Selective Oversight*

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Abstract

The congressional oversight of the bureaucracy rests on the ability of members of Congress (MC) to monitor the behavior of bureaucratic agencies, but existing scholarship argues that oversight may clash with President co-partisans' incentives to protect the image of their party. However, tests of this proposition face significant limitations with respect to data, measurement, and inference. I remedy these limitations with two studies on MCs' information acquisition and evaluation of bureaucracies and show that partisanship triggers *selective oversight*. First, I analyze the transcripts of congressional hearings with natural language processing techniques and show that President co-partisans are less inquisitive towards bureaucratic witnesses. Second, I use a difference-in-differences design to show that President co-partisans respond less negatively to scandals affecting bureaucracies. These findings bring novel data on how oversight is performed and have implications for theories of separation of powers and the partisan nature of Congressional oversight.

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In the US separation of power system, Congress plays a crucial role in overseeing the executive branch, scrutinizing the activities of federal agencies and departments, and ensuring that bureaucracies are held in check. A recurring argument in the literature is that Congress does not always adhere to its constitutional vocation, and oversight is mostly driven by inter-branch partisan conflict, hence intensifying under periods of divided government (e.g., McGrath 2013; Kriner and Schickler 2016). Under unified government, the argument goes, Congress is bound by partisan ties with the President, and can less effectively keep the executive in check. In this research note, I argue that this proposition, which is key to our understanding of partisan government and the separation of power system in the United States, has not undergone the rigorous empirical testing it merits.

Several reasons have been put forward in the literature why oversight should be milder under unified government. Partisan explanations focus on President co-partisans weak incentives to investigate members of the executive branch led by a co-partisan President, for party government leaves little space for within-party, inter-branch disagreement (Parker and Dull 2009; Kriner and Schickler 2016). Ideological explanations underscore the preference similarity between Congress and the executive when the latter is guided by a co-partisan President (Kriner and Schwartz 2008; McGrath 2013; Potter and Lowande 2020; but see Lowande 2018). Either as a result of policy preferences or attachment to the party, the observable implication remains the same: *all else equal*, lawmakers co-partisan with the President exert a lighter touch when overseeing the executive.

However, empirical evidence in support of this proposition suffers three methodological limitations. First, when comparing periods of unified and divided government, it is not possible to hold constant the behavior of executive agencies, and differences in oversight might be driven by changes in what agencies do rather than MCs' incentives to protect the image of their party. Second, since Mayhew's (1991) *Divided We Govern*, very little progress has been achieved in terms of measuring the degree of oversight beyond simple frequency measures of oversight hearings. Parker and Dull (2009), McGrath (2013), Kriner and Schickler (2016), MacDonald and McGrath (2016), for instance, all use the number of investigations or hearing days as proxies of oversight intensity. Focusing on hearings to measure oversight is a sensible choice, for hearings are privileged venues where bureaucrats and their organizations are scrutinized and where members of Congress are informed (Kriner and Schickler 2016; Ban, Park, and You 2022; but see Selin and Moore 2023). However, count measures are not fully informative about how oversight is performed during the hearing. Third, despite the micro-level theoretical architecture of the proposition, grounded in legislators' incentives to acquire information and evaluate the executive, most of the data used in these tests is at a highly aggregate level (e.g., chamber- or committee-year level), failing to detect variation in oversight behavior of individual lawmakers.

In this letter I remedy these three limitations with novel data, measurement, and causal evidence to show that co-partisanship with the President indeed triggers *selective oversight* and undermines MCs' ability to effectively acquire information on bureaucracy and objectively evaluate their performance. I propose two testable hypotheses consistent with the argument of partisanship-driven oversight. The first is that President co-partisans are less inquisitive towards bureaucracy and are less likely to acquire information about what bureaucracy does. Second, President co-partisans are less likely to negatively evaluate bureaucracy compared to when they are in the opposition.

I test these predictions with two studies. In the first one, I provide the first attempt at looking at what happens *inside* oversight hearings. I assemble a novel dataset on witnesses testifying in committee hearings for the period 1999-2021 and test whether President co-partisans are less likely to ask questions to bureaucratic witnesses. I match data on witnesses' appearances with the transcripts of speeches given by MCs in committees and find that MCs ask on average 6% fewer questions to bureaucratic witnesses compared to when they are out-partisans. In the second study, I use a difference-in-differences design where I compare how MCs react to five major scandals involving bureaucratic agencies within separate administrations. Event-study estimates show that, faced with the same exogenous shocks about the reputation and performance of agencies, co-partisans with the President are significantly less likely to talk about agencies in the two months after the scandal and less likely to give them a negative evaluation in their speeches.

These findings provide a richer picture of what happens inside oversight hearings, bringing micro-level data and causal evidence on MCs' oversight behavior that is better suited to test theories on members' incentives to oversee agencies.

Congressional Speeches and Bureaucratic Agencies

To study MCs' selective oversight of the bureaucracy, I rely on several types of unstructured data that I describe in each study section. Two types of data will be common to all the empirical tests that follow: congressional speeches and a comprehensive sample of bureaucratic agencies, which I describe below.

I assemble a corpus of 1,5 and 7,3 million speeches given by members of Congress in floor and committee sessions, respectively. I scraped floor (1994-2022) and committee (2010-2020) speeches from the online version of the Congressional Record and I obtained transcripts of congressional committee sessions for the period 1980-2009 from ProQuest. After replacing the various ways in which agencies are mentioned with a standardized name, I subset all speeches mentioning at least one agency. To build a comprehensive list of agencies, I combine large existing datasets, with information on the type of agency directly obtained from the US government website, for a total of 322 unique agencies. 224,749 floor speeches and 694,207 committee speeches mention the name of at least one agency, 14% and 9% of the total speeches. These two sources of data are at the core of both studies on selective information acquisition and selective evaluation.

Study 1: Selective Information Acquisition

To test the argument about selective information acquisition, I collect original data on the identity and affiliation of witnesses testifying before committees, which I match with the transcript of speeches given in the same hearing and compare how often members of Congress question bureaucratic witnesses when they are President co- or out-partisans.

Data: Questioning Bureaucratic Witnesses

First, I web-scraped original data on the identity of the witnesses appearing in House and Senate congressional committees through the govinfo.gov API. I collect data on witnesses and their affiliation for the universe of hearings from 1999 to 2021, for a total of 17,843 hearings and 88,564 witness appearances. Information for each witness includes name and surname, title, and affiliation. For instance, "John S. Tritak, Director, Critical Infrastructure Assurance Office, Bureau of Export Administration, U.S. Department of Commerce" appeared before the Senate Committee on Governmental Affairs on October 4th, 2001.

I then classify witnesses based on whether they are affiliated with a bureaucratic agency or not. To do that, I build very flexible regular expressions that match the names, acronyms, and abbreviations of each one of the 322 bureaucratic agencies in my sample. Bureaucratic witnesses represent a large category of witnesses, accounting for 25% of the total number of appearances. The top two executive agencies with respect to bureaucrat witnesses' affiliation are the Department of Homeland Security (1,634 appearances) and the Department of Veterans Affairs (1,042).

I then match each speech given by committee members in the same hearings where witnesses testify and count how often members of Congress question individual witnesses through three steps. First, I extract the surname of the witnesses appearing in any given hearing. Second, I split the speeches given by MCs during the same hearing into sentences. Third, I count how many sentences include at the same time the surname of the witness as well as a question mark at the end. The (weak) assumption of these measurement steps is that members of Congress address witnesses by their surname. I read several speeches to validate this assumption. Extracting the surname of witnesses is hard, because the order in which the name, title, role, and affiliation appear in the data varies and state-of-the-art supervised models for entity recognition often fail to detect surnames when classifying words as "person(s)". To overcome this challenge, I rely on large language models for text generation. In particular, I use the `gpt-3.5-turbo` model developed by OpenAI. The model performs extremely well and is very efficient, extracting the surname of witnesses form all 88,564 appearances. On a random sample of 100 witnesses, the model-generated output returns the correct surname 98% of the time.

1,071,782 speeches given by 964 unique MCs are given during hearings with witnesses, 66% (711,525) of them are given when the list of witnesses features a bureaucrat. Eventually, this measure allows me to count the number of times members of Congress question bureaucratic and non-bureaucratic witnesses, conditional on a bureaucrat being invited to testify. I therefore subset the 711,525 speeches given when a bureaucrat appeared among the witnesses and compute the total number of questions by type of witness at the MC-hearing level, which will also be the unit of analysis for the statistical test, for a total of 62,773 MC-hearing pairs. For instance, in 1999, Rep. James A. Gibbons (R-NV), in a hearing on "The impact of the expansion of the Minneapolis St. Paul International Airport on the Minnesota Valley National Wildlife Refuge" questioned Assistant Director for Refuges and Wildlife Mr. Dan Ashe from the U.S. Fish and Wildlife Service two times. The average number of questions asked by MCs to witnesses during hearings is rather small and equal to .34 and .39 for bureaucratic and non-bureaucratic witnesses, respectively. The maximum number of questions asked to bureaucratic witnesses during a hearing is 22 – by Rep. Debbie Mucarsel-Powell (D-FL) – whereas the maximum number of questions asked to non-bureaucrats is 50 – by Rep. Rick Hill (R-MT). On average, Republicans and Democrats ask the same number of questions to bureaucratic witnesses, although when MCs are President co-partisans they ask on average 7% fewer questions.

Evidence on Selective Information Acquisition

To test whether members of Congress' co-partisanship with the President triggers selective information acquisition on bureaucracy, I compare the number of questions asked to different types of witnesses (all, bureaucratic, and non-bureaucratic/other) by members of Congress when they are co- and out-partisan with the President. Because the outcome is a count variable, I estimate the following Poisson regression

$$log(\text{N. Questions}^{w}_{ijh}) = \gamma_j + \psi_h + \tau\text{Co-partisan}_{jh} + \zeta X' + \epsilon_{ijh} \tag{1}$$

where N. Questions$^{w}_{ijh}$ is the number of questions asked by MC j in hearing h to witness type $w \in$ {All, Bureaucratic, Non-Bureaucratic}, γ_j and ψ_h are individual and hearing fixed effects, and X' is a set of legislator-level time-varying covariates from Volden and Wiseman (2020) (namely majority/minority leader status, committee chair, legislative effectiveness score, and seniority). τ estimates the percentage change in the number of questions as a result of shifting from out- to co-partisanship with the President.

This design has several appealing features. First, by comparing the effect of co-partisanship for bureaucratic and non-bureaucratic witnesses, I am implicitly performing a strong placebo test. In fact, selective information acquisition should apply only *vis-à-vis* organizations and individuals for which the executive is held responsible. Second, hearing fixed effects allow to partial out the effect of hearing-level characteristics that can confound the relationship be-

Table 1: Co-partisanship and MCs' questioning of bureaucratic witnesses.

	log(N. Questions to Witnesses)					
	All		Bureaucrats		Other	
	(1)	(2)	(3)	(4)	(5)	(6)
President Co-partisan	-0.028	-0.028	-0.060**	-0.064**	0.004	0.002
	(0.025)	(0.025)	(0.028)	(0.028)	(0.033)	(0.033)
Covariates		✓		✓		✓
Observations	54,775	54,770	48,274	48,269	33,571	33,569
MC FE	✓	✓	✓	✓	✓	✓
Hearing FE	✓	✓	✓	✓	✓	✓

Notes: Poisson estimates. SE clustered by MC. DV is a count variable equal to the number of questions asked by MCs to each type of witnesses in any given hearing.
Signif. codes: ***: 0.01, **: 0.05, *: 0.1

tween co-partisanship and MCs' behavior in committee (e.g., the party of the committee chair, the partisan composition of committees, the committee itself as well as the topic discussed in the committee and the number and identity of witnesses testifying in the hearing). Finally, time-changing characteristics of members of Congress control for their different varying propensity to question witnesses based on their role in Congress and committees or their legislative experience.[1]

Table 1 reports the results.[2] The effect of President co-partisanship is negative and precisely estimated for bureaucratic witnesses alone. When individual legislators switch from out- to co-partisan with the President, they ask on average 6% fewer questions to bureaucratic witnesses, leaving unchanged the frequency at which they acquire information from other types of witnesses.

Study 2: Selective Evaluations

In Study 2, I test for the presence of partisan selectivity in MCs' evaluation of bureaucracy, whereby – holding all else fixed – co-partisanship with the President decreases the probability

[1] The results are robust to using logistic regression on a dichotomized outcome and OLS on the log-transformed number of questions (see Table C.2 in the Appendix).

[2] Full regression tables are reported in Section D in the Appendix.

of giving a negative statement about agencies. The *all else fixed* is a crucial part of the test. When co-partisanship status changes as a result of changing presidencies, new bureaucrats are appointed as agency heads, and agencies receive new, politically distinct directives. Similarly, agencies might change their behavior when there is a change in the party controlling Congress. To account for time-changing agency-level characteristics, I leverage exogenous shocks to the performance of agencies to estimate the partisan discount of MCs' reaction to scandals affecting five federal agencies.

Data: Statements about Bureaucracy

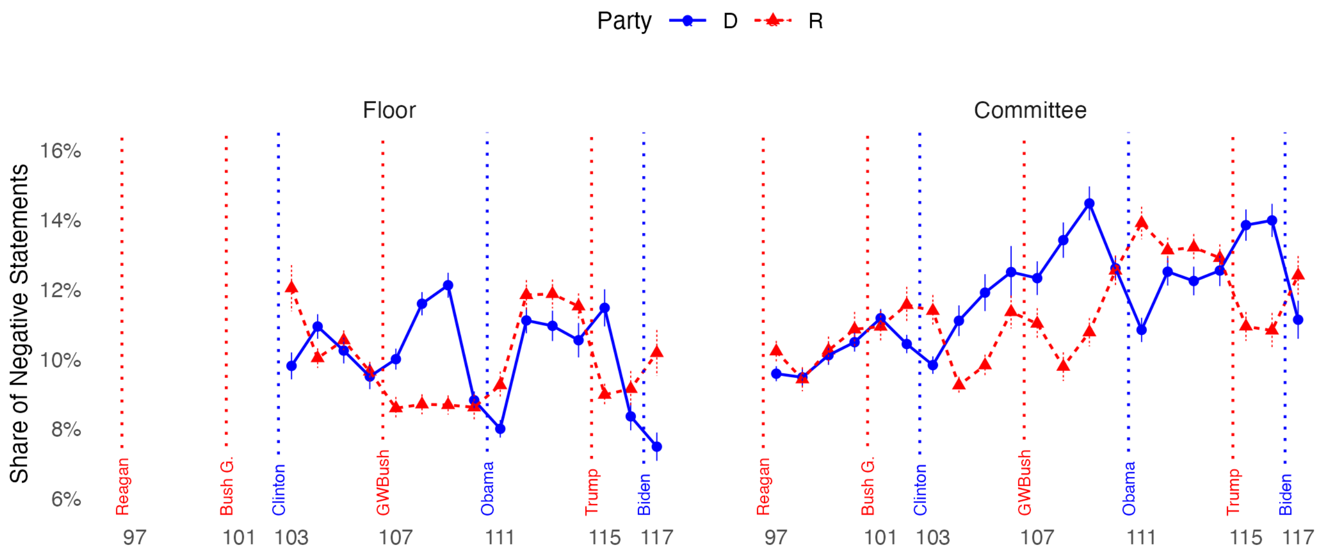
To test the selective-evaluation argument, I split all the speeches given in both floor and committee sessions into sentences, and keep the sentences mentioning the name of a bureaucratic agency. I then use a pre-trained language model to classify the sentiment of the sentence. The classifier assigns one of three labels to each sentence mentioning an agency (negative, neutral, positive). In Table 2, I report three examples of sentences for each of the sentiment labels and I describe the sentiment classification in greater detail in Section A in the Appendix.

Table 2: Examples of sentences assigned to each of the three sentiment labels.

Member	**Year**	**Sentence**	**Label**
Himes, James (D-CT)	2020	And thank you for your extraordinary efforts and the efforts of the Federal Reserve to contribute to the emergency rescue that we have all witnessed.	Positive
Lofgren, Zoe (D-CA)	2010	The Bureau of Customs and Border Protection went from 4.9 billion in fiscal 2004 to 10.1 billion in fiscal year 2010.	Neutral
Aderhold, Robert (R-AL)	2002	In fact, the Department of Education has a very bad record over the last several years when it comes to waste, fraud and abuse.	Negative

I finally obtain 2,055,827 sentences, given by 2,084 MCs, mentioning 316 bureaucratic agencies. 10.6% of sentences are assigned a negative sentiment label by the classifier.

Figure 1: Negative statements about bureaucracy.



Notes: Share of negative statements mentioning bureaucratic agencies over time (Congress) and across presidencies. Vertical dotted line marking changing presidencies.

Evidence on Selective Evaluation

In the aggregate, there is no substantively meaningful difference between the share of negative sentences given by Democrats and Republicans, and the data does not lend support to commonly held accounts portraying Republicans as holding stronger anti-bureaucracy sentiment. However, partisan differences emerge when looking at the time trend. Figure 1 displays the share of negative statements across all agencies for the Democratic and Republican parties across various presidencies, marked by the dotted vertical lines. On average, when there is a Democratic President, statements given by the Democratic party are less negative compared to when there is a Republican President, and *vice versa* for the Republican party's statements.

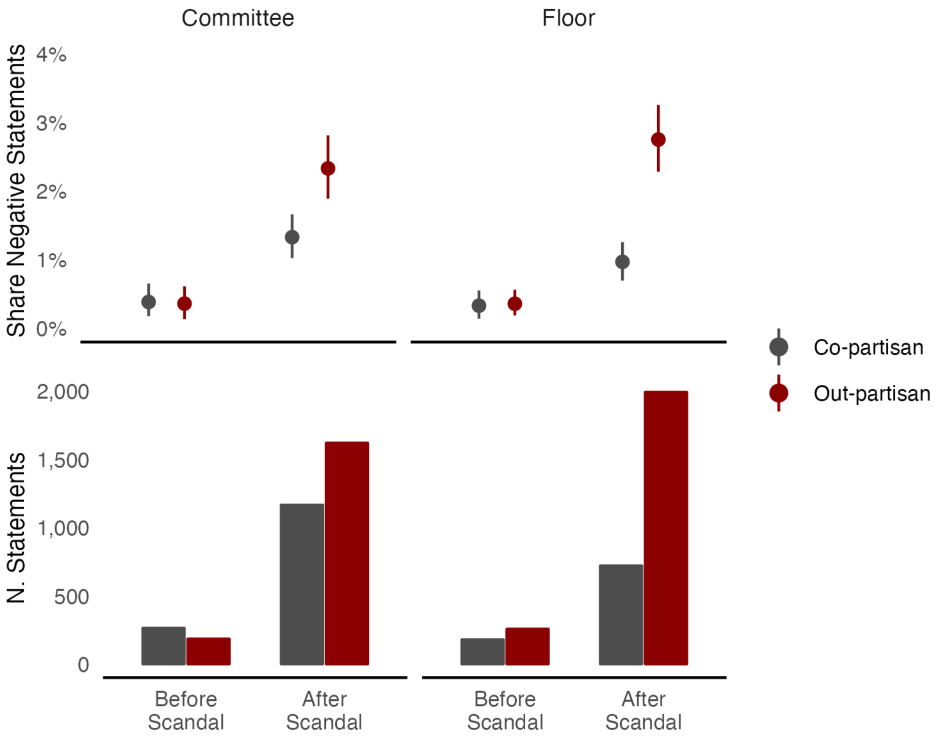
By comparing over-time changes in partisan statements when a new President is elected or when a different party gains control of a legislative chamber does not allow to isolate the effect of changing President from changes in the characteristics of the newly elected legislators and how they interact with bureaucratic agencies, as well as changes in agency behavior. To strengthen causal identification, it is necessary to observe how MCs react to *identical* information. Scandals in the US federal bureaucracy represent a unique opportunity for this purpose. Absent selective evaluation, I should fail to detect a difference in how President co- and out-partisans respond to scandals.

I focus on major scandals involving five federal bureaucracies in the United States: the response of the Federal Emergency Management Agency to Hurricane Katrina in August 2005, the falsified appointment case of the Department of Veterans Affairs (and the Veteran Health Administration) in April 2014, the Internal Revenue Service's undue scrutiny on conservative groups seeking tax-exempt status in May 2014, the whistle-blowing FBI case before September 11th, and the derogatory contents posted on the "I'm 10-15" secret Facebook group by Customs and Border Protection officers in July 2019. These scandals cover three presidencies and both parties (the second G.W. Bush, the second Obama administration, as well as the Trump presidency) and are therefore not limited to one specific direction of co-partisanship (either Democratic or Republican). Qualitative information on the scandals is reported in Section B in the Online Appendix.[3]

I estimate the effect of MC-President co-partisanship on both attention and negative evaluation of the agency affected by the scandal, measured as the probability to give a statement and the share of negative statements about the agency affected by the scandal during the 10 months before and after the scandal. Because silence is itself a strategic choice of members of Congress, I build a dyadic dataset where each MC who gave a speech in Congress during the 10 months before and after each scandal is paired with the agency affected by the scandal. I then count the number of statements given by MC_j mentioning agency_a in month_t as well as the share of statements with a negative sentiment. When MCs do not mention the agency_a in month_t, I assign 0 to both the attention and negative evaluation variables. The dataset consists of 46,088 MC-agency-month observations.

[3]In Figure B.1 in the Appendix I document the salience of these scandals showing the sharp increase in the number of statements about agencies in the aftermath of each scandal.

Figure 2: Evaluation and attention to bureaucracies affected by scandals.



Notes: Share of negative statements and number of statements mentioning agencies affected by the scandal given by MCs in the 2 months before and after the scandal.

Figure 2 already displays a marked differential response to scandals from President co-partisans and out-partisans, both in committee and floor speeches. Right before and after the scandal, and precisely from 60 days before and after, President co-partisans refrain from commenting and giving a negative statement about the agencies, although no clear difference can be detected in the two months before the scandal.

To identify the effect of co-partisanship with the President, I use an event-study design, where I estimate changes in attention and negative evaluation about any given agency for President co-partisans before and after the scandal. In particular, I estimate the following equation

$$y_{ijamt} = \gamma_j + \phi_a + \alpha_m + \delta_t \sum_{k=-10}^{k=9} \beta_k \text{Co-partisan}_{jt} + \zeta X' + \epsilon_{ijamt} \tag{2}$$

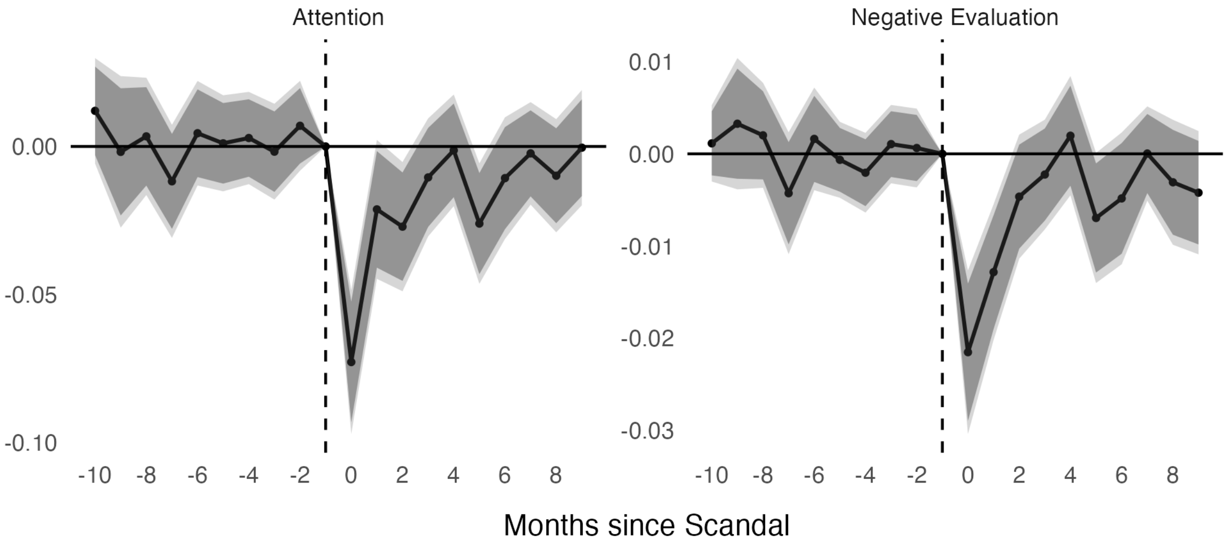
where y_{ijamt} is either a dummy measure equal to 1 when the number of statements given by MC j in month m in year t about agency a, γ_j is at least 1, and 0 otherwise and the share of negative statements mentioning agency a for the same combination of MC-month-agency. ϕ_a, α_m, and δ_t are MC, agency, month-from-scandal, and year of scandal fixed effects, $\zeta X'$ a vector of time-varying speech-level (whether given in floor or committee sessions) and MC-level covariates (same as in Equation (1)). β identifies the dynamic effect of MC-President co-partisanship on the attention and negative evaluation resulting from the scandal. Standard errors are clustered at the dyad (MC-agency) level. The appealing feature of this design is that it allows to identify how co-partisanship shapes legislators' *subjective* reaction to *identical* information (i.e., a clear federal-level scandal).

Figure 3 displays the results.[4] Grey shaded areas around the point estimate represent 90 and 95% confidence intervals. For both outcomes, there is a large negative effect in the 30 days following the scandal (month 0), with the effect persisting during the following 30-60 days. As evidenced by the pre-scandal period, President co-partisans were not on a different trend before the scandal.

When looking at the month of the scandal, President co-partisans are 12 p.p. less likely to mention the name of the agency affected by the scandal and the share of negative statements is 3 p.p. lower compared to out-partisans. These effects remain negative and statistically significant from 0 at standard confidence level up until 90 days from the scandal for the measure of attention, and 60 days from the scandal for the negative evaluation measure. These findings suggest that, even when facing the same unambiguously negative information about bureaucracy, MCs selectively evaluate bureaucracies: more positive if co-partisan with the President, more negative if out-partisan. This is a conservative test of the selective-evaluation argument, for it exposes MCs to clearly negative information about the bureaucracy. In fact, selective evaluation of bureaucracies might be more pronounced when the valence of the information

[4]Regression table reported in the Appendix (see Table B.1).

Figure 3: Event-study results.



Notes: Event-study plot for both attention and negative evaluation outcomes with 90% and 95% confidence intervals. Month of scandal = 0.

leaves space for ambiguity.

Discussion

Politicians' ability to effectively oversee bureaucracies is a central topic in political science and a cornerstone of bureaucratic legitimacy. In this letter, I remedy major empirical limitations of existing work and bring new data and evidence in support of what I refer to as selective oversight. By looking at how oversight is performed during hearings, I found that legislators acquire less information about bureaucracy and give less negative evaluations when co-partisan with the President. Covering both the information acquisition and evaluation steps of oversight, this paper brings new evidence consistent with the partisan nature of bureaucratic oversight, addressing several methodological limitations of existing empirical literature on the partisan discount of members of Congress' incentives to monitor the bureaucracy.

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Online Appendix

Contents

A Sentiment Classifier

Pre-trained models benefit from domain-specific training and yield better performance when compared to dictionary-based approaches relying heavily on the correct specification of the list of words. Because bureaucracies are highly technical bodies, I use the FinBERT model used by Huang, Wang, and Yang (2023) to classify the sentiment of financial communication text and train on a large financial communication corpus. FinBERT is a three-label classifier which takes as input a string of text (i.e., a sentence) and returns two outputs: one of the three sentiment labels (negative, neutral, positive) as well as the probability that the text belongs to the label.

B Scandals Involving Federal Agencies

I focus on three major scandals affecting US bureaucracy that undermined the reputation of agencies.

- **Federal Emergency Management Administration**: FEMA "was criticized for poor preparation and a slow response to Hurricane Katrina" (Roberts 2006, 57) and its response the Hurricane Katrina on 23 August 2005 is still acknowledged as "another grand failure for FEMA"[5].

- **Internal Revenue Services**: A report published by the US Treasury Inspector General for Tax Administration on 14 May 2013 found that the Internal Revenue Service targeted conservative groups applying for tax-exempt status (TIGTA 2013).

- **Department of Veterans Affairs**: Finally, "the Department of Veterans Affairs in 2014 was embroiled in a scandal over massive wait times in its health-care system". In some hospitals, the staff falsified appointment records to appear to meet the 14-day target. Some patients died while they were on the waiting list.[6]

- **Federal Bureau of Investigation**: The FBI was accused of missed signals before the Sept. 11 terror attacks as resulted from the agency's director and an FBI whistle-blower testifying before a Senate committee.[7]

- **Customs and Border Protection**: The media found out about a secret Facebook group with more than 9,000 members where CPB agents joked about migrants' death and posted sexist memes. Members of a secret Facebook group for current and former Border Patrol agents joked about the deaths of migrants, discussed throwing burritos at Latino members of Congress visiting a detention facility in Texas on Monday and posted a vulgar illustration depicting Rep. Alexandria Ocasio-Cortez engaged in oral sex with a detained migrant, according to screenshots of their postings.[8]

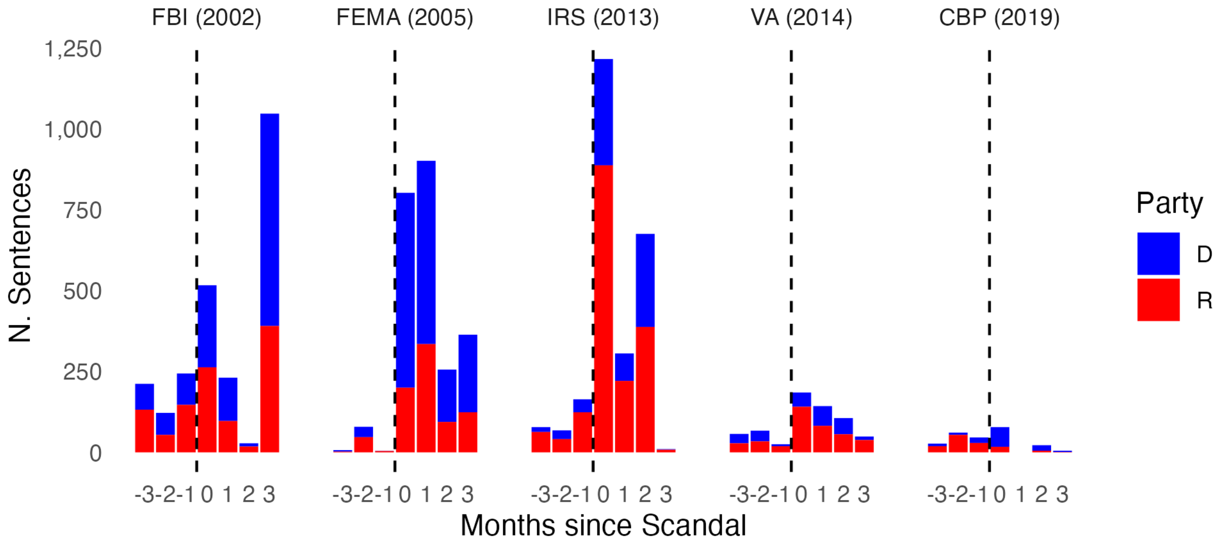
[5]See https://timeline.com/fema-hurricane-andrew-snapshots-7a764f017614?gi=523eefba5d42

[6]See https://vox.com/2014/9/26/18080592/va-scandal-explained

[7]See https://abcnews.go.com/US/story?id=91584&page=1

[8]See https://www.propublica.org/article/secret-border-patrol-facebook-group-agents-joke-about-migrant-deaths-post-sexist-memes

Figure B.1: Statements before and after scandals.



Notes: Number of statements before and after scandal for each agencies by party.

Table B.1: Event-study estimates.

	Pr(Statement about agency = 1) (1)	Share of Negative Statements (2)
President Co-partisan × Month since scandal = -10	0.012	0.001
	(0.009)	(0.002)
President Co-partisan × Month since scandal = -9	-0.002	0.003
	(0.012)	(0.004)
President Co-partisan × Month since scandal = -8	0.003	0.002
	(0.010)	(0.003)
President Co-partisan × Month since scandal = -7	-0.012	-0.004
	(0.009)	(0.003)
President Co-partisan × Month since scandal = -6	0.004	0.002
	(0.009)	(0.003)
President Co-partisan × Month since scandal = -5	0.001	-0.001
	(0.008)	(0.002)
President Co-partisan × Month since scandal = -4	0.003	-0.002
	(0.008)	(0.002)
President Co-partisan × Month since scandal = -3	-0.002	0.001
	(0.008)	(0.002)
President Co-partisan × Month since scandal = -2	0.007	0.001
	(0.008)	(0.002)
President Co-partisan × Month since scandal = 0	-0.073***	-0.022***
	(0.012)	(0.004)
President Co-partisan × Month since scandal = 1	-0.021*	-0.013***
	(0.012)	(0.004)
President Co-partisan × Month since scandal = 2	-0.027**	-0.005
	(0.011)	(0.004)
President Co-partisan × Month since scandal = 3	-0.010	-0.002
	(0.010)	(0.003)
President Co-partisan × Month since scandal = 4	-0.001	0.002
	(0.009)	(0.003)
President Co-partisan × Month since scandal = 5	-0.026**	-0.007*
	(0.011)	(0.004)
President Co-partisan × Month since scandal = 6	-0.011	-0.005
	(0.010)	(0.004)
President Co-partisan × Month since scandal = 7	-0.002	0.000
	(0.009)	(0.003)
President Co-partisan × Month since scandal = 8	-0.010	-0.003
	(0.010)	(0.004)
President Co-partisan × Month since scandal = 9	0.000	-0.004
	(0.010)	(0.003)
Floor	-0.015***	-0.001
	(0.003)	(0.001)
Legislative Effectiveness	-0.003	0.000
	(0.004)	(0.001)
Majority Leader	0.019	0.005
	(0.021)	(0.006)
Minority Leader	0.005	-0.004
	(0.023)	(0.007)
Committee Chair	0.002	0.000
	(0.010)	(0.004)
R^2	0.173	0.084
Observations	58,073	58,073
MC-Agency FE	✓	✓
Month since scandal FE	✓	✓
Year FE	✓	✓

Notes: Event-study estimates (OLS). SE clustered by MC. Outcome of Column (1) is a dummy measure equal to 1 if the MC mentions the agency affected by scandal and 0 otherwise in any given month. Outcome of Column (2) is the share of negative statements about the agency affected by the scandal. 0 is used for MC-month-agency observations with no mentions, hence the estimates capture the effect of co-partisanship with the President at the extensive margin.
Signif. codes: ***: 0.01, **: 0.05, *: 0.1

C Robustness Tests

Table C.2: Co-partisanship and questioning bureaucratic witnesses.

	Logit (dummy DV)			OLS (log-transformed DV)		
	All	Bureaucrats	Other	All	Bureaucrats	Other
	(1)	(2)	(3)	(4)	(5)	(6)
	Logit	Logit	Logit	OLS	OLS	OLS
President Co-partisan	-0.026	-0.069*	0.020	-0.003	-0.006**	0.001
	(0.034)	(0.036)	(0.040)	(0.004)	(0.003)	(0.002)
Committee Chair	-0.726***	-0.544***	-0.822***	-0.075***	-0.048***	-0.046***
	(0.174)	(0.162)	(0.215)	(0.018)	(0.013)	(0.012)
Majority Leader	-0.178	-0.224	0.239	-0.021	-0.024	0.014
	(0.174)	(0.178)	(0.228)	(0.017)	(0.015)	(0.014)
Minority Leader	-0.021	-0.143	0.338	-0.002	-0.009	0.011
	(0.226)	(0.253)	(0.213)	(0.024)	(0.023)	(0.013)
Seniority	0.031	0.101***	0.002	0.003	0.008**	0.000
	(0.035)	(0.038)	(0.035)	(0.004)	(0.003)	(0.002)
Legislative Effectiveness	0.054***	0.036*	0.085***	0.005***	0.003*	0.005***
	(0.019)	(0.019)	(0.023)	(0.002)	(0.002)	(0.002)
R^2				0.324	0.314	0.357
Observations	53,639	47,763	33,074	62,766	62,766	62,766
MC FE	✓	✓	✓	✓	✓	✓
Hearing FE	✓	✓	✓	✓	✓	✓

Notes: Logit and OLS estimates. SE clustered by MC. DV is a dummy variable equal to 1 if the speeches in MC-hearing pairs contain at least one question to type of witnesses included in the table header (Cols. 1-3) and the log transformed number of questions (Cols. 4-6).
Signif. codes: ***: 0.01, **: 0.05, *: 0.1

D Full Regression Tables

Table D.3: Co-partisanship and MCs' questioning of bureaucratic witnesses.

	log(N. Questions to Witnesses)					
	All		Bureaucrats		Other	
	(1)	(2)	(3)	(4)	(5)	(6)
President Co-partisan	-0.028	-0.028	-0.060**	-0.064**	0.004	0.002
	(0.025)	(0.025)	(0.028)	(0.028)	(0.033)	(0.033)
Committee Chair		-0.525***		-0.292**		-0.789***
		(0.125)		(0.119)		(0.166)
Majority Leader		-0.043		-0.148		0.109
		(0.110)		(0.104)		(0.166)
Minority Leader		0.079		0.005		0.262
		(0.181)		(0.173)		(0.230)
Seniority		0.030		0.062*		0.001
		(0.024)		(0.031)		(0.027)
Legislative Effectiveness		0.061***		0.033**		0.087***
		(0.013)		(0.014)		(0.019)
Observations	54,775	54,770	48,274	48,269	33,571	33,569
MC FE	✓	✓	✓	✓	✓	✓
Hearing FE	✓	✓	✓	✓	✓	✓

Notes: Poisson estimates with full set of covariates reported in the table. SE clustered by MC. DV is a count variable equal to the number of questions asked by MCs to each type of witnesses in any given hearing.
Signif. codes: ***: 0.01, **: 0.05, *: 0.1

References Appendix

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