Personnel is Policy: Ideology and Political Misalignment in the Rulemaking Process*

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Abstract

This paper studies how political alignment between bureaucrats and the President affects the rulemaking process in the United States. Combining data on the regulatory process with personnel data and voter registration records, we document the presence of significant agency frictions. While politicians seek political alignment with the rule-writing bureaucrats, expertise mismatches prevent full alignment. We find that rules initiated by regulators that are aligned with the President complete the rulemaking process faster. Linking rules to the Code of Federal Regulations, we find that sections revised by an aligned regulator tend to be more concise and better written. These rules are in turn less likely to attract public opposition and to be challenged in court.

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1 Introduction

Regulatory policy is a crucial tool through which governments around the world advance their political agendas, shaping trillions of dollars of economic activity every year (Trebbi et al., 2023; Coffrey et al., 2020; Crain and Crain, 2023). Rarely, if ever, however, do elected leaders craft specific pieces of regulation themselves. In modern administrative states like the U.S., the responsibility for drafting and implementing legally binding rules is typically delegated to small groups of bureaucrats with deep subject-matter expertise. These technocrats are tasked with developing regulations that are technically sound and achieve the policy goals of their political superiors.

Anecdotal accounts, however, suggest that regulators' personal views may sometimes interfere with this mandate. For example, during the first Trump administration, career staff in the Department of Education allegedly attempted to undermine politically sensitive regulations by producing draft rules that would not withstand legal scrutiny. Similarly, attorneys in the Department of Labor allegedly slow-walked departmental priority regulation to the point where frustrated political appointees gave up on these staff and started to write various policy documents themselves.[1] These episodes are consistent with the "resistance" that emerged within the Trump administration described by Miles Taylor – the then-chief of staff in the Department of Homeland Security – in an initially anonymous op-ed published in The New York Times: "many of the senior officials in his [Trump's] own administration are working diligently from within to frustrate parts of his agenda and his worst inclinations."[2] This type of bureaucratic resistance is at the core of the "deep state" narrative, which accuses unaccountable civil servants of undermining the policies put forward by democratically elected leaders.

In this paper, we go beyond anecdotes of the "deep state" to provide the first systematic examination of the causes and consequences of political misalignment in the federal rulemaking process. Our analysis begins by formalizing the idea that individual regulators may pursue divergent goals through the lens of a principal-agent model. In the model, an agency head who is politically aligned with the President chooses a rule drafter among the pool of regulators employed in the agency. Regulators might be politically misaligned with the President, and misalignment might induce effort distortion: the speed of execution and the quality of the rule might suffer if misaligned regulators put less effort into writing a rule im-

[1] Sherk, James, "Tales from the Swamp: How Federal Bureaucrats Resisted President Trump", retrieved from `https://americafirstpolicy.com/issues/20222702-federal-bureaucrats-resisted-president-trump`.

[2] New York Times, "I Am Part of the Resistance Inside the Trump Administration", retrieved from `https://www.nytimes.com/2018/09/05/opinion/trump-white-house-anonymous-resistance.html`.

plementing a policy they dislike, or if they dedicate effort to include clauses or other details to move policy closer to their preferences. When choosing a rule drafter, the agency head often faces a trade-off between alignment and expertise: the most expert potential drafter may be misaligned with the executive, and the most aligned may lack area-specific expertise. Our simple theoretical framework clarifies that, while misalignment has costs, the agency head will choose a misaligned regulator with expertise over an aligned one lacking expertise if the benefits of expertise exceed these costs.

Guided by our theoretical framework, we empirically study the trade-off between political alignment and subject-matter expertise. To this end, we combine personnel records of the U.S. federal bureaucracy with administrative voter registration data and information on all federal rulemaking activity between the spring of 1997 and the fall of 2023. Important for our purposes, these data allow us to identify the specific individuals responsible for more than 35,000 different regulatory processes. They also allow us to identify their partisan leanings. Drawing on this newly constructed data set, we establish three stylized facts.

First, we find that Democrats are over-represented among federal regulators, both relative to their share in the population as well as relative to their share among employees in the same agencies. Second, individual rulemakers are highly specialized. Regulators tend to work on narrow issues and only on particular parts of the Code of Federal Regulations. Third, expertise is highly concentrated. Within most agencies, only relatively few rulemakers work on the same subject areas.

Building on these observations, we investigate the role of partisanship and expertise in the assignment of regulators to rules. Perhaps surprisingly, we find only small partisan cycles. Although new presidential administrations quickly replace misaligned agency heads and other political appointees (Spenkuch et al. 2023), they do not replace politically misaligned rulemakers to nearly the same extent. Even entirely new rules are only a few percentage points more likely to be assigned to co-partisans. Viewed through the lens of our theoretical framework, the apparent absence of large partisan swings suggests that agency heads prioritize continuity of expertise over political alignment. Consistent with this view, we demonstrate that subject-matter expertise matters much more than partisan alignment in the assignment process. In fact, our results imply that regulators' partisan leanings influence assignments only conditional on them being qualified.

The overall picture that emerges is that regulators are assigned to work on particular rules primarily based on their expertise. Since expertise in a given subject area tends to be concentrated in a small number of individuals, agency heads and political appointees often need to work with misaligned rulemakers in order to change or draft new regulation.

We finally turn to studying the consequences of partisan misalignment. Drawing on

presidential transitions generating "within-rule" variation in political alignment, we find that rules overseen by misaligned regulators take systematically longer to complete. This finding is consistent with anecdotal allegations of slow-walking by politically hostile career staff. We also find, however, that the Office of Information and Regulatory Affairs (OIRA) engages in more drawn-out reviews when a rule is authored by misaligned regulators. OIRA is part of the Executive Office of the President. Among other things, it reviews significant draft regulations to ensure that they align with the administration's policy priorities. Although almost all rules eventually clear OIRA review, the fact this process takes longer when it involves misaligned rulemakers is suggestive of either greater suspicion on the part of OIRA, a higher frequency of (perceived) problems with the rule, or both.

A speedier rulemaking process need not necessarily reflect greater productivity. To speak to potentially quality-related outcomes, we turn to the notice-and-comment process and the content of the regulatory changes. Leveraging state-of-the-art natural language processing tools, we classify more than 700,000 comments as supporting or opposing the rule. We find that proposed rules initiated by politically aligned regulators are less likely to be opposed and more likely to be supported by interested parties. Consistent with misalignment creating actual differences in the text of the rule, our analysis of the Code of Federal Regulation (CFR) – the "stock" of current rules created by executing departments and agencies – uncovers the presence of alignment effects. Drawing on tools from computational linguistics, we show that the sections of the CFR introduced or modified by rules that were authored by misaligned regulators are significantly longer and more difficult to read. In this context, it is important to note that the Plain Writing Act of 2010 requires federal agencies to use clear, concise, and well-organized language; and that OIRA itself uses some of the same tools we do to assess the readability of draft regulations. Absent countervailing effects on other margins, it appears that political misalignment is associated with lower-quality rulemaking.

To further corroborate our interpretation, we rule out the alternative possibility that greater textual complexity is indicative of higher precision and legal accuracy, in which case misaligned rulemakers might produce regulations that are overall better. To that end, we analyze court challenges to major rules, i.e., rules with an annual economic impact of $100 million or more. For each of major rule, legal experts at the Institute for Policy Integrity coded whether that rule had been the subject of at least one federal lawsuit (Goodson et al., 2024). Our final result shows that, if anything, rules authored by misaligned regulators are more rather than less likely to be challenged in court.

Broadly summarizing, our empirical results imply that misaligned regulators produce rules that take longer to review and enact, are more verbose, generate more negative feedback from interested parties, and are, if anything, more likely to be challenged in court. These

findings are consistent with a simple principal-agent model of rulemaking, suggesting the presence of agency frictions due to ideological mismatch.

Our findings imply that the partisan misalignment of regulators comes with a clear cost to their political principals. At the same time, however, our findings do not lend themselves to general statements about welfare. Given that expertise dominates alignment in the revealed preferences of agency heads, the removal of misaligned rulemakers, for example, is likely to decrease the expertise level of the pool of potential rule drafters. Even absent any explicit trade-off between partisanship and expertise, political frictions in rulemaking might be socially desirable in order to constrain the power of the executive. In this sense, the existence of a "deep state" may be good or bad.

Contribution. Our paper contributes to three strands of literature. First, we contribute to the literature on the rulemaking process in political economy. While the study of regulation enjoys a long tradition in economics (e.g., Stigler, 1971), how regulation comes about remains understudied.[3] Our findings on the partisan determinants of rulemaking build on and corroborate earlier efforts – primarily within political science and administrative law – to uncover how ideological conflict between the bureaucracy and political principals shapes the rulemaking process within the U.S. system of separation of powers (for a review, see Yackee, 2019).[4] Potter (2017), for instance, shows that federal agencies can strategically delay rulemaking to avoid political oversight and enhance the likelihood that an agency decision stands, and Bolton et al. (2015) and Acs and Cameron (2013) find that ideological disagreement between the President and agencies increases the time that rules remain under OIRA review. We introduce several innovations to this literature, including the first micro-level investigation of partisan conflict within the executive branch, measured at the level of individual bureaucrats. Additionally, we present the most extensive empirical analysis of rulemaking to date, both in terms of temporal coverage and the number of agencies studied.

[3] In political science the principal-agent model began to be applied in the 1980s, examining the delegation of functions from Congress to legislative committees and bureaucratic agencies (see, for instance, Weingast and Moran (1983); Moe (1987)). However, the within agency rule drafting assignment and the analysis of the whole process of rule making has not been addressed in political science either.

[4] Political science research focused largely on the problem of keeping agents with differing preferences aligned with those of their principals (Gailmard and Patty, 2012). Scholars explored the issue of information asymmetry between principals and agents, with particular attention to the control/oversight mechanisms Congress could employ (see, for instance, McCubbins et al. (1987); Epstein and O'halloran (1994); Gailmard (2002); Huber (2002); Volden (2002); Lowande (2018); Bolton (2022)). The literature consistently emphasizes the trade-off between the costs of institutions and procedures to control agents and the benefits of achieving desired preferences (Bendor, 1988; Gailmard and Patty, 2012). Some theoretical findings suggest that it is not always optimal for the principal to choose agents with aligned preferences (Prendergast, 2003). Similar findings are present in the recent work on loyalism in bureaucracy (see, for instance, Sasso and Morelli (2021). We contribute to this debate by offering the first empirical analysis with individual-level data of the trade-off between expertise and preferences in the context of U.S. bureaucracy.

Our analysis goes beyond traditional outcomes like duration and delay to explore the quality of regulatory text, public support through a comprehensive analysis of comments, and legal challenges in the courts. Our study opens the black box of the regulatory process, studying canonical agency issues between politicians and bureaucrats. To the best of our knowledge, we are the first to link individual regulators to voter registration records, providing novel evidence for the presence of principal-agent frictions driven by ideological differences.

Second, our paper speaks to the literature on the role of ideology in shaping outcomes in organizations. A growing literature in political economy has shown the role of ideology in shaping performance. Within public organizations, Spenkuch et al. (2023) find that bureaucrats ideologically aligned with the President reduce the cost overruns on procurement contracts. Felipe and Tuttle (2024) study police departments in the U.S., providing evidence that marginal applicants to police work are more likely to become conservative once joining the police force. Similarly, Wirsching (2023) finds that the New York Policy Department 911 response time is slower in districts of non-aligned local politicians. In the private sector, Colonnelli et al. (2022) show that Brazilian business owners are more likely to employ copartisan workers, and Chinoy and Koenen (2024) present evidence of significant partisan segregation at the workplace in the United States. Going beyond rank-and-file workers, Fos et al. (2022) document the increasing polarization of the C-suite in the U.S., a pattern driven by an increased assortative matching of executives on political affiliation. In our analysis, we focus on the role of ideology for employees of regulatory agencies, showing its importance in determining a broad range of regulatory outputs and outcomes.

Finally, we contribute to the recent literature on the costs and benefits of regulation, which has become central in political economy (Bombardini et al., 2024; Trebbi et al., 2023), by linking regulatory processes to changes in the code and measuring their quality in terms of length and readability, as well as the consequences of these changes in terms of litigation and public attitudes. In doing so, we link the study of bureaucracy to other lines of work in political economy that have examined the causes and consequences of regulation. Ash et al. (2025) look at the effects of regulation coming from policy learning across U.S. states over the last 50 years. They find that this regulation leads to more economic growth for those topics that are under-regulated and in economic uncertainty periods.[5] On the causes of regulation, Gratton et al. (2021) show that when bureaucracies are overloaded and cannot implement legislation, politicians are incentivized to propose more legislation to signal competence, disregarding the potential negative consequences, as voters will not bear the policy costs due

[5]Other studies look at the situations when regulation is unnecessary and hence it leads to negative outcomes. Osnabrügge and Vannoni (2024) examine the effects of regulation as a consequence of bargaining among EU member states and find that this regulation reduces compliance during implementation.

to implementation failures. Our analysis shifts the attention from politicians' incentives to bureaucrats' incentives. We also look at the consequences of complex regulation, another main topic of this strand, by looking at legal challenges and public attitudes.

2 Conceptual Framework

Consider a world where the agency head – the principal – relies on regulators – agents – to write rules. The agency head and regulators can either have red (r) or blue (b) preferences. Since agency heads are typically political appointees, we assume that their preferences match those of the President. Without loss of generality, we assume that both the President and agency head have red (r) preferences.

Nature gives a mandate to the agency head h to find a way to draft a new rule. The new rule is typically for the implementation of one or more bills that passed in the current or some previous Congress (c). Thus, Nature chooses a rule drafting task that is close to the preferences of the red President with probability p_c, $c = r, b$.

Let there be two regulators that the agency head h can choose for the rule drafting task, namely m and a. Regulator m has blue preferences (is thus misaligned) and ability level θ_m, while and regulator a has red preferences (is thus aligned) and ability level θ_a. To illustrate the trade-off between expertise and agency frictions, we assume that the misaligned regulator has greater expertise than the aligned regulator ($\theta_a < \theta_m$).[6] The agency head h cares about the quality of the rule given her red preferences. The quality evaluation q_r is increasing in both the ability θ and the effort choice α of the regulator. The regulator assigned to write the rule chooses the fraction $\alpha \in [0, 1]$ of time to devote to improving the quality of the rule, while $(1-\alpha)$ goes to activities that do not improve the quality of the rule. This could capture attempts to include details that render the rule closer to the regulator's own preferences, or shirking due to low morale in the case of misalignment. Thus, the aligned regulator a would choose full effort $\alpha_a = 1$, whereas the misaligned regulator would choose $0 \leq \alpha_m < 1$.[7]

The assignment decision by the agency head boils down to whether the ability differential parameter $\Delta\theta = \theta_m - \theta_a$ and its marginal impact on quality q_r are bigger or smaller the marginal impact of differential effort ($\Delta\alpha = 1 - \alpha_m$) on quality q_r. Thus, this guiding model produces, even without specific functional forms, the following set of predictions for the

[6] We will see below that the restriction to this binary choice is only for simplicity, but the logic extends more generally.

[7] If the agency head had blue preferences, utility may not be increasing in both expertise and effort, since a blue agency head h may have the same desire to inject some blue concerns in the rule. Hence the $1 - \alpha$ fraction of effort of the rule drafter would be welcome in that case. That is why we emphasize that what is surely increasing in both θ and α is q_r, i.e. the quality that induces utility for the aligned h.

binary choice of our typical agency head h:

1. **Agency heads:** Whenever the agency head h is faced with the binary choice described above, i.e., in the absence of a possible agent with both high expertise and aligned preferences, the agency head will choose the misaligned agent whenever the $\Delta\theta$ and/or its marginal impact on the expected quality of the rule exceed the expected effort level α and/or its marginal impact on quality.

2. **Rule drafters:** When a regulator chosen to draft a rule has ideological preferences that are different from those of the overseeing principal (the President) the produced rule should be expected to be of lower quality due to the attempts to inject compromise clauses between the opposing objectives and preferences of principal and agent and/or due to lower willingness to exercise maximum care in the precision of the rule, all summarized by a lower α.

In this simple framework involving only a single binary choice, assumptions about the functional form of q_r are not necessary for the above predictions to hold. The specific way in which ability θ and effort α enter the utility of the agency head h, however, matters when faced with a larger set of possible choices.[8] In our empirical setting, multiple agency heads make assignment decisions for different rules spanning varied expertise domains and involving choice sets of regulators with different ability and alignment levels. Our empirical analysis will focus on studying systematic determinants of rule assignment, quantifying the weights regulators assign on average to expertise θ and agency concerns α.

Put differently, our empirical analysis will (i) evaluate whether, on average, agency heads evaluate the misalignment costs to be higher or lower than the expertise gap, and (ii) whether agency frictions are sufficiently large to impact the quality of rulewriting.

3 Data and Context

Our analysis combines data on the rulemaking activities of the U.S. federal government, information on the evolution over time of the text of the Code of Federal Regulations (CFR), and data on the partisan affiliation of registered voters. In this section, we describe the sources of these data, how we link them, and how we use them to construct the variables used in our analysis. Additional details are provided in the Appendix.

[8] For example, if there is a third possible rule drafting regulator who is halfway between the blue and the red preferences, her expected α should be higher than that of the surely misaligned m, and hence she could be the chosen one even if her ability is slightly below θ_m, so that the choice could fall on someone who is neither the most aligned nor the most talented.

3.1 The Federal Rulemaking Process

Federal agencies use the regulatory process to issue and enforce legally binding regulations. This process is primarily governed by the Administrative Procedure Act (APA) of 1946, which established a framework for public participation and transparency in federal rulemaking. The rulemaking process involves several key stages, including the drafting of proposed rules, solicitation of public comments, and the eventual issuance of final rules, affecting the body of regulations – the Code of Federal Regulations (or CFR).

First, an agency identifies a need for regulation, often prompted by statutory mandates, agency-specific policy goals, or emerging issues. The agency then drafts a proposed rule or Notice of Proposed Rulemaking (NPRM), which announces and explains the agency's plan to address a problem or accomplish a goal. This proposal is published in the Federal Register, which is a single, uniform publication for Executive agency rules and notices. The publication includes details about how and when the public can submit comments. Following the publication of the proposed rule, the agency typically opens a public comment period, which generally lasts between 30 to 90 days. During this time, individuals, organizations, and businesses can submit their feedback, raise concerns, suggest modifications, or support the proposal. Agencies are required to review and respond to these comments. After considering the public feedback, the agency may revise the proposed rule and subsequently publish a final rule in the Federal Register. Once published, the rule modifies or adds sections of the Code of Federal Regulations (CFR), which is the codification of the rules published in the Federal Register by the departments and agencies of the federal government. The CFR is organized into 50 titles that represent broad areas subject to federal regulation, and each title is divided into chapters, which usually bear the name of the federal agency responsible for the policy area. Finally, chapters consist of multiple parts, which represent narrower areas of regulation (e.g., Title 12 "Banks and Banking" includes Chapter 2 "Federal Reserve System", which itself includes Part 201 "Extensions of Credit by Federal Reserve Banks").

In crafting the body of regulations, federal agencies do not act in a vacuum and the President has opportunities to influence the pace and direction of major rules. Once the rule is drafted, it can be reviewed by the Office of Information and Regulatory Affairs (OIRA), which is part of the Office of Management and Budget (OMB), an agency within the Executive Office of the President. The OIRA Administrator is appointed by the President and confirmed by the Senate. OIRA reviews all economically significant rules to ensure that agencies comply with the regulatory principles stated in the executive orders and, importantly, that the President's policies and priorities are reflected in agency rules. OIRA review affects two formal stages of the rulemaking process, before the agency issues its NPRM and before it issues the final rule. Rules may be reviewed at one or both of these stages, and

OIRA officials may also provide informal feedback to regulators throughout other phases of the regulatory process. As a result of this review, OIRA can return the rule to the agency for reconsideration. Once OIRA has reviewed the draft and the agency has complied with OIRA's recommendations, a proposed or final rule is published in the federal register.

3.2 Data on the Rulemaking Process

Information on the regulatory activities of U.S. federal agencies comes from the Unified Agenda of Federal Regulatory and Deregulatory Actions (UA). Published seminannually (in the Spring and in the Fall) by the U.S. General Services Administration, the goal of the UA is to provide the public with information about all rulemaking actions under development throughout the government.[9] Each regulatory *process* is identified by a Regulation Identifier Number (RIN), which allows following the development of the regulatory process from its initiation to its completion.[10] The first issue of the UA in which the RIN appears coincides with the moment in which the agency starts working on the regulatory process. Throughout the process, agencies adopt regulatory *actions*, including notices of proposed rulemaking, proposed rules, and final rules. The RIN then appears in each subsequent issue of the UA until the completion of the process and, in the vast majority of cases, the process ends with the publication of the final rule. As an example, Appendix Figure Figure A.1 shows the timeline for RIN 2050-AG83, a regulatory process by the Environmental Protection Agency, which lasted from the Spring of 2015 until the Spring of 2018.

For our purposes, the UA contains two useful types of information on each regulatory process. First, at each point in time, the UA allows us to observe a timetable with all actions that the agency has taken, or plans to take, in order to complete the regulatory process. Panel A of Appendix Figure A.2 shows the timetable for RIN 2050-AG83 in the first issue of the UA in which the RIN appears (Spring 2015), where we observe the intention of the agency to publish a notice of proposed rulemaking in July 2015. Panel B of the figure shows the timetable at the end of the rulemaking process (Spring 2018), where we observe that the notice of proposed rulemaking was published on November 1, 2016, the final rule was completed on February 7, 2018, and it became effective on the same date. This allows us to measure the overall duration of the rulemaking process, as well as the amount of time between the start of the process and the publication of the notice of proposed rulemaking.

In addition, the UA includes rich information on the characteristics of each rulemaking process. Besides the agency in charge, we have information on the priority status that the

[9] Only one issue of the unified agenda was published in 2012.

[10] Throughout the paper, we use the terms regulatory process and rulemaking process interchangeably, whereas we refer to proposed and final rules as regulatory actions.

agency assigns to the rulemaking process, on whether the rule is predicted to have a major economic effect (defined as having an annual economic impact of at least $100 million), and whether the rule will likely impact small businesses.

Crucially for our purpose, the UA includes information on the regulator (or regulators) who are responsible for navigating the rule through the various steps of the rulemaking process (West and Raso, 2012). Appendix Figure A.3 shows information on the two regulators assigned to RIN 2050-AG83.

The final data set for our analysis includes 35,657 regulatory processes initiated between the Spring of 1997 and the Fall of 2023, and 14,848 regulators who are assigned to at least one regulatory action during this period.

3.3 Matching Regulators to Voter Registration Records

In order to recover information on the partisanship of regulators, we link them to the data on the partisan affiliation of U.S. bureaucrats used in Spenkuch et al. (2023), who matched data on federal employees from the Office of Personnel Management (OPM) to the universe of registered voters in the United States.[11]. We match our regulators to this data relying on a combination of name (first name, last name, and middle name when available), agency, and years in which we observe regulators working on a regulatory process. Overall, we are able to recover partisan affiliation for 8,249 of the 14,848 regulators in our data, for a 56 percent matching rate.[12]

4 Descriptive Facts About the Regulatory Bureaucracy

4.1 Who Are the Regulators?

We first begin our empirical analysis by establishing key descriptive facts. Table 1 compares the characteristics of regulators (columns 1–2) with those of other federal government workers (columns 3–4). To facilitate a comparison across both personnel and voter registration data, we restrict the sample to bureaucrats who were linked to the partisan registration data in Spenkuch et al. (2023). In Panel A, we focus on characteristics from the personnel records. On average, regulators tend to be younger at entry into government service than other federal government workers. They also have higher levels of qualification, with 58%

[11]Data on registered voters come from the non-partisan for-profit data vendor L2, Inc. It includes data on the partisan registration of individuals who are registered to vote during at least one election cycle between 2014 and 2020. See Spenkuch et al. (2023) for additional details.

[12]We assign partisan affiliations to regulators only if they are uniquely matched, or if they are matched to multiple individuals only as long as all these individuals share the same partisan affiliation.

holding more than a college degree compared to only slightly more than a quarter for other federal government workers. On average, regulators have served much longer in the federal government. On average, regulators also enjoy higher pay than their non-regulator counterparts. Two thirds of the regulators are stationed in D.C., while only 12% of the other federal government workers are located in the capital.

Leveraging the voter registration data in Panel B, we can also compare the partisanship of regulators with those of other federal government workers. Among regulators, 63% are registered as Democrats, while the share among other federal government workers is 49%. 20.6% (16.2%) of regulators are registered Republicans (Independent), compared to 29% (22%) among other federal government workers.

Figure 1 reports the share of rules that are assigned to bureaucrats with different party affiliations covering 1997–2023, broken down by the major departments and agencies.[13] There is considerable variation in partisanship across agencies. In some agencies, such as the Department of Justice, the Department of Housing and Urban Development, and the Securities and Exchange Commission, Democrats account for more than 70% of regulators. In the Departments of Defense, Agriculture, and Homeland Security, however, a majority of regulators are Republican or Independent.

Regulators are also highly specialized. The high degree of specialization in rulewriting is evident in Figure 2. The figure plots a measure of specialization – the Herfindahl-Hirschman Index (HHI) based on the distribution of assigned rules across different expertise areas as a function of the number of rules a regulator has written. Expertise areas are measured by specific title-chapter-*parts* of the CFR, which represent narrower areas of regulation (see subsection 3.1). As the figure shows, the actual specialization of regulators is high for any given number of assignments.[14] The dashed lines shown in the figure provide benchmarks against which to assess the observed degree of specialization. The long dashed line shows the counterfactual HHI if regulators were randomly assigned to rules within the same agency. The short dashed line shows the counterfactual HHI if regulators were randomly assigned rules across the entire bureaucracy. As both lines show, the corresponding levels of specialization – as captured by the HHI – are substantially lower. Regulators even within the same agency thus do not appear to work across many different subject areas; instead, they are experts specialized in narrow subjects and parts of the Code of Federal Regulation.

[13]The category "Other" includes all departments or agencies with fewer than 500 rules.
[14]Of course, mechanically, the HHI will be 1 for regulators with a single assignment.

4.2 Political Alignment in the Rulemaking Process

The cross-sectional differences in the party affiliation among regulators raise the interesting question of how rule writing might evolve with party turnover at the executive. In particular, if the executive tries to achieve political alignment with the regulator, we expect the presence of political cycles as presidents of different parties turn over.

Figure 3 depicts the total share of Democrats among regulators over time. Panel A does so for all rules, while Panel B focuses on new rules, i.e., rules that were initiated in a given year. Although theoretical models of the bureaucracy suggest that principals have an incentive to assign rulemaking responsibilities to bureaucrats whose preferences are aligned with their own (Epstein and O'Halloran, 1999; Besley, 2007; Lewis, 2008), we do not observe sharp partisan cycles. While new presidential administrations do tend to quickly replace agency heads and other political appointees with co-partisans (Spenkuch et al. 2023), misaligned rulemakers do not appear to be replaced to nearly the same extent. One potential explanation for the absence of huge partisan swings is that organizational norms prevent a complete reshuffling of regulators, especially when rules have already been assigned. Another, related explanation holds that the principal must trade off preference alignment with expertise. If the principal cannot choose from among multiple regulators with technical expertise in the same area, then she may be better off relegating rulemaking to an ideologically misaligned but competent regulator than to a less competent co-partisan.

Although the first-order pattern is one of continuity rather than sharp changes, Figure 3 does hint at (small) partisan effects in the assignment of regulators to rules. In Table 2, we investigate this possibility by estimating variants of the following econometric model:

$$\text{Share Democratic Regulators}_{rt} = \alpha + \beta \text{Democratic President}_t + X_r^{'}\theta + \epsilon_{rt}. \tag{1}$$

Here, Share Democratic Regulators$_{rt}$ denotes the share of Democrats on the team of regulators assigned to rule r at time t. Democratic President$_t$ is an indicator that equals 1 if the president in office is a Democrat and 0 otherwise. X_r corresponds to a comprehensive vector of controls, such as the predicted duration of the rulemaking process, the number of assigned regulators, and the importance and priority of the rule. Since the Unified Agenda allows us to track the progress of each rule over time, we can also include a rule fixed effect to focus on within-rule variation in alignment. In the respective specifications, all identifying variation comes from within-rule over-time changes in the presidency.

The results in Table 2 confirm the existence of small partisan effects in rule-regulator assignments. Taking the estimates in column 2 of both panels at face value, the share of Democrats (Republicans) working on the average rule increases by about 2 percentage points

when a Democratic (Republican) administration takes office. Despite the modest magnitude of the respective coefficients, they are very precisely estimated. Importantly, we continue to observe changes in regulator alignment even after including rule fixed effects. Regulators, in most cases, cannot be hired and fired at will, but agency heads have the power to pick specific individuals to work on a given rule. The evidence in column 4 implies that new administrations do tend to change at least some pre-existing assignments. The modest size of the estimated effect, however, suggests one of two things. Either partisan alignment is not terribly important to agency heads, or organizational constraints prevent them from acting on their partisan biases. To provide some evidence on the importance of organizational constraints, column 3 restricts attention to new rules, for which such constraints are presumably less important. Consistent with this idea, the estimated coefficients more than double relative to their counterparts in column 2. The evidence, therefore, suggests that agency heads cannot, for the most part, implement their preferred levels of partisan alignment.

4.3 Barriers to Political Alignment: the Role of Expertise

We now provide corroborating evidence for the trade-off between seeking political and expertise alignment. To do this, we study the assignment decisions of the principals at the "choice level." For every rule r, we identify the set of potential regulators $i = \{1...N_r\}$ who could be assigned the rule. Specifically, we define a regulator i to be a potential candidate to write rule r if the regulator is (i) working in the same bureau or agency where the rule is initiated and (ii) is observed writing rules before and after the rule of interest.

We define regulator i to have the technical expertise required for rule r if the regulator has been assigned to write a rule covering the same subject areas in the past. Specifically, we consider the title-parts of the Code of Federal Regulation (CFR) that rule r is seeking to modify or integrate.[15] We then construct a dummy that is 1 if regulator i had previously already worked on a rule dealing with at least one of the same title-parts. For the average rule, 13 percent of the regulators who can potentially be assigned the rule have the relevant technical expertise, reflecting the highly specialized nature of rulewriting.

For each of the potential candidates to be assigned to writing a given rule, we relate a dummy denoting their actual assignment to the rule $d_{ir} = \{0, 1\}$ to the individual's alignment status and expertise status:

$$d_{ir} = \beta \text{Aligned}_{iT(r)} + \gamma \text{Expertise match}_{ir} + \theta_r + \varepsilon_{ir} \quad (2)$$

[15] Recall that the CFR is organized into 50 titles (representing broad areas of policymaking), which are subdivided into parts (covering specific regulatory areas).

where $\text{Aligned}_{iT(r)} = 1$ if the regulator i is politically aligned with the president at the time of rule initiation $t = T(r)$, and $\text{Expertise match}_{ir} = 1$ if regulator i has the technical expertise required by rule r. θ_r are rule fixed effects that restrict the comparison of choices and candidate characteristics to those within the same choice set. ε_{ir} is the error term, and the standard errors are clustered at the rule-level.

Table 3 reports the regression results. To aid legibility, the dependent variable is rescaled by 100. Column 1 includes only rule fixed effects, while columns 2 and 3 progressively include fixed effects for the experience of the regulator, measured as the number of rules on which the regulator has worked in the past, as well as individual regulator fixed effects. We find that regulators with matching technical expertise are significantly more likely to be assigned a rule. The magnitude of the point estimate is orders of magnitude larger than the role of political alignment, whose coefficient becomes insignificant once we include regulator fixed effects (column 3). Put differently, when we consider the assignment decisions of the principals at the "choice level," the alignment status of the potential regulator has a much smaller effect than technical expertise on the probability of being chosen to write the rule.

In column 4, we explicitly test for a potential trade-off between aligning expertise vs. politics by asking whether the alignment effect differs depending on the availability of technical expertise. As the interaction shows, aligned regulators enjoy a higher likelihood of being assigned a rule if their expertise also matches the requirements of the rule. While principals do appear to value achieving political alignment in rule writing, they only do so if it does not come at the expense of assigning the rule to a regulator with no relevant expertise.

5 Political Alignment and the Speed of Rulemaking

The descriptive findings from the previous section suggest that politicians seek ideological alignment with their regulators. At the same time, frictions due to expertise mismatches – the lack of politically aligned regulators with relevant rule-writing skills – prevent the principal from always attaining full alignment. This raises the intriguing question of whether variation in the political alignment of regulators matters for the rulemaking process.

The major empirical challenge in relating political alignment to rulemaking outcomes is that the assignment of regulators to rules is not random (see section 2). In what follows, we rely on two distinct sources of variation in political alignment to test for the presence of alignment effects: (i) within-rule variation in political alignment over time and (ii) within-regulator (team) variation in political alignment across rules. In this section, we first focus on within-rule variation in political alignment.

5.1 Completion and Within-rule Variation in Alignment

There exists substantial variation in how quickly rules move through the bureaucratic process. While the average duration from rule initiation to completion is 654 days, the interquartile range is as high as 765 days. We first ask whether political alignment affects the speed of the rulemaking process.

To implement this analysis, we construct a dataset at the rule-year-month level to conduct our duration analysis. We proceed in several steps. First, we restrict the sample to rulemaking processes that appear at least in two UAs.[16] We then restrict the sample to completed rules that we could match to regulators. The final analysis sample contains 16,204 rules, making up 398,937 rule-year-month observations.

For the duration analysis, we estimate the probability of completion at each rule-year-month. For the rule r observed in month t, we estimate:

$$y_{rt} = \alpha_r + \gamma_{K(r,t)} + \beta \text{Share_Aligned}_{rt} + \zeta x'_{rt} + \varepsilon_{rt} \tag{3}$$

where $y_{rt} = \{0, 1\}$ denotes whether the rule is completed or not in a given year-month. Rules that are completed in t are excluded from the analysis in $t + 1$. $\text{Share_Aligned}_{rt} = [0, 1]$ denotes the share of regulators assigned to the given rule that are co-partisans of the president.[17] α_r are rule fixed effects, $\gamma_{K(r,t)}$ are agency $\times$ start-time $\times$ duration fixed effects; x'_{it} is a vector of rule-level covariates: priority, major, RFA, and the number of regulators. Finally, we cluster standard errors at rule-level r, corresponding to the level at which regulators are assigned.

With these fixed effects in place, we compare rules initiated by the same agency in the same year-month at each point in time, asking whether rules overseen by a larger fraction of regulators contemporaneously aligned with the president are differentially likely to be completed. Leveraging within-rule variation through the inclusion of rule fixed effects, variation in alignment is thus driven by (i) presidential transitions that result in a party change (ii) the reassignment of regulators. The empirical analysis thus compares the same rule over time, asking whether changes in party alignment is predictive of rule completion.

Table 4 reports the results. All regressions include rule FEs and the granular agency $\times$ year $\times$ duration FEs. To aid legibility, we rescale the dependent variable to reflect percent (i.e., ranging from 0-100). As columns 1–2 show, we find systematic evidence that greater

[16] We define the start of a rule process by the date it was first published in the Unified Agenda. This means that we can only compute the durations for rules that appear at least in two UA publications.

[17] Of course, for rules overseen by a single regulator, the variable is binary. In robustness checks, we show that our results hold when restricting the sample to only rules overseen by a single regulator or rules that are initiated under full alignment or full misalignment.

alignment between the regulator and the executive party increases the likelihood a rule is completed at any given time. The point estimates increase when including rule-level controls, with full alignment (relative to full misalignment) increasing the probability of rule completion by 7–15% relative to the unconditional compeltion rate of 3.7%.

Rules can be completed in two ways: by resulting in a rule change made to the Code of Federal Regulations (CFR), or by being withdrawn. In columns 3–4, we break down the overall completion result by asking whether the alignment effects are driven by a greater failure or success rate. Interestingly, we do not find that contemporaneous alignment results in being withdrawn at a differential rate (column 3). Instead, the results suggest that the alignment effects are primarily driven by a greater likelihood of a rule to result in a successful change to the CFR (column 4).

5.2 Political alignment and OIRA review

We now complement the previous analysis to focus on reviews of rules conducted by the Office of Information and Regulatory Affairs (OIRA). Situated in the Executive Office of the President, OIRA reviews are considered a key tool through which the president can align the content of proposed and final rules with its priorities. As such, OIRA reviews have been considered a "check in the rulemaking efforts of career agency officials" (Yackee, 2019). If the content of the rule differs depending on the political ideology of the regulator, we expect alignment to be predictive of the speed of rulemaking.

All major rules (i.e., those with an estimated economic impact of more than $100 million) are required to undergo the review process at OIRA. Such reviews can occur at two stages of the rulemaking process – before the public commenting process, or before publishing the Final Rule. While almost all rules ultimately pass OIRA review, there exists significant variation in how long the review process takes. While the average OIRA review takes 71 days, the interquartile range is 67.

Table 5 relates the overall duration of the OIRA review with the alignment status of the regulator at the time the rule is submitted for review. As the results show, a higher share of politically aligned regulators expedites the OIRA review. This holds both in the most parsimonious specification (column 1) as well as the specification including rule-level controls (column 2). We can also exploit the fact that rules often undergo OIRA review *multiple* times throughout the rulemaking process. This allows us to include rule fixed effects and exploit within-rule variation in alignment due to presidential turnover or changes in the composition of regulators. Reassuringly, for the subset of rules that undergo multiple OIRA reviews, we still find that alignment goes hand in glove with shorter review periods (column 3).

Finally, we ask if alignment predicts whether OIRA submissions are withdrawn or returned (column 4). Consistent with the fact that almost all rules ultimately pass OIRA review – only 6.5% of the rules are withdrawn or returned to the rulewriting agency – we do not find that alignment affects this extensive margin. Overall, the fact the review process takes longer when it involves misaligned rulemakers is suggestive of either greater suspicion on the part of OIRA, a higher frequency of perceived problems with the rule, or both.

6 Political alignment and regulatory outcomes

Our results so far suggest that greater political alignment between the regulator and President is conducive to a faster rulemaking process. Motivated by this finding, we probe deeper to understand whether aligned rules also differ on other margins. In particular, faster rulemaking may come at the expense of quality.

A major empirical challenge in the study of rulemaking is the lack of direct and comparable quality measures. In what follows, we study a range of quality-related measures that paint a coherent picture consistent with potential costs for the principal.

6.1 Political alignment and public support

Public participation in the rulemaking process is a key principle enshrined in the Administrative Procedure Act, aimed at promoting transparency and accountability in agency policymaking (Haeder and Yackee, 2015). Interested parties, both individual citizens and organizations, can submit public comments on agencies' proposed rules during the so-called "notice-and-comment" period. Comments may support or oppose a proposed rule and may contain recommendations or evidence that the authors wish the agency would consider before issuing the final rule. The proposed rule, along with the public comments submitted, serves as the foundation for the final rule. While agencies are not legally required to incorporate criticisms raised during the commenting period, they are obligated to respond to what the courts have characterized as "significant" comments (Garvey, 2017; Yackee, 2019).

Besides promoting transparency, public comments represent large unstructured data which we use to infer public support for a proposed rule. Since 2003, members of the public can submit comments electronically through Regulations.gov, a platform where the majority of federal agencies post regulatory documents and solicit feedback. Regulatory materials are organized in dockets, which are a collection of documents (e.g., proposed and final rules) and materials referenced therein. A detailed description of the way the data is organized on Regulations.gov and how we accessed it is reported in subsubsection A7 in the Appendix.

For each one of the 35,063 regulatory processes in our sample, we extract all actions that are classified as proposed rules or notices of proposed rulemaking in the Federal Register. We remove all actions issued before 2003, when Regulations.gov was launched, for a total of 20,499 proposed rules. Since agencies started partnering with Regulations.gov at different times, we successfully retrieve information for 15,346 rules, 10,175 of which received at least one comment. We locate a total of more than 13 million comments submitted to the rules in our sample, with an average of 874 comments per proposed rule. For each proposed rule, we download all posted comments if the total number of comments is up to 20, and for proposed rules that received more comments, we download a random sample of 5% of comments.[18]

We download all the comment-level data including the author of the comment and text of the comment, for a total of 722,545 comments. Most of the comments, especially those submitted by organizations, are uploaded as attachments in PDF, Microsoft Word, or simple text files. We download the attachments and extract the text performing, when necessary, optical character recognition.

To determine whether a comment expresses support or opposition toward the proposed rule, we build on recent advancements in stance detection. Specifically, we rely on natural language inference (NLI) models designed for entailment classification tasks. These models estimate the probability that a document *entails* a given statement. For example, the comment "I fully support the EPA initiative." has a high probability of entailing the statement "The author of this comment *supports* the proposed rule." NLI operates by taking a premise (i.e., the text of a comment) and a set of hypotheses (e.g., statements such as "The author `supports`, `opposes`, or `is neutral toward` the proposed rule") and identifying the hypothesis most likely to be true based on the comment's text (Burnham, 2024).[19]

55% of comments are classified as conveying a negative stance towards the proposed rule, whereas 37% have a positive stance. The remaining 8% of comments are classified to have a neutral stance. To measure public support for the proposed rule, we group all comments at the rule-level and compute the share of comments with negative and positive stances.[20]

[18] We are in the process of downloading the universe of comments submitted to all proposed rules.

[19] Our approach is superior to standard sentiment analysis, for research shows that stance (i.e., a position or belief about an issue) is often uncorrelated with sentiment (Bestvater and Monroe, 2023). In subsubsection A7 in the Appendix, we report several examples of comments classified as having a positive, negative, or neutral stance and how stance relates to sentiment polarity.

[20] Among the proposed rules with the largest share of opposing comments, there is the Department of Education's rule aimed at clarifying the "obligation of all schools [...] to provide an educational environment free from discrimination on the basis of sex, including through responding to incidents of sex discrimination.", with 86% of opposing comments and a total number of comments equal to 238,987, of which we analyzed a random sample of 12,177. Conversely, the rule proposed by the Department of Defense aimed at "amending the Federal Acquisition Regulation (FAR) to ensure that major Federal agency procurements minimize the risk of climate change" received significant support from interested parties, with 99% of the 1,749 comments analyzed supporting the proposed regulation.

To establish whether proposed rules written by misaligned bureaucrats receive greater criticism from stakeholders, we relate the share of opposing and supporting comments with the share of aligned regulators when the rule was initiated.

Table 6 reports the results. As outlined above, the sample is restricted to rules that underwent the NPRM process and where comment data was made publicly available. All results include regulator team FEs, which restrict the comparison to rules overseen by the same set of regulators but with differing alignment status depending on the president in office. Overall, we find that rules overseen by aligned regulators – as measured by the share of aligned regulators assigned at rule initiation – are significantly less likely to attract comments with a negative stance. While 35% of the comments submitted typically oppose the rule, the fraction of comments with a negative stance declines by 4 p.p. – corresponding to a decline by 11% (column 1).

In column 2, we add controls to hold constant additional observable differences that vary at the rule-level. The results remain comparable, if anything increasing in magnitude. Finally, column 3 also studies the extent to which comments are positive and supportive of the rule (as opposed to negative or neutral). As column 3 shows, we find that initial political alignment also increases the propensity for a rule to be supported. Taken together, the results provide evidence that misaligned rules are met with greater opposition when evaluated by interest groups and the broader public. This is consistent with alignment increasing the quality of the rule.

6.2 Political alignment and CFR outcomes

Measuring changes to the CFR. In order to measure the impact of rulemaking actions on federal regulations, we leverage the text of final rules issued by agencies at the end of the regulatory process. These are published in the Federal Register, the official daily journal of the Federal Government. Each final rule modifies the Code of Federal Regulations (CFR), which represents the stock of regulations, and is published yearly.

For each regulatory action, we identify the final rule published on the Federal Register and we extract the full text, for a total of 36,139 final rules.[21] The text of the final rule includes several sections: a summary of the rule, the effective date the rule, the background of the regulatory actions, a discussion of the comments submitted by stakeholders, as well as a summary of the results of the analyses conducted by the agency in compliance with the

[21] The number of final rules (36,139) is greater than the number of regulatory actions (35,657) because each regulatory action can include multiple documents classified as "Rule" on the Federal Register. For example, agencies can issue rules that delay the effective date or amend some portions of previously issued rules, or offer guidance on how to interpret the rule content.

various executive orders governing the rulemaking process (e.g., cost benefit analysis). The text includes the changes made by the rule to the Code of Federal Regulations.

For example, the final rule of the EPA regulatory action presented above (RIN 2050-AG83) was published on February 7, 2018 with the title "Additions to List of Categorical Non-Waste Fuels: Other Treated Railroad Ties". The rule aims to modify CFR Title 40 "Protection of Environment", Part 241 "Solid Wastes Used as Fuels or Ingredients in Combustion Units". Specifically, the section *List of Subjects* in the text of the final rules lists all the changes that the rule makes to the various sections of Part 241.

Our first goal is to measure how each final rule affects the text of the CFR, essentially comparing the text before versus after the rule becomes effective. Unfortunately, the text of the final rule does not easily allow this comparison: while it includes a description of the changes that the rule implements to each section of the code, it does not allow to precisely reconstruct the new text of the affected sections of the code. To overcome this challenge, we obtain from the text of the final rules the list of sections affected by the final rule. We then compare the text of the CFR sections in the year immediately before the rule became effective to the text of the CFR sections published after the rule became effective. This allows us to measure, for each final rule, and for each section affected by the rule, the characteristics of the text before versus after the rule was codified in the CFR. While in most cases the rule amends the text of an existing section, sometimes the rule deletes a section of the CFR or adds a new section to the CFR.[22]

Estimation. To study how political alignment affects regulatory complexity, we map rules r to the sections i of the CFR they aim to revise.[23] For the complexity measure of section i modified by rule r, we estimate the following regression model:

$$y_{ir}^{Post} = \beta \text{Share_Aligned}_{r0} + \alpha y_{ir}^{Pre} + \gamma' x_r + \theta_{T(r)} + \tau_{P(i)} + \varepsilon_{ir} \tag{4}$$

where y_{ir}^{Post} captures the post-revision outcome and y_{ir}^{Pre} captures the pre-revision outcome. $\text{Share_Aligned}_{r0} = [0, 1]$ captures the share of regulators that are aligned with the president at time of rule *initiation*. x_r is a vector of rule-level characteristics: dummies indicating the priority level of the rule, whether it is a major rule, or falls under the Regulator Flexibility Act. We also include a rule-level measure capturing the predicted duration of the rulemaking process. In all regressions, x_r also captures flexible dummies holding constant the actual timing of the rule making process: granular department $\times$ start-month year FEs to restrict the comparison to rules initiated in the same department and year-month; and department

[22] Section subsection A in the Appendix provides additional details on this step of the data construction.

[23] The mapping of rules r into sections i may result in multiple rules revising the same section in the same year. In this case, we reweigh the data to assign equal weight to each rule.

$\times$ end-month year FEs to restrict the comparison to rules that are completed and effective in the same department and year-month.

The major empirical challenge in this setting is that regulators are not randomly assigned across rules. Indeed, as Table A2, columns 1–2 show, aligned regulators are more likely to be assigned to major rules and rules that fall under the RFA. While the inclusion of the baseline complexity measure and observable rule characteristics help allay some of these endogeneity issues, concerns over the endogenous assignment based on unobservable characteristics correlated with the revision outcome may still remain. To make progress, we include two sets of additional fixed effects. First, we include regulator (team) fixed effects $\theta_{T(r)}$. These fixed effects ensure that we compare only sections and rules assigned to the same regulators aligned vs. misaligned due to turnover of the presidential party. To the extent that certain regulators (e.g., by virtue of their specialist knowledge) tend to be systematically assigned different rules and sections in a time-invariant manner, these fixed effects will purge such cross-sectional differences. Second, we can also include granular fixed effects capturing differences in sections that are targeted in revisions. In particular, we include CFR title-part FEs, which group sections into broader topics (i.e., a part has on average 100 sections). These fixed effects account for the fact that some parts of the federal code tend to be harder to write than others, or more likely than others to be allocated an aligned officer.

With these fixed effects in place, the identifying assumption is that the residual variation in initial alignment is as-good-as-random. In Table A2, column 3, we show that – once conditioning on the department $\times$ time, regulator and CFR part FEs, alignment is largely uncorrelated with characteristics. If anything, we find that aligned regulators are ex-ante assigned to more complex sections, with greater word count and longer words. ε_{ir} is the error term. We cluster standard errors at the rule-level r, corresponding to the level of assignment.

Table 7, Panel A reports the results relating political alignment at the rule making stage to measures of complexity. We first focus on the post-rule word count as a crude measure of word complexity. We find consistent evidence that sections revised through rules overseen by aligned regulators tend to be significantly shorter. Comparing sections revised by the same "team" of regulators, we find that those sections revised through rules under greater overall alignment are significantly shorter (column 1). This pattern holds when including a rich set of rule-level controls (column 2). These include dummies capturing differences in the type of rule (significant, major, under RFA), as well as a summary measure of predicted delay (see Table A1). The results also hold up using variation in political alignment at the time of rule initiation (column 3). Finally, in column 4, we further refine our comparison by including fixed effects for each title-part of the Code of Federal Regulations (CFR). These fixed effects account for the fact that aligned regulator teams might be systematically assigned to revise

different passages of the CFR. If anything, the inclusion of these fixed effects increases the point estimates. Overall, alignment reduces the post-rule word count by 7.5-9%, relative to the mean section's word count.

In Table 7, Panel B, we probe deeper to understand whether the increase in text is driven by an increase at the extensive or intensive margin. Specifically, the CFR can change in complexity through the addition or deletion of sections. In columns 2–3, we ask whether political alignment affects the likelihood of new sections or parts to be added.[24] As the results show, we do not find that the alignment effects are driven by the extensive margin – the addition or removal of sections. Instead, our alignment results even show up when excluding newly added or removed sections (column 4). This suggests that the alignment effect is driven by the increase in complexity – as captured by the word count – in the intensive margin.

While simple, the section word count is an arguably crude measure of complexity. For example, shorter sections may be less comprehensive and incomplete, making the law harder to interpret. We thus complement our results by drawing on "readability" scores, which provide a summary measure of how readable a text portion is independent of the overall word count. Our main focus is on the Flesch/Flesch-Kincaid scores – two widely used and validated measures of readability that are also referred to in the Plain Writing Act of 2010. Both measures are computed as a weighted average of two factors: (i) the total words / total sentences and (ii) the total number of syllables / total words.[25] This readability index reflects the intuition that longer sentences and longer words are harder to read. In robustness checks, we repeat our exercise using a wide range of alternative readability measures.

Table 8 reports the results. We rely on the most stringent specification of Table 7 as the preferred specification throughout. In columns 1–2, we first focus on how alignment affects each of the two components of the Flesch/Flesch-Kincaid readability scores. This provides a more transparent summary of where any potential changes in the readability scores come from. Interestingly, we find that political alignment decreases the average sentence length (column 1), while leaving the average syllables per word unaffected (column 2). Overall, we observe a significant improvement in readability using both the Flesch and Flesch-Kincaid measures. On average, aligned sections tend to have a readability score that is 0.03 SD higher than misaligned sections. This suggests that sections revised by rules overseen by

[24] For sections that are removed, the post-rule word count is 0. Similarly, for sections that are added, the pre-rule word count is 0.

[25] The Flesch score is computed as `Flesch = 206.835 - 1.015 (total words/total sentences) - 84.6 (total syllables/total words`. The Flesch-Kincaid score is computed as `Flesch-Kincaid=0.39 (total words/total sentences) + 11.8 (total syllables/total words)-15.59`. We standardized our readability scores, inverting the Flesch-Kincaid score so that higher numbers always indicate greater readability.

aligned regulators are not only more concise, but also more accessible.

Our results hold up to a range of robustness checks. To ensure that our results are not driven by outliers, we show that our results are robust to different winsorization cut-offs Table A4. Importantly, the results also hold up using a range of alternative readability scores. In Figure 4, we summarize the alignment coefficients for a range of readability scores. All scores are standardized and transformed so that higher numbers indicate greater readability. As the figure shows, we observe a consistently positive alignment effect on readability throughout the plurality of readability scores. When taking the standardized index across all scores, we still observe a consistently positive alignment effect – greater alignment increases the readability of the revised section.

6.3 Political alignment and legal challenges

So far, our evidence suggests that rules overseen by misaligned regulators (i) take longer to complete and pass the OIRA review process (ii) are more likely to attract negative comments and (iii) tend to be lengthier and less readable. Although this combined evidence is consistent with the interpretation that misaligned rules are associated with negative outcomes, it is still unclear whether the resulting rules are necessarily of lower quality. For example, it could be that greater textual complexity is indicative of higher precision and legal accuracy, in which case misaligned rulemakers might produce regulations that are better overall.

In order to provide additional evidence to adjudicate between these two interpretations, we analyze court challenges. Federal lawsuits are a common tool for interest groups to challenge rules. At the same time, lodging federal lawsuits is a costly process. Basic economic theory suggests that the propensity to challenge a rule in court is increasing with the probability of success. Assuming that poorly written rules are less likely to withstand legal scrutiny, we can thus study differences in the propensity of aligned vs. misaligned rules to be challenged as a measure of the rule's underlying quality.

We leverage a database by the Institute for Policy Integrity, which tracks federal court challenges to major rules, i.e. rules with an annual economic impact of $100 million or more, covering all rules finalized between 1993–2023. For each of the major rules in our sample, legal experts coded whether that rule had been subject of at least one federal lawsuit. We test whether this measure varies by misalignment.

Table 9 shows the results. As the mean of the dependent variable suggests, almost a quarter of all major rules are challenged in court. Rules that are – at time of initiation – assigned a larger share of aligned regulators, however, are 5.2 p.p. less likely to be challenged (column 1). Note that this specification relies on the comparison of aligned vs. misaligned

rules issued by the same agency in the same year. As such, our results do not simply capture the fact that certain agencies tend to face more legal challenges under certain administrations. For example, the inclusion of the Year × Agency FEs rule out that rules finalized by the EPA under a Democrat president are more likely to face partisan legal challenges – challenges that might be lodged irrespective of whether they are likely to succeed or not.[26]

Columns 2–3 demonstrate the robustness of the results when including more stringent controls and fixed effects. The results remain very comparable when including rule-level controls to capture potential differences in rules correlated with alignment (column 2). Importantly and strikingly, the results hold up – even increasing in point estimate – when including regulator team fixed effects (column 3). While the estimates are admittedly less precise given the number of major rules, both point estimates and statistical significance remain stable throughout. Overall, rules overseen by aligned regulators are less likely to be challenged in court, consistent with the interpretation that aligned rules are of better quality.

7 Conclusion

Regulatory policymaking is a cornerstone of modern governance. Politicians and lawmakers rely on regulatory agencies to translate broad policy objectives into specific rules that govern the economy and society. This delegation of regulatory tasks to bureaucrats creates a theoretical trade-off between expertise and control. On the one hand, bureaucrats possess the specialist knowledge and experience to implement policies. On the other hand, however, they may not necessarily agree with the policies chosen, giving rise to potential agency frictions. Empirical evidence documenting the presence of such frictions, however, has remained elusive due to data constraints.

In this paper, we open the black box of the regulatory process. Combining data from the U.S. rulemaking process with personnel and voter registration records, we study the role of political alignment between regulators and the President in the rulemaking process.

Our empirical results uncover the presence of significant agency frictions within the U.S. federal bureaucracy. While expertise remains the dominant factor in the assignment of regulators to rules, politicians exhibit a systematic preference for assigning rulewriting tasks to politically aligned regulators. The uneven distribution of partisanship across regulators, however, limits the extent to which assigned regulators can always be aligned.

Our findings highlight real consequences of political misalignment. Bureaucrats who are misaligned with the administration in power tend to produce rules that take longer to

[26]Unfortunately, limited sample size and variation in the outcome prevents us from testing whether the success rate of challenges varies by alignment. Overall, only 30% of the challenges are successful in court.

complete and attract more negative feedback during the public commenting process. Importantly, misalignment also shapes final regulatory outcomes. Leveraging natural language processing methods to analyze changes to the codification of regulation in the Code of Federal Regulation, we find that rules overseen by misaligned regulators are more likely to result in amendments that make the resulting text longer and harder to read. Finally, we provide tentative evidence that rules written by misaligned regulators are also more likely to be challenged in court. These combined findings are inconsistent with a "Weberian bureaucracy, " in which regulators act as technocrats that efficiently implement the goals of their political superiors.[27] Instead, our results highlight the importance of political alignment and agency frictions throughout the rulemaking process.

Our research also points to open questions. While our findings imply that partisan misalignment of regulators bears costs to the political principals, the implications for welfare are ambiguous. While our study demonstrates the costs of political misalignment, it also raises important questions about the desirability of a fully politicized bureaucracy where perfect political alignment can be attained. Political frictions, for example, may help dampen abrupt changes in policy by constraining the power of the executive. Future research might explore the balance between political control and bureaucratic independence, as well as the broader consequences of misalignment on economic and social outcomes.

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[27] Max Weber famously argued that "bureaucracy develops the more perfectly, the more it is 'dehumanized', the more it completely succeeds in eliminating [...] all purely personal elements" (Weber 1922).

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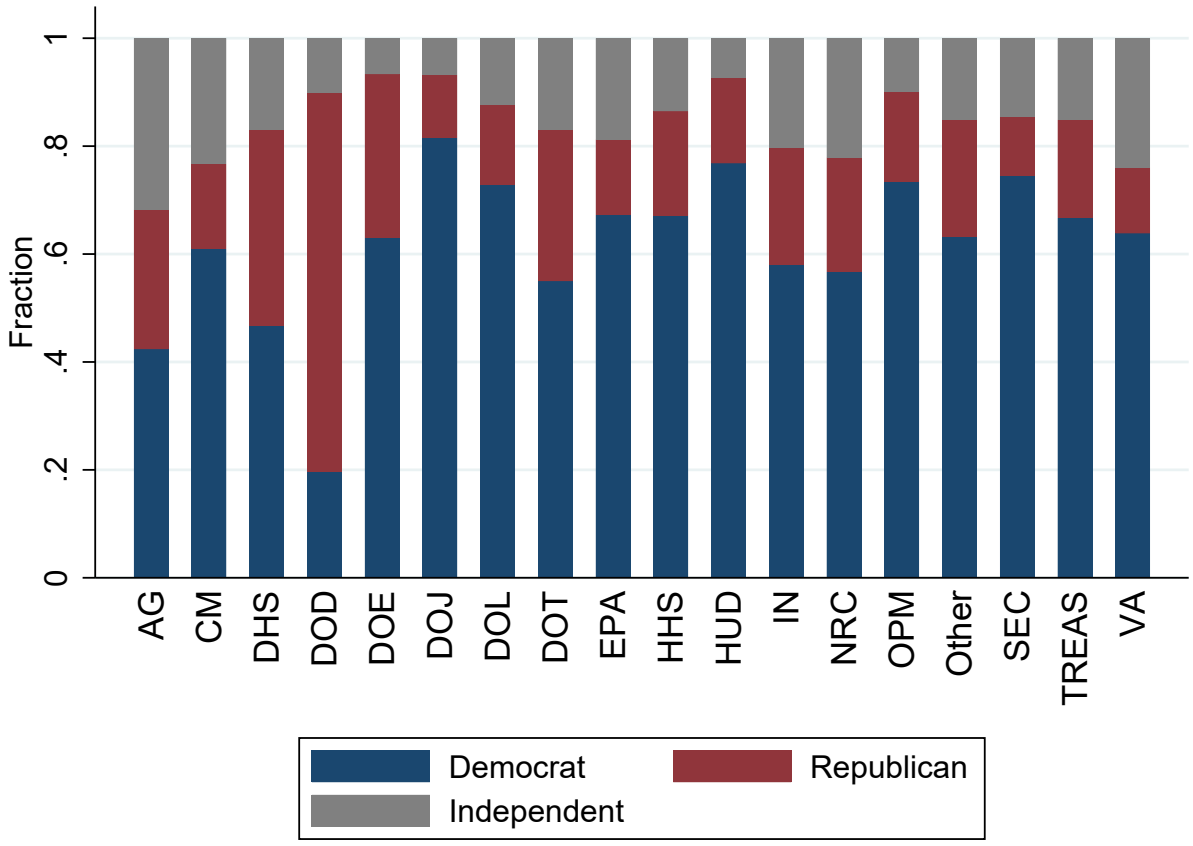
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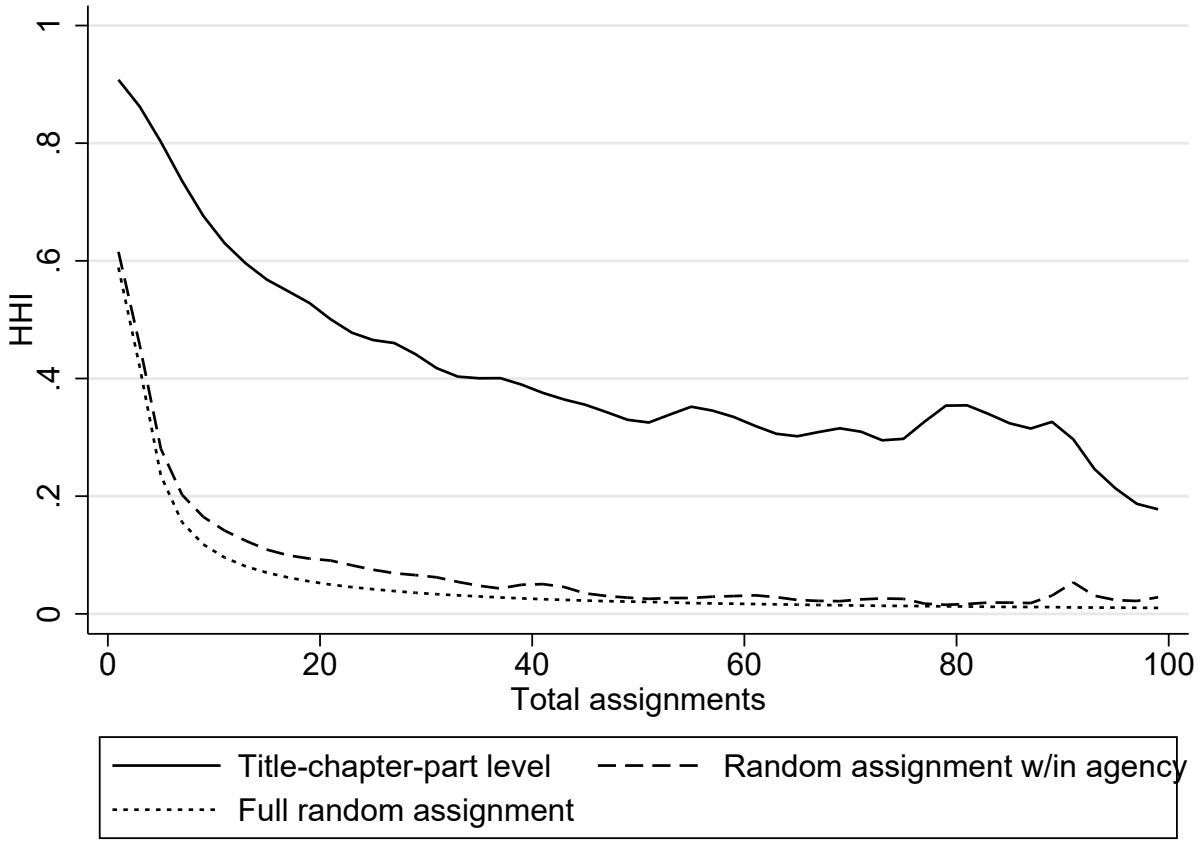
Figures

Figure 1: Party Affiliation of Regulators, by Department



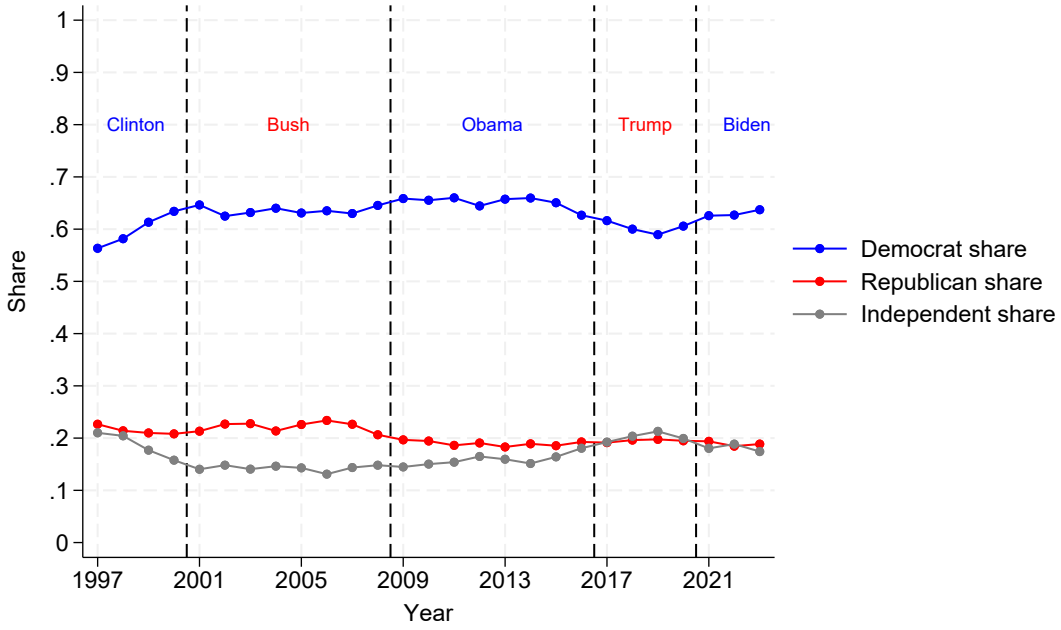
Notes: Figure shows the share of Democrat regulators by department/major agency.

Figure 2: Regulator specialization and number of assignments

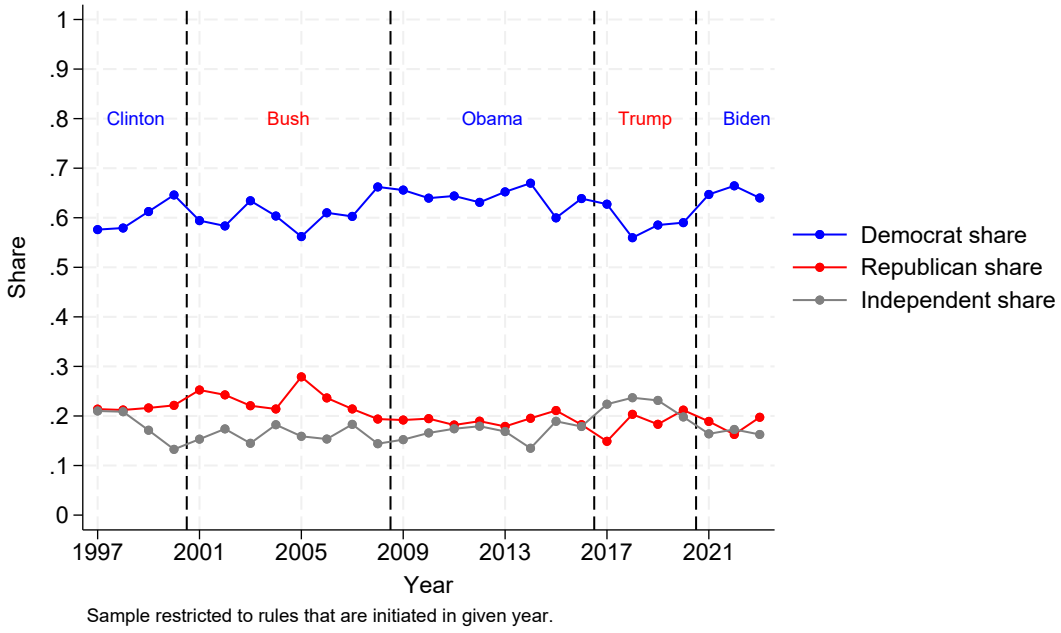


Notes: Figure plots the Herfindahl Index (HHI) for the specialization of regulators to different title-chapter-parts of the Code of Federal Regulation (CFR) as a function of the number of total rules assigned. The solid line shows the *actual* level of specialization – as captured by the HHI – of regulators. The long dashed line shows the counterfactual level of specialization if regulators within the same department/major agency were randomly assigned to rules originating from the same department/major agency. The short dashed line shows the counterfactual level of specialization if regulators were randomly assigned to write rules originating from any department/major agency.

Figure 3: Share of rules by partisanship of regulator



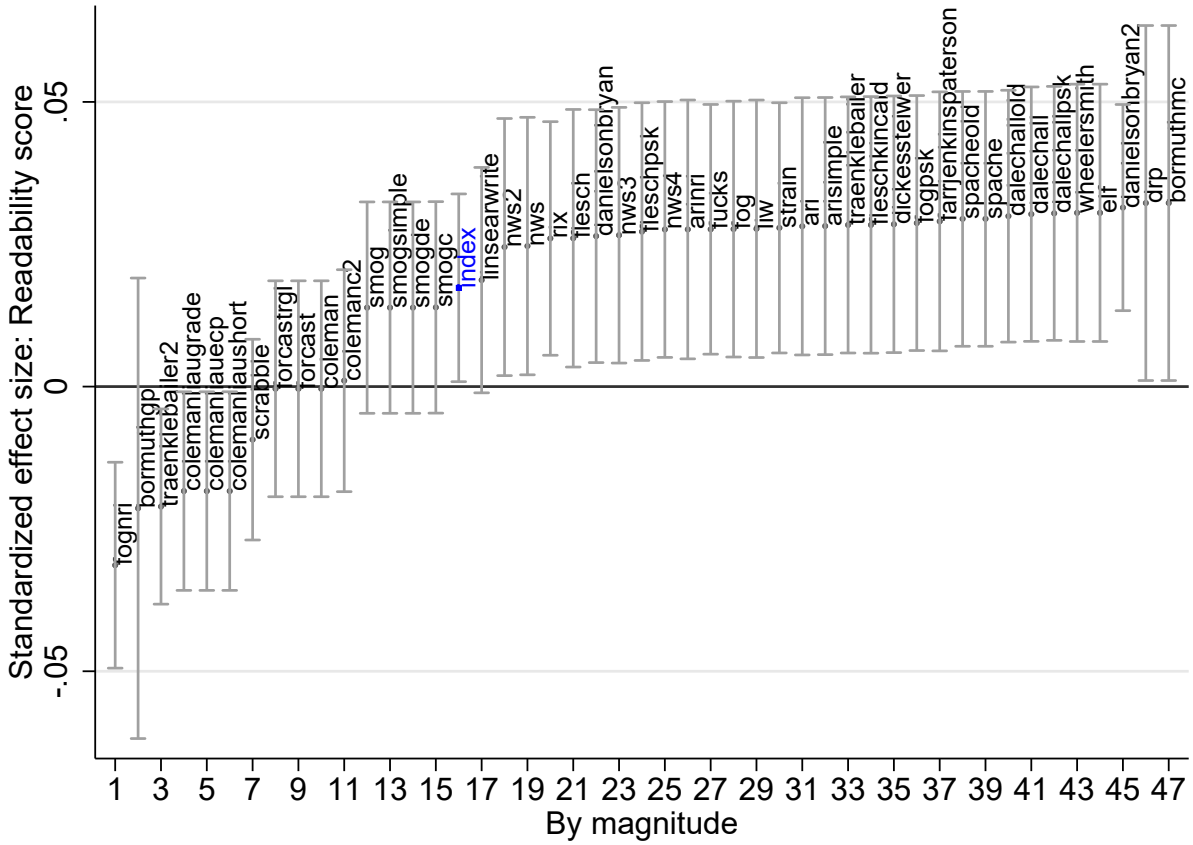
(a) All rules



(b) New rules

Notes: Figures plot the share of rules by partisanship of the assigned regulator. Panel (a) shows the shares for the stock of all rules that are in progress over time. Panel (b) shows the shares for the flow of newly initiated rule over time.

Figure 4: Political alignment and readability



Notes: Figure plots point estimates and their corresponding 95% confidence intervals for the alignment effects based on different readability scores, ordered by magnitude. All point estimates are based on the specification in Table 8 with varying (standardized mean 0 and SD 1) readability scores. The "index" outcome labelled in blue marks the average standardized effect size.

Tables

Table 1: Comparing regulators with other bureaucrats in the federal government

	(1)	(2)	(3)	(4)
	Regulators		Other bureaucrats	
	Mean	SD	Mean	SD
Panel A: Demographic characteristics				
Age at entry less than 30	0.486	0.499	0.423	0.499
Age at entry 30-40	0.293	0.454	0.259	0.437
Age at entry 40-50	0.124	0.329	0.173	0.378
Age at entry 50-60	0.073	0.261	0.110	0.312
Age at entry more than 60	0.023	0.149	0.035	0.185
Highest education: college	0.248	0.432	0.232	0.422
Highest education: more than college	0.581	0.493	0.264	0.441
Quarters in federal bureaucracy	74.08	46.54	43.14	44.04
Annual pay (in USD)	51,227.6	43,831.6	40,021.7	34,125.8
Employed in DC	0.659	0.473	0.121	0.326
Political appointment	0.011	0.103	0.004	0.066
Panel B: Voting record characteristics				
Democrat	0.630	0.482	0.490	0.499
Republican	0.206	0.404	0.288	0.453
Independent	0.162	0.369	0.220	0.414
Observations	9,125		1,976,601	

Notes: Comparing mean and SD of regulators and all other bureaucrats of in the OPM dataset. The sample is restricted to all bureaucrats who could be linked to L2.

Table 2: Political alignment and regulator partisanship

Panel A: Democrats	(1)	(2)	(3)	(4)	(5)
	Share Democrat regulators				
Mean dep. var.	0.630	0.630	0.617	0.630	0.631
Democrat president	0.019***	0.021***	0.034***	0.020***	0.014***
	(0.005)	(0.005)	(0.007)	(0.005)	(0.004)
Year		-0.001	0.001***	-0.000	-0.003**
		(0.000)	(0.000)	(0.000)	(0.001)
Rules in sample	All	All	New	All	All
Agency FEs				✓	
Rule FEs					✓
Observations	109,141	109,141	21,625	109,139	105,005
Panel B: Republicans	(1)	(2)	(3)	(4)	(5)
	Share Republican regulators				
Mean dep. var.	0.204	0.204	0.205	0.204	0.203
Republican president	0.022***	0.019***	0.021***	0.019***	0.009***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.003)
Year		-0.001***	-0.002***	-0.002***	0.001
		(0.000)	(0.000)	(0.000)	(0.001)
Rules in sample	All	All	New	All	All
Agency FEs				✓	
Rule FEs					✓
Observations	109,141	109,141	21,625	109,139	105,005

Notes: The unit of observation is a rule-year-month. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major, falls under the regulator flexibility act (RFA), and its priority level. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Political alignment, expertise match and assignment to rule

	(1)	(2)	(3)	(4)
	Assigned to rule (× 100)			
Mean dep. var. no aligned and no expert	0.361	0.361	0.361	0.361
Aligned	0.037***	0.041***	0.007	-0.031**
	(0.013)	(0.013)	(0.016)	(0.014)
Expertise match	6.895***	6.777***	7.711***	7.515***
	(0.076)	(0.074)	(0.079)	(0.093)
Expertise match × Aligned				0.478***
				(0.125)
Rule FEs	✓	✓	✓	✓
Experience FEs		✓	✓	✓
Regulator FEs			✓	✓
Observations	2,455,818	2,455,818	2,455,773	2,455,773

Notes: The unit of observation is a rule-regulator. For every rule, the set of regulators are restricted to "potential regulators"), defined as those serving in the same department of the rule's origin department and observed writing rules both before and after the rule of interest. Aligned is a dummy that is 1 if the regulator is aligned with the president at the time the rule is initiated, and 0 otherwise. Expertise match is a dummy that is 1 if the regulator has ever written a rule covering the same Code of Federal Regulation's Title-Part that the rule of interest plans to modify, and 0 otherwise. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Political alignment and rule completion

	(1)	(2)	(3)	(4)
	Rule completed		Withdrawn	Final
Mean dep. var.	3.7230	3.7230	0.9288	2.7942
Share aligned	0.230*	0.531***	0.067	0.464***
	(0.123)	(0.124)	(0.078)	(0.099)
Rule FEs	✓	✓	✓	✓
Agency × Year-Month × Duration FEs	✓	✓	✓	✓
Controls × Duration FEs		✓	✓	✓
Observations	412,894	412,894	412,894	412,894

Notes: The unit of observation is a rule-year-month. *Share aligned* captures the share of regulators assigned to a rule in a given rule-year-month that are politically aligned with the president in office. In columns 1–2, the dependent variable *Rule completed* (scaled by 100) is a dummy that is 1 if the rule was completed in the given rule-year-month. In column 3, *Withdrawn* (scaled by 100) is a dummy that is 1 if the rule was withdrawn in the given rule-year-month; similarly, in column 4, *Final* (scaled by 100) is a dummy that is 1 if the rule was successfully finalized in a given year-month. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major, falls under the regulator flexibility act (RFA), and its priority level. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Alignment and OIRA review outcomes

	(1)	(2)	(3)	(4)
		Duration of OIRA review		Withdrawn/ returned
Mean dep. var.	71.30	71.30	70.72	0.065
Share aligned	-7.107***	-7.186***	-15.110***	0.018
	(2.722)	(2.685)	(5.305)	(0.021)
Agency × Year-Month FEs	✓	✓	✓	✓
OIRA review Year-Month FEs	✓	✓	✓	✓
Controls		✓		
Rule FEs			✓	✓
Observations	6,772	6,772	4,888	4,888

Notes: The unit of observation is a rule-OIRA review period. *Share aligned* captures the share of regulators assigned to a rule that are politically aligned with the president in office at the time of OIRA review. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major, falls under the regulator flexibility act (RFA), and its level of priority. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Political alignment and comment stance

	(1)	(2)	(3)
	Negative stance		Positive
Mean dep. var.	0.35	0.35	0.31
Initial share aligned	-0.040**	-0.043***	0.035*
	(0.017)	(0.017)	(0.018)
Start year ×month ×Agency FEs	✓	✓	✓
Initial regulator team FEs	✓	✓	✓
Controls		✓	✓
Observations	6,400	6,400	6,400

Notes: The unit of observation is a rule. *Initial share aligned* is the share of regulators at rule initiation who are politically aligned with the president. In columns 1–2, the dependent variable *Negative stance* captures the share of comments who are opposing the rule. In column 3, the dependent variable *Positive* captures the share of comments who are supporting the rule. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major, falls under the regulator flexibility act (RFA), and its priority level. Robust standard errors. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Political alignment and regulatory text length

Panel A: Overall word count	(1)	(2)	(3)
	Post-rule word count		
Mean dep. var.	1173	1173	1173
Initial share aligned	-56.314**	-60.875**	-59.580*
	(28.336)	(28.607)	(33.052)
Initial regulator team FEs	✓	✓	✓
Start year ×month ×Agency FEs	✓	✓	✓
End year ×month ×Agency FEs	✓	✓	✓
Pre-rule (baseline) word count	✓	✓	✓
Controls		✓	✓
CFR Title-Part FEs			✓
Observations	182,032	182,032	182,032
Panel B: Extensive margin	(1)	(2)	(3)
	CFR part		Post-rule
	Added	Removed	word count
Mean dep. var.	0.23	0.03	1465
Initial share aligned	0.006	0.002	-54.735*
	(0.013)	(0.006)	(28.439)
Initial regulator team FEs	✓	✓	✓
Start year ×month ×Agency FEs	✓	✓	✓
End year ×month ×Agency FEs	✓	✓	✓
CFR Title-Part FEs	✓	✓	✓
Controls	✓	✓	✓
Remove added/deleted sections			✓
Observations	182,032	182,032	131,706

Notes: The unit of observation is a rule-CFR title-part. *Initial share aligned* is the share of regulators at rule initiation who are politically aligned with the president. In Panel A, columns 1–3, the dependent variable is the post-rule word count. In Panel B, column 1 and 2, the dependent variables are dummies for whether a CFR part was added or removed, respectively. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major, falls under the regulator flexibility act (RFA), and its priority level. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Political alignment and regulatory text readability

	(1)	(2)	(3)	(4)
	Avg words/ sentence	Avg syllables/ word	Readability scores	
			Flesch	Flesch-Kincaid
Mean dep. var.	57.49	1.74	-0.005	-0.010
Initial share aligned	-1.407**	0.002	0.026*	0.028**
	(0.652)	(0.001)	(0.014)	(0.014)
Initial regulator team FEs	✓	✓	✓	✓
Time × Agency FEs	✓	✓	✓	✓
CFR Title-Part FEs	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	131,588	131,588	131,588	131,588

Notes: The unit of observation is a rule-CFR title-part. *Initial share aligned* is the share of regulators at rule initiation who are politically aligned with the president. In column 1, the dependent variable is the average words per sentence. In column 2, the dependent variable is the average syllabes per word. In column 3, the dependent variable is the standardized Flesch score; in column 4, the dependent variable is the standardized Flesch-Kincaid score. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major, falls under the regulator flexibility act (RFA), and its priority level. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

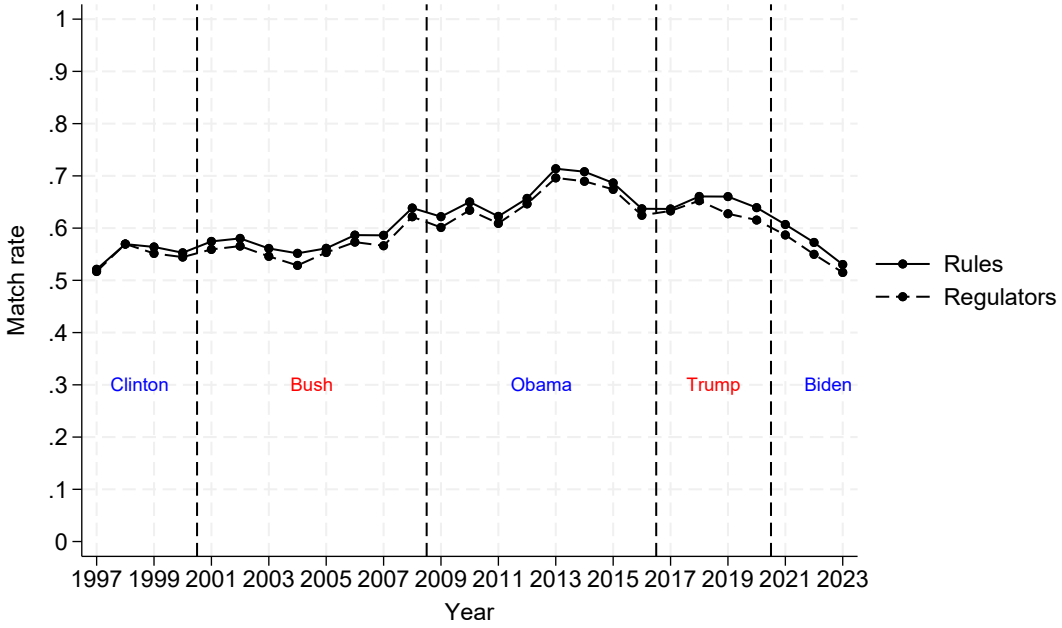
Table 9: Political alignment and legal challenge

	(1)	(2)	(3)
	Legal challenge		
Mean dep. var.	0.23	0.23	0.16
Initial share aligned	-0.052*	-0.057*	-0.091*
	(0.030)	(0.030)	(0.051)
Year × Agency FEs	✓	✓	✓
Controls		✓	✓
Regulator team FEs			✓
Observations	1,000	1,000	413

Notes: The unit of observation is a rule. The sample is restricted to major rules. *Initial share aligned* is the share of regulators at rule initiation who are politically aligned with the president. The dependent variable *Legal challenge* is a dummy that is 1 if the rule was challenged in federal court, and 0 otherwise. Robust standard errors. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix

Figure A1: Matching Rate



Notes: Figure shows the fraction of rules and regulators who could be matched to the voter registration data (L2) over time. The solid line shows the fraction of rules for whom at least one regulator could be successfully matched to L2. The dashed line shows the fraction of regulators who could be matched to L2.

Table A1: Baseline characteristics of matched vs. unmatched sample

	(1) Mean unmatched	(2) Raw mean matched-unmatched	(3) Obs.
Panel A: Regulator-level			
Number of rules assigned	13.330	2.009***	17,150
		(0.658)	
Panel B: Rule-level			
Number of regulators	1.03	0.129***	20,056
		(0.005)	
Predicted delay (log)	6.44	-0.057***	20,056
		(0.006)	
Significant rule	0.03	0.017***	20,056
		(0.003)	
Major rule	0.02	0.014***	20,056
		(0.003)	
Under RFA	0.07	0.021***	20,056
		(0.004)	
Panel C: Section-level			
Word count	972	39.035	251,775
		(28.538)	
Word count (excl. added/deleted sections)	1284	35.762	192,595
		(36.997)	
Avg. words/sentence	55.69	1.577**	192,595
		(0.747)	
Avg. syllables/word	1.74	0.000	192,595
		(0.003)	
Flesch score	0.015	-0.033*	192,595
		(0.017)	
Flesch-Kincaid score	0.016	-0.033**	192,595
		(0.016)	

Notes: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2: Political alignment and baseline characteristics

	(1)	(2)	(3)	(4)
	Mean	Mean diff aligned-misaligned		
	misaligned	Raw	Conditional	Obs.
Predicted delay (log)	6.47	0.010	0.010	181,970
		(0.010)	(0.013)	
Significant rule	0.09	0.024	0.016**	181,970
		(0.016)	(0.008)	
Major rule	0.07	0.034**	0.001	181,970
		(0.015)	(0.008)	
Under RFA	0.11	0.031**	0.017	181,970
		(0.015)	(0.018)	
Word count	1056	-48.497	148.883	181,970
		(31.045)	(97.196)	
Word count (excl. added/deleted sections)	1388	-25.109	70.589	134,320
		(36.097)	(115.185)	
Avg. words/sentence	57.47	-1.337	-2.406	134,320
		(0.833)	(1.588)	
Avg. syllables/word	1.738	0.005*	0.008**	134,320
		(0.003)	(0.004)	
Flesch score	-0.014	0.018	0.038	134,320
		(0.018)	(0.034)	
Flesch-Kincaid score	-0.018	0.025	0.046	134,320
		(0.018)	(0.034)	

Notes: Flesch and Flesch-Kincaid scores are standardized, with higher scores indicating greater readability. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: Political alignment and rule duration

	(1)	(2)	(3)	(4)
	Days until completion			
Mean of dep. var	524.2	524.2	524.2	524.2
Predicted duration	0.812***	0.734***	1.007***	0.921***
	(0.046)	(0.046)	(0.046)	(0.048)
Average share aligned	-64.167***	-57.613***		
	(22.137)	(21.819)		
Initial share aligned			-8.337	-4.956
			(20.910)	(20.691)
Start year × month × agency	✓	✓	✓	✓
All regulator team FEs	✓	✓		
Controls		✓		✓
Initial regulator team FEs			✓	✓
Observations	12,885	12,885	12,885	12,885

Notes: The unit of observation is a rule. Controls: (log) predicted duration, dummies for whether rule is major, falls under the regulator flexibility act (RFA), and its priority level. Robust standard errors. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Robustness: Political alignment and regulatory text – winsorizing

	(1)	(2)	(3)	(4)	(5)
		Winsorization (two-tailed)			
Winsorizing	None	0.1%	0.5%	1%	2.5%
Post-rule word count					
Initial share aligned	-449.341*	-194.760**	-81.836***	-70.113***	-44.718**
	(259.724)	(96.158)	(28.844)	(26.302)	(19.036)
Avg. words/sentence					
Initial share aligned	-2.146*	-1.505**	-1.407**	-1.342**	-0.954**
	(1.097)	(0.751)	(0.653)	(0.567)	(0.444)
Avg. syllables/word					
Initial share aligned	0.001	0.001	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Flesch score					
Initial share aligned	2.058*	1.451*	1.308*	1.172*	0.844*
	(1.123)	(0.788)	(0.690)	(0.609)	(0.482)
Flesch-Kincaid score					
Initial share aligned	0.820*	0.576*	0.536**	0.496**	0.349**
	(0.429)	(0.296)	(0.258)	(0.225)	(0.176)
Regulator team FEs	✓	✓	✓	✓	✓
Start year ×month ×Agency FEs	✓	✓	✓	✓	✓
End year ×month ×Agency FEs	✓	✓	✓	✓	✓
Pre-rule (baseline) word count	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Observations	131,588	131,588	131,588	131,588	131,588

Notes: The unit of observation is a rule-CFR title-part. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major, falls under the regulator flexibility act (RFA), and its priority level. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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A Data on Rulemaking

In this section, we describe the four sources of rulemaking data we use throughout the analysis and how we link them together. First, the Unified Agenda of Federal Regulatory and Deregulatory Actions (UA) defines our sample of rulemaking processes. Second, the Federal Register (FR) represents the flow of regulations, where regulatory actions (e.g., proposed and final rules) are published and announced. Third, the Code of Federal Regulations (CFR) represents the stock of rulemaking, including all effective regulatory provisions. Fourth, comments data for regulatory actions is obtained from Regulations.gov, the official online portal where agencies deposit the comments received during the notice-and-comment process.

A1 Unified Agenda

The Unified Agenda (UA) describes the regulatory processes that agencies are developing or have completed. The UA is published twice a year, in the spring and fall. A Regulation Identifier Number (RIN) is assigned to each regulatory process, allowing us to track the progress of the rulemaking process and the adoption of regulatory actions over time. Figure A.1 shows how a regulatory process is carried over through several issues of the UA. The proposed rule associated with RIN 2050-AG83 first appears in the UA in the Spring issue of 2015, while the action is reported as completed three years later, in the Spring issue of 2018.

Figure A.1: Example of RIN progress through multiple sessions of the Unified Agenda.

Agency	Agenda Stage of Rulemaking	Title	Publication	RIN
EPA/SWER	Proposed Rule Stage	Non-Hazardous Secondary Materials--Additions to List of Categorical Non-Waste Fuels; Other Treated Woods	Spring 2015	2050-AG83
EPA/SWER	Long-Term Actions	Non-Hazardous Secondary Materials--Additions to List of Categorical Non-Waste Fuels; Other Treated Woods	Fall 2015	2050-AG83
EPA/OLEM	Proposed Rule Stage	Non-Hazardous Secondary Materials - Additions to List of Categorical Non-Waste Fuels; Other Treated Railroad Ties and Used Oil	Spring 2016	2050-AG83
EPA/OLEM	Proposed Rule Stage	Non-Hazardous Secondary Materials -- Additions to List of Categorical Non-Waste Fuels; Other Treated Railroad Ties and Used Oil	Fall 2016	2050-AG83
EPA/OLEM	Final Rule Stage	Non-Hazardous Secondary Materials--Additions to List of Categorical Non-Waste Fuels; Other Treated Railroad Ties	Spring 2017	2050-AG83
EPA/OLEM	Final Rule Stage	Non-Hazardous Secondary Materials--Additions to List of Categorical Non-Waste Fuels; Other Treated Railroad Ties	Fall 2017	2050-AG83
EPA/OLEM	Completed Actions	Non-Hazardous Secondary Materials--Additions to List of Categorical Non-Waste Fuels; Other Treated Railroad Ties	Spring 2018	2050-AG83

Notes: UA records for RIN 2050-AG83 as reported on the Unified Agenda website.

Each RIN-UA issue pair captures the progress of the rulemaking process. Two of them are displayed Figure A.2 below. Panel A shows the status of the process reported in the Spring issue of 2015, whereas Panel B shows the status of the regulatory process in its latest issue in 2018.

Figure A.2: Example of RIN across two UA issues.

A) Spring 2015 Issue

EPA/SWER **RIN:** 2050-AG83 **Publication ID:** Spring 2015

Title: •Non-Hazardous Secondary Materials--Additions to List of Categorical Non-Waste Fuels; Other Treated Woods

Abstract:

In the 2013 Non-Hazardous Secondary Materials (NHSM) final rule, the EPA established a rulemaking process for categorical determinations for adding NHSMs as non-waste fuels. Persons requesting rulemakings for adding NHSMs to the list of categorical non-wastes will have to demonstrate how the NHSMs successfully meet the criteria listed in 40 CFR 241.4(b)(5). The Treated Wood Council has submitted a petition for various types of treated wood to be added as categorical non-waste fuels.

Agency: Environmental Protection Agency(EPA)
Priority: Substantive, Nonsignificant
RIN Status: First time published in the Unified Agenda
Agenda Stage of Rulemaking: Proposed Rule Stage
Major: No
Unfunded Mandates: No
CFR Citation: 40 CFR 241
Legal Authority: 42 U.S.C. 6903 42 U.S.C. 6912 42 U.S.C. 7429
Legal Deadline: None
Timetable:

Action	Date	FR Cite
NPRM	07/00/2015	

Regulatory Flexibility Analysis Required: No
Government Levels Affected: None
Small Entities Affected: No
Federalism: No
Included in the Regulatory Plan: No

B) Spring 2018 Issue

EPA/OLEM **RIN:** 2050-AG83 **Publication ID:** Spring 2018

Title: Non-Hazardous Secondary Materials--Additions to List of Categorical Non-Waste Fuels; Other Treated Railroad Ties

Abstract:

The non-hazardous secondary material (NHSM) regulations under the Resource Conservation and Recovery Act (RCRA) identify which NHSMs are, or are not, solid wastes when burned in combustion units as ingredients and fuels. Under 40 CFR 241.4(b), persons can petition the EPA to list additional NHSMs as categorical non-waste fuels.

The Agency received a petition from the Treated Wood Council in April 2013 requesting that nonhazardous treated wood biomass be categorically listed as non-waste fuels. In August 2015, the Treated Wood Council requested that the Agency move forward on a categorical non-waste listing for a subset of materials that were identified in the April 2013 petition; specifically, other treated railroad ties that are treated with the preservatives creosote-borate, copper naphthenate, and copper naphthenate-borate. On February 7, 2018, EPA issued a final rule that added these other treated railroad ties to the categorical non-waste fuel list.

Agency: Environmental Protection Agency(EPA)
Priority: Other Significant
RIN Status: Previously published in the Unified Agenda
Agenda Stage of Rulemaking: Completed Actions
Major: No
Unfunded Mandates: No
EO 13771 Designation: Deregulatory
CFR Citation: 40 CFR 241
Legal Authority: 42 U.S.C. 6903 42 U.S.C. 6912 42 U.S.C. 7429
Legal Deadline: None
Timetable:

Action	Date	FR Cite
NPRM	11/01/2016	81 FR 75781
Final Rule	02/07/2018	83 FR 5317
Final Action Effective	02/07/2018	

Additional Information: Docket # EPA-HQ-OLEM-2016-0248
Regulatory Flexibility Analysis Required: No
Government Levels Affected: None
Small Entities Affected: No
Federalism: No
Included in the Regulatory Plan: No

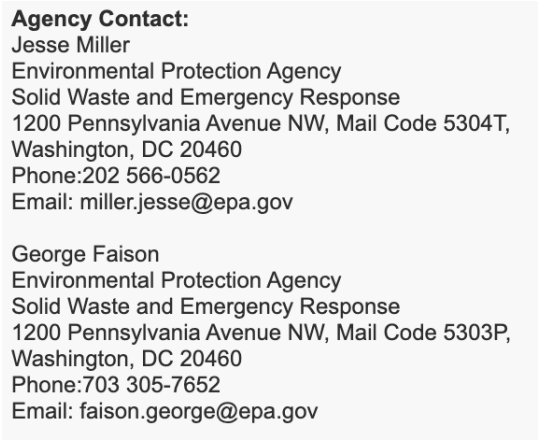
Notes: UA entry across issues for RIN 2050-AG83 as reported on the Unified Agenda website.

The information reported in each issue of the UA retains the same structure. In addition to self-explanatory details such as the title, abstract, RIN, stage of rulemaking, and agency, the UA reports rule-specific characteristics: whether the rule is considered "Major" (i.e., is expected to have a significant economic impact), the title and part of the Code of Federal Regulations that the rule proposes to amend, the statutory authority granting the rulemaking agency the power to issue a rule on this matter, whether the rule is subject to a legal deadline,

the priority status of the rule (whether it is considered significant or not), unfunded mandates (i.e., imposes increased costs on non-federal government entities), whether the rule falls under the Regulatory Flexibility Act (RFA), whether the rule is included in the regulatory plan, and whether it affects government levels, federalism, or small entities.

Importantly, the UA provides information on the names and contact details of the bureaucrats assigned to every action throughout the regulatory process. For RIN 2050-AG83, for example, each of the seven issues of the UA from 2015 to 2018 lists the same two bureaucrats, whose contact information is shown in Figure A.3 as it appears in the UA.

Figure A.3: Example of bureaucrats assigned to RIN 2050-AG83.



Notes: Contact information of bureaucrats assigned to regulatory actions as reported on the Unified Agenda website.

Finally, each record in the UA includes a timetable of the regulatory process until the publication of that issue, presented in tabular format, where each row reports a single action adopted over time along with its respective date of adoption. Such actions can include, for example, the Notice of Proposed Rulemaking (NPRM) or the final rule. In most cases, actions are documented in the Federal Register and referenced by an FR Cite that identifies the Volume (83, for the final rule) and the page number (5,317). Figure A.4 shows the initial information regarding the publication of the final rule in the Federal Register. The heading of the page reports the volume and page of the Federal Register. The text of the entry presents some of the same information already described above and reported in the UA. The Federal Register also includes the full text of the rule, which for RIN 2050-AG83 spans 24 pages.

Figure A.4: Federal Register entry for the final rule of RIN 2050-AG83.



ENVIRONMENTAL PROTECTION AGENCY

40 CFR Part 241

[EPA–HQ–OLEM–2016–0248; FRL–9969–80–OLEM]

RIN 2050–AG83

Additions to List of Categorical Non-Waste Fuels: Other Treated Railroad Ties

AGENCY: Environmental Protection Agency (EPA).

ACTION: Final rule.

Notes: Publication of the final rule from RIN 2050-AG83 in the Federal Register, volume 83, page 5,317.

We download the universe of rulemaking processes published in the UA directly from the UA website, which includes a XML file for each UA issue.[28] Each element of the XML file is a RIN-UA issue observation, containing all the information we described and displayed above. In total, we observe 41,625 regulatory processes (RINs). 34,414 regulatory processes include regulatory actions with a valid FR cite, for a total of 71,185 unique regulatory actions. 7,211 regulatory processes list actions without any valid FR cite.

To identify the changes that final rules make to the CFR and to access stakeholder comments on proposed rules, we augment the UA data by linking each regulatory action to its corresponding entry in the Federal Register (FR). This step is necessary to map the changes to the Code of Federal Regulations (CFR) and the comments on specific actions within the regulatory process.

Specifically, while the UA provides information on the CFR parts affected, it does not specify which sections are amended - sections are the lowest and most specific unit of organization in the CFR, as explained below. CFR parts associated with a RIN can include multiple sections, and regulatory actions may impact only a subset of those. Only by parsing the full text of the rule can we extract the specific sections affected by each regulatory action, and such data is available through the FR.

Additionally, although the UA includes a unique identifier for accessing comments data through Regulations.gov (i.e., the Docket # entry immediately below the timetable of actions

[28] XML files were accessed at the following link: https://www.reginfo.gov/public/do/eAgendaXmlReport.

in Figure A.2), it does not allow us to map comments to single regulatory actions. To achieve this, we need to first retrieve the unique identifier assigned by the FR to each action and then parse all comments submitted to each action through Regulations.gov.

Though seemingly simple, this exercise required extensive data collection, manual checks, and record linkage steps, often compensating missing information and the lack of consistent use of unique identifiers through the four sources of data. In the following sections, we describe the information we retrieve from the FR and provide extensive information on our record linkage approach.

A2 Federal Register

The Federal Register (FR) serves as the official daily publication for rules, proposed rules, and notices of federal agencies. It contains regulatory documents having general applicability and legal effect. The FR is organized following a chronological format, with one volume for any given year and one issue for any give date. Each entry in the FR is assigned an FR document number and the same FR Cite used in the UA.

For our purposes, we rely on two types of information reported in the FR: a rich array of action-specific metadata and the text of the regulatory action (e.g., proposed or final rules). Similarly to the UA, the FR reports information on the publication and effective date of the action, the type of action (notices, proposed rules, final rules, corrections), and the parts of the CFR affected. Second, unlike the UA, the FR includes the full text of actions and a detailed description of the CFR parts and sections amended.

Extending the example from the previous section, the EPA regulatory process RIN 2050-AG83 includes two regulatory actions, each one with an FR document number. Table A.1 below reports the two RIN-FR Cite-FR Document number triplets.

Table A.1: Linking Unified Agenda and Federal Register.

RIN	FR Cite	FR Document Number	FR Type	FR Action
2050-AG83	81 FR 75781	2016-26381	Proposed Rule	Proposed Rule
2050-AG83	83 FR 5317	2018-02337	Rule	Final rule

Notes: The table reports the regulatory process ID (RIN), the citation of the regulatory action in the Federal Register (FR Cite), and unique identifier assigned to the action by the Federal Register (FR Document number) and the type of action the FR uses to describe the regulatory action (FR Type of action).

A3 Linking the Unified Agenda and the Federal Register

In this section, we describe how we link the Unified Agenda (UA) to the Federal Register (FR). The unit of observation in the UA is the RIN-FR cite. The unit of observation in the Federal Register is the FR document number. Our goal is to assign each of the 71,185 RIN-FR cite pairs from the UA an FR document number from the Federal Register. This allows us to link each regulatory action in the UA (e.g., proposed rule, final rule) to the corresponding text in the FR.

Three features of the data make this task particularly challenging.

1. **Multiple RINs can map into a single FR cite:** Since the FR cite is defined by a combination of the volume number of the Federal Register and the page (e.g., 81 FR 75781), multiple RINs can have the same FR cite if they are printed on the same page. This case occurs for 7.8% of the 65,522 unique FR cites in the UA.

2. **Multiple RINs can map into a single FR document number:** When multiple agencies jointly issue a rule, the UA reports a separate regulatory process for each agency, resulting in multiple RINs. The Federal Register, however, creates only one FR document number. This case occurs for 5.9% of the 34,414 unique RINs in the UA.

3. **Missing RIN information:** Many documents in the Federal Register report an FR document number and an FR cite but no corresponding RIN.

To overcome these challenges, we proceed in multiple steps:

Step 1: Matching via Federal Register API

- We use the Federal Register API to obtain for each of the 34,414 unique RINs (from our 71,815 RIN-FR cite pairs) the associated FR document numbers.[29] We are able to retrieve at least one FR document number for 28,054 of the RINs (81.5%). We then query the API to obtain FR cites associated with each of the document numbers retrieved.

- This results in a RIN-FR cite-document number crosswalk covering 66% of the 71,185 RIN-FR cites in the UA.

The API was unable to return document numbers for all RINs. In Step 2, we verify whether the missing RINs (28.5%) are reported in the printed version of the Federal Register.

[29] An example of the API call is the following: https://www.federalregister.gov/api/v1/documents.json?conditions%5Bregulation_id_number%5D=RIN

Step 2: Matching with Federal Register XML files

- We access XML bulk data from the printed edition of the Federal Register and for each element (i.e., each document printed in the FR) we scrape information on the FR cite, FR document number, and – when available – the RIN.
- We then merge this data with the remaining, unmatched RIN-FR cites, keeping only unique matches. For cases that cannot be matched, we only match uniquely based on the FR cite. This allows us to improve the coverage for the crosswalk to 87% of the 71,185 RIN-FR cites in the UA.

In Step 2, we improved the coverage of the RIN-FR cites crosswalk by uniquely matching RIN-FR cites and FR cites to the XML data. 2,455 RIN-FR cites could not be matched in this step because the XML data listed multiple FR document numbers for the same RIN-FR cite. To make progress, we now disambiguate by using the title information provided in the UA and the FR.

Step 3: Matching based on title

- For each of the RIN-FR cite pair with multiple FR document numbers (Step 2), we retrieve the document title through the Federal Register API. We then match the UA title associated with an RIN to the document title from the FR.
  To allow for fuzzy matching, we use a deep learning model for record linkage to extract for each RIN-FR cite the FR document number whose title is most similar to the UA title (Arora and Dell, 2023). The model uses sentence transformers to convert titles to dense vectors and returns the title with the largest cosine similarity between the UA-title and every FR document-titles. A research assistant manually validated all the matches and removed false positives.
- Step 3 allows us to recover FR document number for 74% of the 2,455 RIN-FR cite pairs, increasing the coverage for the cross-walk to 89.5% of the 71,185 RIN-FR cites.

Step 4: Relaxing matching by allowing for typos

After Steps 1-3, 7,473 RIN-FR cite pairs remain without a corresponding FR document number. Extensive manual inspection revealed that this is often due to two frequent types of errors in reporting the FR cite.

1. The FR cite in the UA and the FR cite in the FR might have a 1-page difference. If documents are long, they are printed over multiple pages in the Federal Register, and the FR may report FR cite k and the UA FR cite $k \pm 1$.

2. A common data entry error, whereby the middle digit of the FR cite is shuffled (e.g., 1234 instead of 1324).

Informed by our manual checks, we thus relax our matching criterion to allow for $\pm$ 1 page difference in the FR cite as well as the middle digit shuffling. This allows us to recover 3,704 additional RIN-FR cite-FR document linkages. At the end of the Step 4, we are able to assign a FR document number to 95% of the 71,185 RIN-FR cites.

Step 5: Supplementary cases

Finally, 7,211 RINs report actions without a valid (i.e., a missing) FR cite. To rule out the possibility that these actions have a valid entry in the Federal Register that was simply not reported in the UA, we replicate Step 1 for each of the 7,211 RINs.

- For each RIN, we search through the Federal Register API and retrieve the associated FR document numbers. We then poll the API again to extract the FR cite for each of the FR document numbers.

We recover at least one FR document number for 9% of the 7,221 RINs, for a total of 1,437 RIN-FR cite-FR document tuples, which we add to the regulatory actions matched through Steps 1 to 4. Overall, these steps allow us to build a comprehensive crosswalk of 72,658 unique RIN-FR cite-FR document number observations, thus allowing us to link the vast majority of regulatory actions with their full text (from the Federal Register) and the comments submitted by stakeholders (from Regulations.gov) by using the common FR document number identifier.

A4 Code of Federal Regulations

The Code of Federal Regulation (CFR) is the stock of active and effective regulatory provisions. Specifically, the CFR "is the codification of the rules published in the Federal Register by the departments and agencies of the Federal Government."[30]

The CFR is divided into 50 titles that represent broad areas subject to federal regulation. Each title is divided into chapters, which usually bear the name of the issuing agency. Each chapter is further subdivided into parts that cover specific regulatory areas. All parts are organized in sections.

[30]Detailed description of the CFR is available through GovInfo, a government service that provides free public access to official publications from all three branches of the Federal Government, via the following link: https://www.govinfo.gov/help/cfr#about.

The titles are updated once each calendar year, on a staggered basis.[31] The annual update cycle is as follows:

- titles 1-16 are revised as of January 1
- titles 17-27 are revised as of April 1
- titles 28-41 are revised as of July 1
- titles 42-50 are revised as of October 1

The staggered update of titles is important information we leverage when determining the year when the changes made by a final rule are expected to be codified in the CFR. For example, a rule that is effective in March affecting Title 29 will be codified in the same year. Conversely, a rule published in the same month amending a section of Title 10 will be codified in the following year.

In the following section, we describe the steps we follow to extract sections. Table A.2 shows the CFR titles, parts, and sections affected by the final rule of the EPA regulatory process RIN 2050-AG83.

Table A.2: Linking Unified Agenda and Federal Register.

			CFR		
RIN	**FR Cite**	**FR Document Number**	**Title**	**Part**	**Section**
2050-AG83	83 FR 5317	2018-02337	40	241	2
2050-AG83	83 FR 5317	2018-02337	40	241	4

Notes: The table reports the regulatory process ID (RIN), the citation of the regulatory action in the Federal Register (FR Cite), and unique identifier assigned to the action by the Federal Register (FR Document number), and the sections of the CFR affected by the rule.

We download the yearly edition of the CFR directly from the GovInfo.gov portal.[32] Each yearly edition contains 50 XML files, one for each title. Each XML file is organized into multiple XML elements, one for each section.

[31] Since 2017, an online version of the CFR has been updated on a daily basis. However, given the limited time coverage of the online version, our analyses rely on the yearly publications.

[32] Bulk data can be accessed at https://www.govinfo.gov/bulkdata/CFR.

A5 Detecting Rules' Changes to the Code of Federal Regulations

Final rules, when enacted, modify sections of the CFR. Recall the CFR is organized into titles, parts, and sections, and we need to extract the sections affected by the rule. While both the UA and the FR document-specific metadata report the CFR parts affected, only the text of the rule describes how the rule amends or revises each section.

To extract the title-part-sections affected by final rules, we perform four steps:

1. We collect the CFR title-parts affected by the rules and contained in the FR metadata.

2. From the yearly editions of the CFR, we compile a list of the universe of CFR title-part-sections codes ever published between 1997 to 2024, for a total of 609,591 unique title-part-section codes.

3. For every rule, we subset the list of section codes to keep only those contained in the CFR title-parts listed in the FR metadata of the rule, and we build a flexible regular expression that collapses all the possible title-part-sections (this allows us to flexibly extract even the most complicated section codes, e.g. 7.319.56-2d).

4. We extract each section mentioned in the text of the final rule (in the *List of Subject* section, where the rule describes regulatory changes).

Once we have a dataset at the FRdn-CFR title-part-section level (see Table A.2), we assign for each section the year when we expect to see the changes codified in the CFR. Because titles are updated yearly but on a staggered basis, the year of codification depends on the CFR title the rule amends and the effective date of the rule.[33]

We then take the text of each CFR title-part-sections published in any year between 1997-2024 that have been affected by the final rules in our sample and we extract the text as published in year t, after codification, and year $t-1$, prior to codification, in order to compare the two versions of the text. If a rule in year t introduces a new section, this will not have a text in $t-1$. Similarly, if a rule repeals a section from the CFR published in year $t-1$, the section will not have a text in year t.

From our crosswalk of RIN-FR cite-FRdn triplets, we have 33,048 unique documents that are classified as final rules in the Federal Register. For 98.9% of them, we can get information on the CFR title-part affected from the Federal Register API, and for 88.9% we successfully extract the affected CFR sections from the text of the rule. For 3,654 rules we are not able to extract any CFR section affected.

[33]The effective date of the rule is often the same as the publication date. When we are not able to extract information on the rule's effective date, we use the publication date.

Continuing with our example from regulatory process 2050-AG83, our data shows that the final rule issued, FRdn 2018-02337, amends two sections of the CFR: title 40, part 241, sections 2 and 4. Now consider the portion of the rule amending section 2. The text of the rule is displayed in Figure A.5. The rule adds three new definitions to CFR section 2.

Figure A.5: Text of rule from Federal Register.

PART 241—SOLID WASTES USED AS FUELS OR INGREDIENTS IN COMBUSTION UNITS

■ 1. The authority citation for part 241 continues to read as follows:

Authority: 42 U.S.C. 6903, 6912, 7429.

■ 2. Section 241.2 is amended by adding in alphabetical order the definitions ''Copper naphthenate treated railroad ties'', ''Copper naphthenate-borate treated railroad ties'', and ''Creosote-borate treated railroad ties'' to read as follows:

§ 241.2 Definitions.

* * * * *

Copper naphthenate treated railroad ties means railroad ties treated with copper naphthenate made from naphthenic acid and copper salt.

Copper naphthenate-borate treated railroad ties means railroad ties treated with copper naphthenate and borate, including borate made from disodium octaborate tetrahydrate.

* * * * *

Creosote-borate treated railroad ties means railroad ties treated with a wood preservative containing creosols and phenols and made from coal tar oil and borate, including borate made from disodium octaborate tetrahydrate.

* * * * *

This rule became effective on February 7, 2018. Because titles 28-41 are updated as of July 1, the revisions of the rule are codified already in the 2018 edition of the CFR. We therefore compare the text of the section in 2017 (pre-codification) and in 2018 (post-codification). Figure A.6 shows the two versions of the section, respectively the 2017 (Panel A) and 2018 (Panel B) version.

Figure A.6: Text of CFR section before and after revision.

A) CFR 2017

§ 241.2

the environment considering the nature and toxicity of the non-hazardous secondary material.

Control means the power to direct the policies of the facility, whether by the ownership of stock, voting rights, or otherwise, except that contractors who operate facilities on behalf of a different person as defined in this section shall not be deemed to ''control'' such facilities.

Creosote treated railroad ties means railway support ties treated with a wood preservative containing creosols and phenols and made from coal tar oil.

Established tire collection program means a comprehensive collection system or contractual arrangement that ensures scrap tires are not discarded and are handled as valuable commodities through arrival at the combustion facility. This can include tires that were not abandoned and were received from the general public at collection program events.

B) CFR 2018

§ 241.2

the environment considering the nature and toxicity of the non-hazardous secondary material.

Control means the power to direct the policies of the facility, whether by the ownership of stock, voting rights, or otherwise, except that contractors who operate facilities on behalf of a different person as defined in this section shall not be deemed to ''control'' such facilities.

Copper naphthenate treated railroad ties means railroad ties treated with copper naphthenate made from naphthenic acid and copper salt.

Copper naphthenate-borate treated railroad ties means railroad ties treated with copper naphthenate and borate, including borate made from disodium octaborate tetrahydrate.

Creosote treated railroad ties means railway support ties treated with a wood preservative containing creosols and phenols and made from coal tar oil.

Creosote-borate treated railroad ties means railroad ties treated with a wood preservative containing creosols and phenols and made from coal tar oil and borate, including borate made from disodium octaborate tetrahydrate.

Established tire collection program means a comprehensive collection system or contractual arrangement that ensures scrap tires are not discarded and are handled as valuable commodities through arrival at the combustion facility. This can include tires that were not abandoned and were received from the general public at collection program events.

Notes: Panel A reports the text of CFR section 40.241.2 in the 2017 publication of the CFR. Panel B reports the same section in the 2018 version of the CFR. The red box highlights the three definitions that are added.

A6 Measuring Text Length and Readability

Once we have a pre-post codification version of the text for each title-part-section-year observation, we apply various measures of length and readability to both texts. We compute the number of characters, words, and sentences, as well as 46 different readability indexes. To compute such indexes we use the `quanteda` library in R (Benoit et al., 2018).[34]

In the analysis, we use two of the most popular indicators: Flesch's Reading Ease Score (Flesch, 1948) and the Flesch–Kincaid Grade Level (Thomas et al., 1975). The score is a numerical measure designed to evaluate the readability of English texts, indicating how easily a reader can understand a passage. The score is calculated using the average sentence length and the average number of syllables per word. Higher scores indicate simpler, more

[34]For a description of each index see Package documentation `quanteda.textstats` on CRAN, pp. 13-19, accessible at https://cran.r-project.org/web/packages/quanteda.textstats/quanteda.textstats.pdf.

accessible text. The Flesch–Kincaid Grade Level is a readability metric designed to estimate the educational grade level necessary for a reader to understand a given text. It calculates a score based on the average number of words per sentence and the average number of syllables per word. The resulting score corresponds to a U.S. school grade level; for example, a score of 8.0 indicates that an eighth grader would typically be able to comprehend the text. These metrics are widely used in education, publishing, and content creation to tailor materials to specific audiences.[35] These indicators are now commonly used by government agencies and departments. The U.S. Army first used it for assessing the readability of technical manuals in 1978 and it is now a standard for the U.S. Department of Defense, the Internal Revenue Service and the Social Services Administration.[36]

To showcase how these scores are computed, let us consider USDA regulatory process RIN 0518-AA02, titled "Rules of Conduct at the United States National Arboretum". The USDA issued a final rule on September 23, 2005, with FRdn 05-18991. The rule amends 21 sections of CFR title 7, part 500. Due to its effective date, we compare the 2005 and 2006 editions of the CFR. Table A.3 shows the text of the section, the number of words, and the Flesch score before and after the adoption of the rule.

Table A.3: Example of CFR section before and after adoption of rule.

Section Text	**CFR Year**	**Nr. Words**	**Flesch Score**
Entering U.S. National Arboretum property or the operation of a motor vehicle thereon, by a person under the influence of intoxicating beverages or narcotic drug, or the consumption of such beverages or the use of such drug in or on U.S. National Arboretum property, is prohibited.	2005	52	29.4
(a) Entering USNA property or the operation of a motor vehicle thereon, by a person under the influence of intoxicating beverages or a narcotic drug, is prohibited. (b) Except as provided in subpart B of this part, possession of or consumption of intoxicating beverages on USNA property is prohibited. (c) The sale of alcoholic beverages on the grounds of the USNA is prohibited. (d) The possession of or use of narcotic drugs on the grounds of the USNA is prohibited.	2006	95	-26.6

Notes: Text of CFR section 7, title 7, part 500 before and after the section was revised by rule FRdn 05-18991. Columns 2 to 4 report the editions of the CFR, the number of words of the section, and the Flesch score (higher values signify easier readability - here values have been standardized to facilitate the analysis).

Not only does the section become longer but it also becomes more complex. Both texts

[35]Note that higher readability is associated with a higher Flesch score and a lower Flesch-Kincaid score. In the analysis, all scores are rescaled so that larger values are associated with greater readability.

[36]Source: https://medium.com/@annwylie/flesch-kincaid-grade-level-how-hard-is-it-ebb0bfcdfa87.

require a college-level reading ability but the 2006 version is less readable because it contains a longer sentence and more instances of long words such as 'intoxicating', 'possession' etc.

A7 Comments Data

We access comments data through Regulations.gov, an online platform where individuals and organizations can submit comments to government regulations issued by federal agencies.

All executive departments and major independent agencies partner with Regulations.gov to solicit and publicize comments, although several smaller agencies and independent commissions are not partner agencies. While the time coverage of comments on Regulations.gov dates back to 2002, data by agency can vary depending on when the agency became a participating member.

The unit of observation in Regulations.gov is the docket ID-document level. A Docket is an electronic collection of documents related to rulemaking processes. The Docket may contain documents related to one or more Federal Register actions (e.g., proposed rules, notices, and final rules), materials specifically referenced in those documents, and other documents relevant to the rulemaking process the agency seeks to make accessible to the public.

We prompt the Regulations.gov API programmatically through five steps. First, for each FR document number, we retrieve a unique identifier assigned by Regulations.gov: the object ID. Second, for each object ID, we then extract the total number of comments. Third, for documents with a number of comments greater than 0, we extract all comments' unique identifiers. Fourth, we extract a random sample of 5% of comments for each object ID, whereas we select all comments for object IDs with up to 20 comments. Fifth, we retrieve comment-specific metadata, including the author of the comment, the text of the comments, and the attachments to the comments.

To continue the example of EPA regulatory process 2050-AG83, in Table A.4 we report the object ID of the proposed rule identified with FR document number 2016-26381. This proposed rule received four comments, each one with a comment ID and a title, as reported in the table.

Table A.4: Linking Federal Register and Comments Data.

FR Document Number	Regulations.gov		
	Object ID	Comment ID	Comment Title
2016-26381	0900006482362 6f9	0900006482448f6a	Comment submitted by Michael Schon, Vice President and Counsel for Government Affairs and Elizabeth Horner, Director and Assistant Counsel for Government Affairs, Portland Cement Association (PCA)
2016-26381	0900006482362 6f9	0900006482448466	Comment submitted by Jeffrey T. Miller, President and Executive Director, Treated Wood Council (TWC)
2016-26381	0900006482362 6f9	0900006482448370	Comment submitted by Seth L. Johnson, Attorney, Earthjustice
2016-26381	0900006482362 6f9	0900006482447693	Comment submitted by Robert D. Bessette, President, Council of Industrial Boiler Owners (CIBO)

Notes: The table reports the FR unique identifier (document number) assigned to the proposed rule from RIN 2050-AG83, and the respective object ID from Regulations.gov. The object ID returned four comments (with their unique identifiers), reported in the middle columns. The final columns reports the title of the comments.

When submitting a comment, users can type the text of their comments or they can attach a file including one or multiple comments. Downloading attachments is key to accessing relevant comments, for organizations and interest groups generally upload their comments as a PDF or MS Word file. For comments that are typed, we extract the text in machine-readable format directly through the Regulations.gov API. For comments uploaded as attachments, we download the attachment, and based on the format of the file, we apply several optical character recognition technologies to extract from the file text in machine-readable format. When comments both have attachment and typed text, we collate the two sources into a single body of comment text.

We classify the stance of the comment towards the proposed rules with state-of-the-art Natural Language Inference (NLI) techniques. An alternative, promising approach to stance detection that can effectively handle the complexities of varying linguistic contexts across different policy areas and agencies.

NLI leverages pre-trained language models that are designed for entailment classification

tasks. A document *entails* a statement with some probability. For example, the statement "I fully support the EPA initiative." has a high probability of entailing "The author of this comment *supports* the proposed rule." NLI operates by taking a premise (i.e., the comment) and a set of hypotheses (i.e., statements that are either true or false with some probability given the premise) and identifies the hypothesis with the highest probability of being true based on the comment's text (Burnham, 2024).[37]

For example, our random sample of comments includes one submitted by Seth K. Johnson, attorney at Earthjustice. Mr. Johnson submitted a 4-page long file with the following opening statement:

> Earthjustice submits the following comments on the proposed rule in the above-named matter. For the reasons given below, EPA should not finalize the rule as proposed.

The full document represents the premise. The hypotheses are the three possible stances and the stance with the largest probability returned by the model is "Opposes" (p = .99).

55% of comments are classified as conveying a negative stance towards the proposed rule, whereas 37% have a positive stance.

[37] A simpler approach would be to perform some standard sentiment analysis on the entire text of the comment. However, research shows that stance (i.e., position or beliefs about an issue) is frequently uncorrelated with sentiment (Bestvater and Monroe, 2023).

B Predicting the Duration of the Rulemaking Process

In this section, we describe the procedure we implement to predict the duration of the rulemaking process. When comparing the duration of rulemaking processes assigned to teams of aligned or misaligned regulators, one key inferential challenge is that rules assigned to aligned regulators might be systematically shorter or longer to complete compared to rules assigned to misaligned ones. To mitigate this concern, we include the predicted duration of the rulemaking process in the battery of rule-specific covariates x'_r. Our approach follows the procedure proposed by Iaria et al. (2024), who compute the predicted number of citations of academic publications to examine gender gaps in citations.

We train a machine learning classifier on the text of the abstract of the rulemaking process to predict the latent duration of the process.

- First, we subset our sample of rulemaking processes to those with fully misaligned bureaucrats (13,056 out of 35,657 unique RINs). By restricting the training data to rulemaking processes assigned to misaligned bureaucrats alone, we purge the bias that stems from unobserved differences in the samples of rulemaking processes assigned to teams of aligned and misaligned regulators.

- Second, we apply standard text preprocessing steps to the text of the abstract: we remove stopwords and punctuation, we lowercase, and lemmatize each word.

- Third, to produce a matrix of predictors, we represent the set of abstracts as a matrix X of dimensions $R \times F$, where R is the number of abstracts and F is the total number of unique features, i.e. 1,2,3-grams (words). Each entry x_{rf} is a weighted frequency (*tf-idf*) of the n-gram in each abstract, which assigns greater weight to rare words.

- Fourth, to reduce the importance of outliers, we winsorize the training data to rules with duration up to the 99th percentile.

- Fifth, we train a Ridge regression model on 80% of the training data, and we test the performance of the classification on the 20% of held-out test data.

We find that the predicted duration explains 5% of the variance in the actual duration of rulemaking processes ($R^2 = 0.05$).