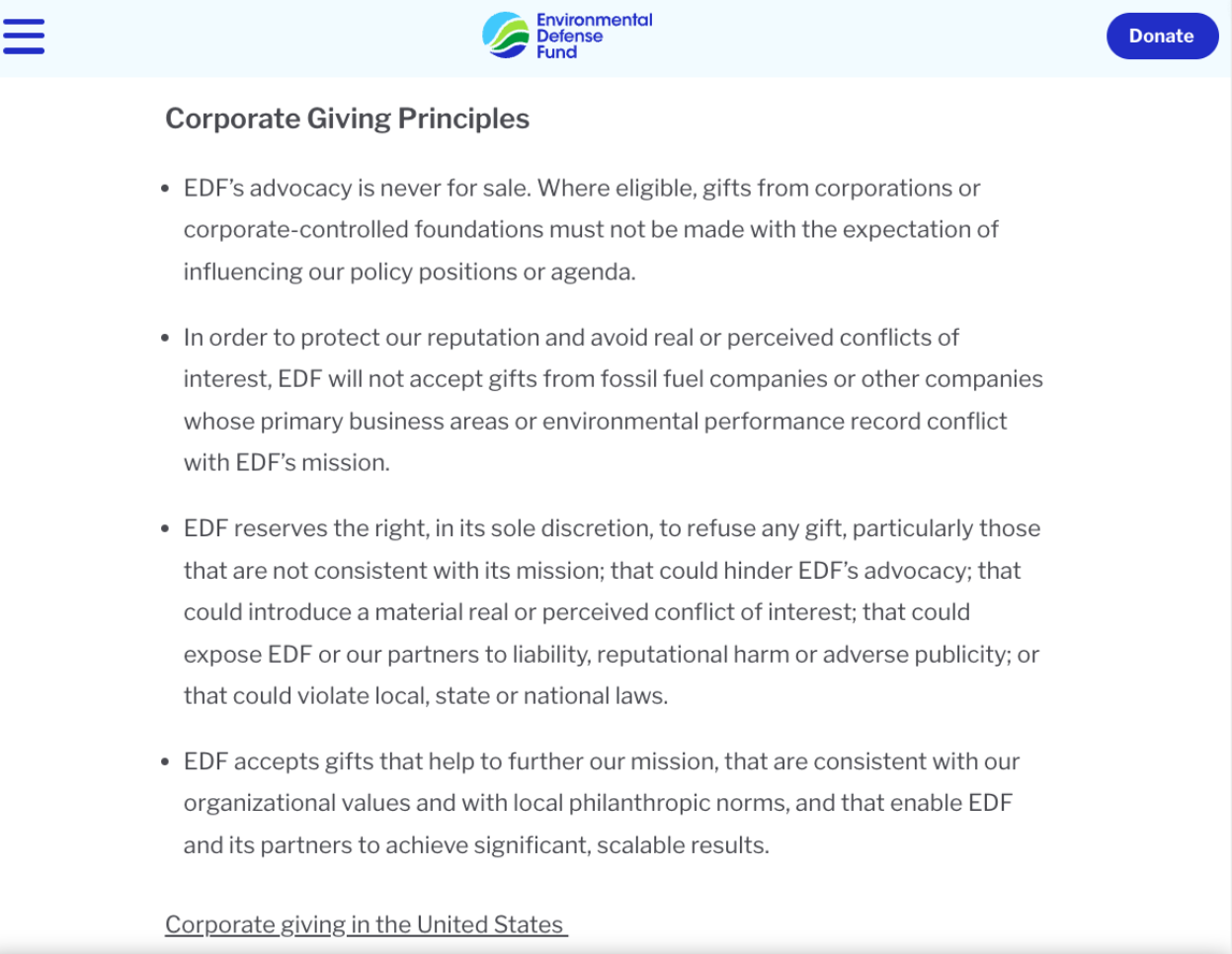
[6] See Docket ID No. EPA-HQ-OAR-2010-0505-12447.

B. Footnote

FIGURE E.3. A Final rule posted on March 12, 2018

However, as shown in the case of the rule posted on March 12, 2018 (Figure E.3),[4] EPA officials explicitly cite comment IDs or commenters in the footnote, in contrast to other final rules focused on Emission Standards. Based on this evidence, we can infer whose comments were considered by EPA officials and influenced the updated policy. Therefore, the analysis, which relies on the citation patterns by bureaucrats, is mainly focused on the rule posted on March 12, 2018. While the analysis is limited to this particular rule, further exploration into responses by EPA officials after the commenting period can further enrich the discourse.

FIGURE F.1. Corporate giving policy of Environmental Defense Fund



F. Corporate Giving Policy of Environmental Groups

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[4]The full text is available at https://www.regulations.gov/document/EPA-HQ-OAR-2010-0505-12503

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