Bureaucrats in Congress: The Politics of Interbranch Information Sharing[*]

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Abstract

Congress often relies on bureaucrats' information for policy production. However, scholars lack an empirical understanding of what drives information sharing between bureaucrats and legislators. We argue that the partisan alignment between a bureaucrat and legislator determines the amount and type of information transmitted. Using new comprehensive data on bureaucratic witnesses in committee hearings, as well as a new measure of the informational content of testimonies, we show that less analytical information is transmitted between a bureaucrat and legislator pair when the legislator is a presidential out-partisan than a co-partisan, and that this effect is heightened when the bureaucrat is a political appointee. At the aggregate hearing level, the collective amount of analytical information from bureaucrats is lower under divided government than unified government but is offset by the analytical information from non-bureaucratic witnesses. These dynamics provide a nuanced understanding of the information transmission between bureaucrats and Congress.

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The relationship between Congress and the executive agencies is central to the separation of powers in American politics: Congress makes laws, and the executive branch executes the laws through its system of bureaucratic agencies. Scholars have studied how partisanship across this separation of powers system affects outcomes, such as legislative productivity (e.g., Binder 1999; Coleman 1999; Howell et al. 2000; Phillips and Kirkland 2018), oversight and investigations (Kriner and Schwartz 2008; Kriner and Schickler 2016), and the degree of delegation to the bureaucracy (Epstein and O'Halloran 1996, 1999).

Beyond these outcomes, however, lies a broader information asymmetry between the two branches: The division of responsibilities leads each side of the interbranch relationship to gain different information and perspectives about policymaking (Banks and Weingast 1992; Bendor, Taylor, and Gaalen 1987). Bureaucrats in executive agencies—who implement policy—acquire a relatively higher awareness and on-the-ground knowledge about the realities of policy implementation and its consequences compared to lawmakers in Congress. While Congress also can collect this information from others during the legislative process, bureaucrats remain one of their best sources of expertise about policy implementation and execution (Gailmard 2002; Gailmard and Patty 2012).

How, then, do partisan divides across the legislative and executive branches influence interbranch information sharing? We argue that the partisan alignment between legislators and bureaucrats drive the amount and type of interbranch information exchange. When a legislator and bureaucrat pair is misaligned in committee hearings—that is, when a legislator is of one party and the bureaucrat is from an executive branch controlled by the other party—the flow of policy-relevant information may be impeded by the strategic interactions between legislators and bureaucrats who are both conscious of their partisan goals and political incentives.

Since the agenda and all other specific aspects of a committee hearing are determined by committee members, and witnesses can speak only if they are given the opportunity to respond to a question from a legislator, the overall policy discourse that occurs in hearings is predominantly shaped by legislators. Legislators may ask different questions that elicit different types of information based on whether they are interacting with bureaucratic witnesses whose preferences are aligned with their partisan goals. For example, a legislator may take the opportunity to score partisan points through grandstanding and increased political messaging or aggressiveness (Park 2021, 2023). This incentive may be stronger when a legislator is questioning a bureaucrat from an executive branch controlled by the opposite party. The amount and type of information exchanged between a bureaucrat and legislator thus may be influenced by how the legislator, driven by the partisan alignment between herself and the bureaucrat, *elicits* this information.

Simultaneously, bureaucrats have their own incentives that steer their interactions with Congress and may play a similar role in determining the amount and type of information shared with Congress. Bureaucrats' behavior in sharing policy expertise with politicians may also depend on who they are specifically interacting with from a bureaucrat's perspective. Bureaucrats may provide more policy-relevant information to assist presidential co-partisans than they do to presidential out-partisans, or they may provide more valuable information to out-partisans to convince out-partisan legislators. Further, the partisan alignment between bureaucrats and legislators may be more salient for politically appointed bureaucrats compared to careerists, given the partisan nature of appointments. Thus, the amount and type of information provided to legislators also may be influenced by how the bureaucrat, driven by partisan alignment between herself and the legislator, *responds* to information requests.

Combining the incentives of legislators and bureaucrats, it is not clear ex ante how partisan alignment would affect information transmission between a bureaucrat and legislator at the pair level. We investigate this empirically and examine information sharing between bureaucrats and Congress in one major venue through which Congress can request, receive, and publicly disseminate information from the bureaucracy: committee hearings. Previous work has focused on hearings specific to oversight or investigative matters (McGrath, 2013; Kriner and Schickler, 2016). Beyond the oversight context, hearings can facilitate the exchange of information for legislative matters more broadly and, specifically, reveal the content of the information provided to Congress (Quirk 2005). While there are other channels through which legislators and bureaucrats can transmit information, such as in phone calls, written correspondence, or private meetings, hearings represent a public, formal channel of information transfer. This venue is an impactful setting for information transmission and dissemination since the information is observed by other legislators, bureaucrats, and officials in both branches of government as well as monitored by stakeholders in the policy area.

As not all information is equal, we use House committee hearing transcript data from 1997 to 2014 and a crowd-sourced supervised learning method to capture a specific aspect of information conveyed in both bureaucrats' and other types of witnesses' testimonies. While there are various ways to characterize informational content, we focus on a type of information that is closely linked to policy expertise, central to technical policy development, and applicable across issue areas: information that uses falsifiable statements on the policy under consideration, which we term analytical information. This approach is a significant improvement over other measures of information as it uses human judgment to measure the intensity of the concept of interest in the committee hearing context, rather than using a binary classifier for analytical statements (Esterling 2011) or depending on a set of researcher-selected words that may be incomplete (Ban, Park, and You 2023). Specifically, 1) we employed a highly sophisticated measurement process involving large-scale human coding of sample testimonies using online workers, 2) trained multiple machine learning algorithms to predict the level of analytical information conveyed in witness testimony, and 3) combined their predictions through an optimization process to generate the final measurement for each of the 981,633 testimonial statements that witnesses made in 14,092 hearings. We then conducted a set of extensive statistical and substantive validations of our new measurement.

We use this new measure of information in combination with a novel dataset on bureaucratic witnesses from 1977 to 2014. We collect the federal agency affiliation and appointment type for each bureaucrat who testified in all House committee hearings during this extensive time span, as well as the content of their testimonies and their responses to questions from members of Congress in all committee hearings. The result is a dataset that, for the first time, provides the name of the agency of each bureaucrat who appeared in a congressional hearing (1977-2014), and links to the content of information bureaucrats provided to Congress for a subset of the time period (1997-2014). Further, while previous work on bureaucrats in hearings has been limited to aggregated counts of hearings or witnesses at the Congress-level, we create pair-level data at the politician-bureaucrat level by parsing hearing transcripts, which allows us to analyze dyadic interactions between a member and a witness.

At the pair level between a legislator and bureaucrat, we find significantly less analytical information is transmitted from bureaucrats to legislators when bureaucrats face an out-partisan legislator compared to a legislator of the same party of the president. This lower transmission of analytical information between misaligned legislator-bureaucrat pairs occurs in both legislative hearings and oversight hearings and after controlling for the legislator's questioning style, which we capture by the amount of grandstanding, analytical keywords used, and sentiment displayed. Using bureaucrat fixed effects, we also find that the same bureaucrat provides significantly less information to legislators who are presidential out-partisans compared to presidential co-partisans in the same hearing. The effect of partisan alignment is more salient in hearings on more polarized issues, among political appointees—especially those from executive departments—in oversight hearings, and in more prestigious and policy oriented committees. The effect is further amplified for the agencies that are more aligned with the president. A placebo test with non-bureaucratic witnesses shows that these information sharing dynamics are not present for other types of witnesses, suggesting that partisan alignment has a distinct effect on bureaucrats, which leads them to change their information provision to Congress.

In addition to the pair-level exchange of information between a bureaucrat and legislator, we also examine the effects of partisan alignment at the overall hearing level. Even if information exchange is impeded when a bureaucrat faces a legislator from a party opposite to the president's, in any given hearing, there are other witnesses who may also provide analytical information. Does partisan alignment between the legislative and executive branches drive the *collective* amount of analytical information shared between the branches at the hearing level? We use the presence of divided government as a measure of partisan alignment between the legislative and executive branches, and capture the total number of question and answer pairs between legislators and witnesses as well as the total amount of analytical information provided in a hearing. We find that during divided government, members of Congress ask more questions of witnesses, a behavior that is primarily driven by presidential out-partisan members and especially when they question non-bureaucratic witnesses. Our results show that while the total amount of analytical information from bureaucrats is lower under divided government compared to unified government, this negative effect of divided government is offset by the analytical information provided by non-bureaucratic witnesses.

Altogether, this article reveals the complex nature of the relationship between partisan alignment across government and interbranch information sharing. Our findings provide a nuanced understanding with implications not only for how partisan alignment affects the information transmitted between pairs of legislators and bureaucrats, but also how it affects legislators' behavior with non-bureaucratic witnesses and the collective amount of analytical information gained by Congress.

Expertise and information are critical sources of the bureaucracy's power. While there has been ample theoretical attention devoted to information asymmetries between the two branches (e.g., Banks and Weingast 1992), how bureaucrats' selection and learning can affect the development of expertise within the executive branch (e.g., Gailmard and Patty 2012), and how bureaucrats may act strategically in response to Congress (e.g., Potter 2019; Lowande 2019), there has been surprisingly little attention paid to the resulting provision of information from the bureaucracy to Congress. Our findings contribute to the literature by revealing how the pair-level partisan incentives of legislators and bureaucrats and the presence of divided government affect how much policy-relevant information is shared from the bureaucracy to Congress in both legislative and oversight contexts. As information is the input to policy, our findings shed new light on how the interbranch relationship can affect the policymaking process vis-à-vis information flows.

Interbranch Information Sharing

The information advantage that bureaucrats have concerning program implementation is a crucial factor in the canonical power balance between Congress and the bureaucracy. While traditional delegation models, such as Huber and Shipan (2002), focus on how Congress can influence this power balance by choosing the amount of delegation Congress gives to the bureaucracy, another way to influence the interbranch relationship is by controlling *information*. It has been theorized that the institution that has more information about the costs and consequences of policy implementation holds an "informational advantage" in this interbranch relationship (Banks and Weingast, 1992; Bendor, Taylor, and Gaalen, 1987).

What do we mean by policy-relevant information or expertise? Bureaucratic expertise has been measured in various ways. For instance, Clinton et al. (2012) measures the policy expertise of federal bureaucrats in each agency using the proportion of technical and proportion of professional employees. As another example, Richardson, Clinton, and Lewis (2018) use a survey approach, and ask federal bureaucrats to rate their workforces from which they construct a measure of skill and competency for each agency. Their work shows that expertise varies across agencies and implies that it varies across bureaucrats within agencies as well. In this paper, we focus on a type of information that is closely linked to policy expertise and central to technical policy development: information that uses falsifiable statements on the policy under consideration, which we term *analytical information* (more explanation is provided in Section 4.2).

Scholars have documented that bureaucrats, who are responsible for the implementation and evaluation of their agencies' programs and policies, have deep familiarity and expertise specific to their agency's jurisdiction. This work has focused on how bureaucrats both bring expertise to, and develop expertise on, their jobs. Research has argued that politically appointed bureaucrats bring high levels of human capital, responsiveness, and energy to the executive agencies (Moe, 1985). Career bureaucrats, especially those who have advanced through the ranks, are seen to possess subject area expertise and public management skills (Helco, 1977), and research shows that this translates into higher federal program performance (Lewis, 2007; Gallo and Lewis, 2012). Further, Gailmard and Patty (2012) emphasize the ways bureaucrats learn and acquire expertise on the job, saying that "bureaucrats are not born with all the skills they need" and that their expertise is gained through incentives in public service.

Regardless of where bureaucratic expertise originates, it remains constant in the literature that bureaucrats possess expertise and an informational advantage over Congress. Recent research has shown that politicians do, in fact, seek to obtain and rely on this information, and that politicians' preferences can indeed be shaped by how bureaucrats frame an issue (Blom-Hansen, Baekgaard, and Serritzlew, 2020) and the ideological alignment with bureaucrats (Esterling, 2009; Bellodi, 2023).

Given that bureaucrats hold the informational advantage and Congress can benefit from this information when producing policy, how is information shared between the bureaucracy and Congress? Congress can request information from bureaucrats through a variety of methods, including phoning or writing to agencies (Lowande 2018; Ritchie 2018; Ritchie and You 2019; Ritchie 2023), but one formal, public way Congress requests and receives information from the bureaucracy is through committee hearings (Quirk and Bendix 2011; Park 2017). In hearings, Congress can examine the amount of information bureaucrats hold and request specific pieces of that information. Committees call bureaucrats to testify at hearings and answer questions; they use the power of subpoena, if necessary (Heitshusen, 2017). Perhaps the most conspicuous way bureaucrats appear in hearings is when committees conduct oversight of the bureaucracy. Unsurprisingly, scholars have used oversight hearings as a measure of the amount of oversight that committees conduct (Kriner and Schickler 2016; McGrath 2013).

Outside of studies that examine the frequency of congressional oversight on agencies, there is limited work on the information exchange between bureaucrats and members of Congress. May, Koski, and Stramp (2016) find that bureaucrats' testimony is an important conduit of expertise, and that issue maturity and salience affect the supply and demand for this expertise. Their analysis, however, is limited to hearings specifically concerned with critical infrastructure protection. Ban, Park, and You (2023) find that when committees hold legislative hearings, they invite fewer bureaucrats during periods of divided government and substitute for them with witnesses from think tanks and universities. Eldes, Fong, and Lowande (2024), in analyzing the content of oversight hearings, show that oversight hearings can be informational and confrontational at the same time, and that confrontation decreases when the legislator shares the same partisanship with the president. Bellodi (2023) analyzes legislators' citation of bureaucratic information in floor and committee speeches and shows that ideological differences and agency independence are important factors determining how often members of Congress cite the information provided by bureaucrats.

However, the existing research, neglects a fundamental question about the supply of information presented to the legislature from the executive branch: What determines the information flow from the bureaucracy to Congress? The answer to this question requires examining the incentives of two groups of actors: legislators and bureaucrats. The behaviors legislators employ when requesting information from bureaucrats can determine the amount and type of information they elicit. Similarly, the way a bureaucrat provides information in response may affect the amount and type of information transmitted to the legislators. We go beyond what the previous literature has documented: we provide empirical evidence for how partisan alignment between the legislature and the executive branch influences legislator and bureaucratic behavior in committee hearings, thus shaping interbranch information flows.

Partisan Alignment and Interbranch Information Flows

We consider how partisan alignment at the individual level may shape the transmission of information between bureaucrats and legislators in committee hearings. Due to heightened partisan competition for majority status in Congress as well as the White House, legislators look for any opportunity to tarnish the image of the other party in order to make the next election favorable to their own party (Lee 2016). A legislator questioning a bureaucrat from an executive branch controlled by the other party is presented with an opportunity to target the other party through messaging. Thus, it is likely that the presidential out-partisan legislator may ask questions in a more aggressive tone or increase the political messaging in their questioning to criticize the other party or to enhance the legislator's own partisan reputation. While the legislator still could request information to assist in policymaking, the incentive to target the bureaucrat presenting the interest of the other party for political points may be dominant. When facing a bureaucrat from an executive branch controlled by their shared party, however, the legislator has less of an incentive to aggressively attack the bureaucrat and more of an incentive to request information that can assist in forming a policy of their shared preference.

The literature on the bureaucracy also suggests that bureaucrats can also act strategically. Bureaucratic subversion, shirking, and sabotage are well documented (Brehm and Gates 1997; Gailmard 2002) and bureaucrats have been shown to strategically use procedural tools, such as the timing of final rule publication, to avoid oversight by Congress and other political actors (Potter 2017, 2019). We adapt this view of strategic bureaucrats to congressional hearings and their interactions with legislators. Bureaucrats may be motivated by partisan incentives to be more willing to assist Congress—providing expertise that allows legislators to develop effective policy if the bureaucrats feel that Congress would use their information to pass a shared policy platform. If this is the case, then we would observe more analytical information exchanged between a partisan aligned bureaucrat and legislator pair.

When a bureaucrat is misaligned with a legislator—when the bureaucrat represents an executive branch controlled by a party opposite to the legislator's party—how much analytical information a bureaucrat responds with is less clear. On one hand, bureaucrats may not want to assist Congress in passing a diverging policy platform. When holding a legislator's question constant, bureaucrats may provide less analytical information when questioned by an out-partisan legislator than a co-partisan legislator to the president, to avoid giving information that could support the opposing party's policy. On the other hand, a bureaucrat may alternatively prefer to provide more analytical information to an opposing party's legislator, in an effort to still influence what the misaligned legislator decides. The effect of partisan alignment on bureaucrats is thus less clear.

If we were to see an effect of partisan alignment on bureaucrats, however, it is likely to be amplified for bureaucrats who are politically appointed. Bureaucrats vary across one stark partisan-driven characteristic: whether they are politically-appointed bureaucrats or career bureaucrats. The partisanship of political appointees closely follow the party of the president (Spenkuch, Teso, and Xu 2023), therefore legislators may see bureaucrats as more closely linked to the president when they are interacting with political appointees compared to careerists (non-appointees). When presidential out-partisan legislators are motivated to publicly criticize the administration, they are likely to engage more in messaging activities and less in information-seeking discourse when they face political appointees compared to careerists during hearings. At the same time, politically appointed bureaucrats may face a different political context because their positions may be subject to that president remaining in power or to maintaining that president's favor. Political appointees are more likely to have shorter-term outlooks that are more sensitive to the current political environment and thus are more responsive to the partisan goals of the president (Lewis 2008; Dahlstrom, Fazekas, and Lewis 2021). Aligning with the party of their appointing president and working to ensure that Congress produces (doesn't produce) legislation that is aligned (misaligned) with the president may be a more salient concern for politically appointed bureaucrats. Therefore, when examining interactions between bureaucrat-legislator pairs, the partisan alignment of the pair on the information exchanged may be more salient when the bureaucrat is a political appointee than when the bureaucrat is a careerist.

Data and Descriptive Statistics

In this paper, we rely on two datasets. First, we construct the data on bureaucratic witnesses who appeared in hearings in the House of Representatives for the period of 1977-2014. We use this data to present the descriptive statistics on bureaucrats who testified in Congress. Second, we use House hearing transcripts for the period of 1997-2014 to analyze the transmission of analytical information from witnesses to committee members in these hearings. Using the hearing transcript data, we introduce a new measure capturing the level of analytical information conveyed in witnesses' testimonies through text-analytic methods and construct various measures for committee members' speaking tones. We then merge the two datasets and construct member-witness pair-level data for the main statistical analysis, which covers the period of 1997-2014.

Data on Bureaucrats Testifying in Congress

We construct a new dataset on bureaucratic witnesses who testified in congressional hearings. We begin by using data from Ban, Park, and You (2023), which were collected from the ProQuest Congressional, to identify witnesses who are federal bureaucrats, and we focus on hearings in the House. We then cleaned these affiliations to match them with the official name of the parent agency. We referred to various sources, such as the Office of Personnel Management (OPM) website,[1] to compile a complete list of federal government agencies and their parent organizations.[2] We performed both automated and extensive manual cleaning processes to identify the parent agency for each bureaucratic witness's affiliation.

Next, we use the OPM data to identify whether a bureaucratic witness is a political appointee or a career bureaucrat. We use the data from BuzzFeed News's Freedom of Information Act request for federal government personnel records from 1977 to 2014.[3] Following Lewis (2011), we define an individual as a political appointee if the appointment type corresponds to one of the following types in the OPM data: PAS (presidential appointments with senate confirmation), PA (presidential appointment without senate confirmation), SES (senior executive service), and C (Schedule C appointments).[4] We merged this political appointee data to the witness data by a bureaucrat's last

[1] OPM website: https://www.opm.gov/about-us/open-government/Data/Apps/Agencies/

[2] We additionally checked the US Government manuals to see if the sub-agencies were properly assigned to parent Executive Departments or Other Agencies: https://www.govinfo.gov/app/collection/GOVMAN

[3] https://www.buzzfeed.com/tag/opm. One limitation of this data is that it omits some agencies or individuals, such as agencies directly related to national security. Given the substantial number of bureaucrats from the Department of Defense in our dataset, we manually identified their political appointee status based on their titles that appeared in the United States Government Policy and Supporting Positions (Plum Book).

[4] The OPM webpage (https://dw.opm.gov/datastandards/referenceData/1585/current?index=T) provides 18 types of appointments for federal bureaucrats. Among them, the codes 36 and 46 are PAS; the codes 55, 60, and 65 are PA; the code 44 is Schedule C appointments; and the code 50 is noncareer SES. We consider the remaining types as career bureaucrats.

name, first name, agency name, and year. Due to the years covered in the OPM data, our data on testifying bureaucrats spans from 1977 to 2014.

Through this process, we constructed a comprehensive dataset that includes 65,347 bureaucrat witnesses, from 15 executive departments and 55 other agencies, who testified in House hearings from 1977 to 2014. It is important to note that outside of MacDonald and McGrath (2016), who recorded the agency information for bureaucrats who testified in oversight hearings from 1999 to 2011, existing research has only tracked the frequency of bureaucrats' appearances in these hearings without examining the variations of their agency affiliations. Our dataset, thus, provides the first opportunity to analyze the features of bureaucratic agencies with which testifying bureaucrats are affiliated with, in all types of House hearings from 1977 to 2014.

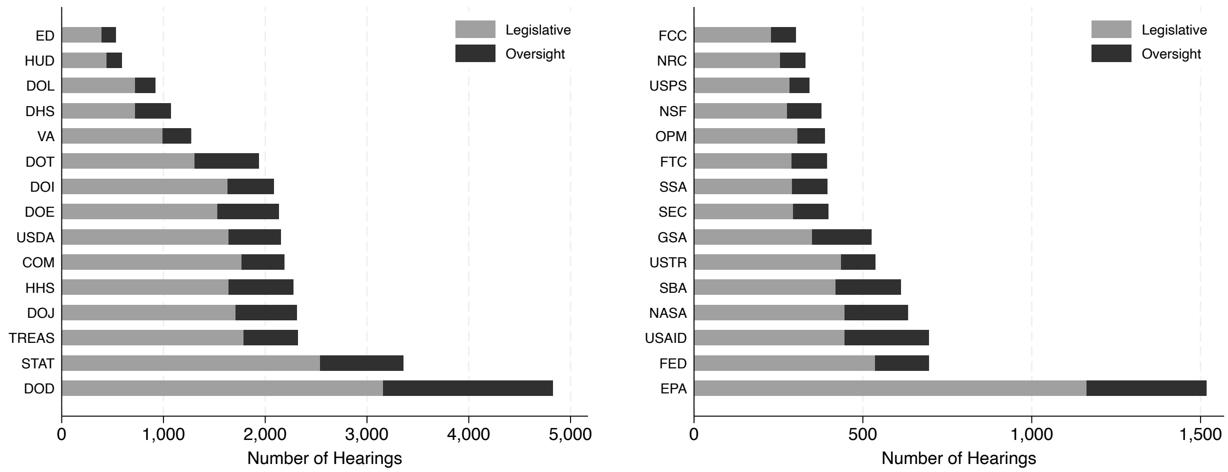
In addition, our dataset includes the following hearing-level information: the name of the committee that held a hearing, the type of the hearing (legislative vs. oversight, including investigative),[5] full-committee vs. subcommittee, and referral vs. non-referral depending on whether a hearing refers to a specific bill or not), the type of major issue discussed in the hearing, and the total number of witnesses.

Here we provide descriptive statistics of bureaucrats who testified in hearings. Figure 1 shows the number of legislative and oversight hearings in which at least one bureaucrat testified by (a) the executive departments and (b) other agencies. These graphs show significant variation across departments and agencies. The Department of Defense (DOD) has the highest frequency of hearings followed by the Departments of State (STAT), Treasury (TREAS), and Justice (DOJ). Among other agencies (i.e., non-executive department), bureaucrats from the Environmental Protection Agency (EPA) testified most often in hearings, followed by the Federal Reserve (FED), and US Agency for International Development (USAID). Figure 2 shows the number of career bureaucrats and political appointees testifying, by executive department in Panel (a) and by the top 15 other agencies who had the highest numbers of testifying bureaucrats in Panel (b). The ratio of testifying

[5] We follow the classification by McGrath (2013) which relies on a set of keywords indicating investigative and oversight hearings and the description of a hearing in the Policy Agenda Project database. We classify hearings that are neither oversight nor investigative as legislative hearings. Among the hearings that have at least one bureaucrat appearing, 73% are legislative and 27% are oversight.

bureaucrats who are political appointees ranges from 10% in Veterans Affairs (VA) to 49% in the National Transportation Safety Board (NTSB).[6]

Figure 1: Legislative and Oversight Hearings with Bureaucratic Witnesses, 1977-2014



(a) Executive Department

(b) Other

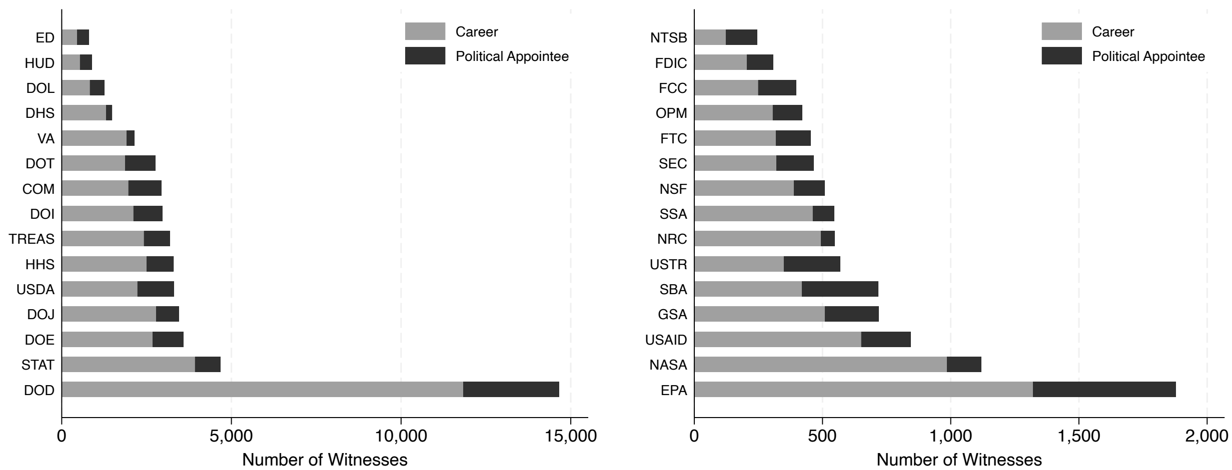
Hearing Transcript Data and A New Measure of Analytical Testimony

We develop a new measure that captures the level of analytical information conveyed in witness testimonies to test our hypotheses about what impacts bureaucrats' information sharing with Congress. This measure includes all testimonies made by both bureaucrats and non-bureaucrat witnesses.

Witnesses can provide various types of information, such as an analytical, scientific analysis of the current state of a program or its potential causes and consequences, personal experiences of practitioners or those affected by a policy, or political information identifying groups benefiting from or harmed by a policy. In this study, we focus on the analytical aspect of witness testimonies for several reasons. First, previous studies have shown that legislators engage in searching for "falsifiable" or "technical" information, which we alternatively call "analytical," when making

[6]In Appendix Figures A1 and A2, we present the over time patterns for the types of bureaucratic witnesses and the share of political appointees.

Figure 2: Career vs. Political Appointees among Bureaucratic Witnesses, 1977-2014



(a) Executive Department

(b) Other

laws (Esterling 2004; Krehbiel 1991). Second, analytical information is a necessary component of technical parts of a bill. Third, as recent studies find that the analytical capacity of Congress has declined over time (LaPira, Drutman, and Kosar 2020), it is important to construct a valid measurement for analytical testimony provided by external witnesses to Congress.

To construct this measurement, we employ U.S. House committee hearing transcript from Park (2021) based on raw transcripts available on the Government Publishing Office website and a crowd-sourced supervised learning method that follows previously established practices (Carlson and Montgomery, 2017; Park, 2021).[7] This approach improves upon previous methods such as in Ban, Park, and You (2023), which only used a dictionary of researcher-selected words. Instead, by using large-scale human coding of sample testimonies and training machine learning algorithms, we arrive at a significantly improved measure of analytical information for testimonies in Congress.

First, we define a testimony as analytical if it is 1) fact-based, 2) verifiable through research or

[7] A supervised learning method is preferred over unsupervised learning models when a researcher has a preset idea about how to classify texts. It provides a more delicate measure than a dictionary-based approach for two reasons. The dictionary method is 1) often agnostic about the importance of each word in relation to the concept and treats each with an equal weight and 2) has a potential problem with a homonym being used for a different meaning. Our approach resolves these issues because it relies on human judgment which captures the concept of interest more holistically and considers the context in which a word is used through a construction of n-grams or word-embeddings.

data-driven analysis, or 3) objective. This set of concepts is largely consistent with the definition of "falsifiable" information presented in Esterling (2004).[8] Second, 3,929 sample statements were coded by online workers at Amazon Mechanical Turk (MTurk). (See Appendix Section D.1 for more details about the coding process.) We presented a randomly selected pair of two statements to the online workers and asked them to choose the one that was more analytical. Using their binary responses to 43,000 of these pairwise comparisons, we fit a Bradley-Terry model which is a Bayesian model that facilitates estimating the probability that a document j will be chosen when compared with another document i by a worker k using Hamiltonian Markov Chain Monte Carlo sampling. The following equation presents the model specification and the priors for key parameters

$$Pr(y_{ijk} = j) = \frac{exp(b_k(a_j - a_i))}{1 + exp(b_k(a_j - a_i))} \tag{1}$$

$$a_j \sim N(0,1) \qquad b_k \sim trN(0,\sigma^2) \qquad \sigma \sim trN(0,3) \tag{2}$$

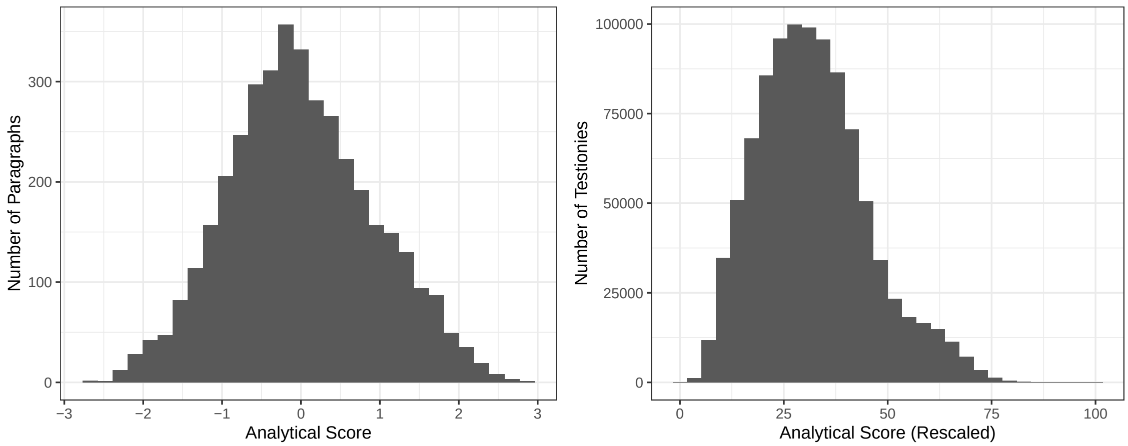
where N denotes the normal distribution, and trN denotes the normal distribution truncated at zero to allow positive values only. The model estimates the analytical feature of each document, a_j, and each worker's quality, b_k. The model produced a score for each sample statement ranging from -2.7 to 2.8, as shown in the left panel of Figure 3.

Third, we randomly selected 3,500 sample statements to be used as a training set, reserved 426 statements as a validation set, and ran eight machine learning models.[9] Fourth, we constructed the final model using the ensemble Bayesian model averaging technique that assigns weights to each model to achieve the optimal prediction performance (Montgomery, Hollenbach, and Ward

[8] To help clarify the concept, we also define what is non-analytical. A statement is non-analytical if it is 1) opinion-based or normative, 2) anecdotal or experiential, 3) subjective or preferential (i.e., reveals preferences of certain groups), 4) procedural statements, or 5) anything else not containing the analytical information as defined above. Our measure of analytical information is fundamentally based upon the presence of falsifiable information, following other work such as Esterling (2004). However, we note that non-falsifiable statements can still provide information that has to do with analysis and is useful in writing laws. Thus, while our measurement for analytical information is based upon falsifiable information, we caution that it does not capture the full extent of information that may be analytical.

[9] We constructed two document-level matrices: a term-document frequency matrix and a doc2vec matrix. For each matrix, we fit four learners: support vector machine, Kernlab's support vector machine, LASSO, and Gradient Boosting Machine. These choices are explained in Appendix Section D.3.

Figure 3: Distribution of the Analytical Score



Notes: The left panel shows the distribution of the analytical score for the sample statements. The right panel shows the distribution of the (rescaled) analytical score for the entire corpus of the witness testimonies for the 105th-115th Congresses.

2012). Using the final model, we predicted the score for the entire corpus of witness testimonies and rescaled the measurement to range between 0 and 100. In the remainder of the paper, we will refer to the predicted score as the "analytical score." The graph in the right panel of Figure 3 shows the distribution of rescaled, predicted scores for all witness testimonies in the entire corpus.

To statistically validate the measurement, we checked how our final model predicts the human-coded labels of the validation set that was set aside. The Pearson correlation coefficient between the human-coded labels and the model predictions is 0.81, and the Root Mean Squared Errors (RMSE) is 0.53 (see Figure A3 in the Appendix). Compared to other prediction practices (Park 2021; Park and Montgomery 2024) that used similar measurement processes, our model achieved a relatively high level of prediction performance suggesting that it effectively captured the aspects of the latent trait we intended to measure.

In addition, for substantive validation, we present three statements with the highest, median and lowest analytical scores in Table 1. We can see that the most analytical statement makes the budget justification referring to the source of expert information; in the statement with the median score, the witness says that she does not have enough knowledge at the moment but would like to provide accurate information sourced from other bureaucrats in the future; lastly, the least

Table 1: Sample Statements with Varying Levels of the Analytical Score

Analytical Score	Speech	Witness
100	"Preventing the extinction of this unique frog will require the restoration of ponds and surrounding habitats and the reintroduction of frogs from the one remaining population. In addition, as part of the $3.7 million increase for Pacific Northwest salmonid, a $0.6 million program increase will help the Service meet its obligations as set forth by the Federal Columbia River Power System Biological Opinions. ..."	Steven A. Williams, Director of Fish and Wildlife Service, U.S. Dept. of the Interior
30.08	"So let me be very explicit about this. ... I would love to get you that information. Again, I am not an enforcement agency. So I am not as familiar with these details as some of my other assistant secretaries might be. So I would love to keep the door open so that I could get you more accurate information on that from our attorneys and the people in the enforcement agencies."	Jane Oates, Assistant Secretary for the Employment and Training Administration, U.S. Dept. of Labor
0	"I guess I don't know what to think of it. I was surprised by it. I believe that they are friends and–but I don't know."	Mary Schapiro, Chairman, U.S. Securities and Exchange Commission

Notes: The first statement was made in a hearing held by the Committee on Resources in 2002 on Fish and Wildlife Service Agencies and their budget requests for 2003. Due to the space limit, only the front part of this statement is shown. The second statement is part of a Judiciary Committee hearing held in 2011 on H-2A visa program. The third statement is from a joint hearing between subcommittees of the Financial Services Committee and the Oversight and Government Reform Committee held in 2011 on how conflicts of interest is handled within U.S. Securities and Exchange Commission.

analytical statement emphasizes the speaker's lack of information about what was being asked. These examples substantially validate our measurement. We present additional examples of analytical and non-analytical statements and statistical validation metrics of the analytical score in the Appendix Section D.4.

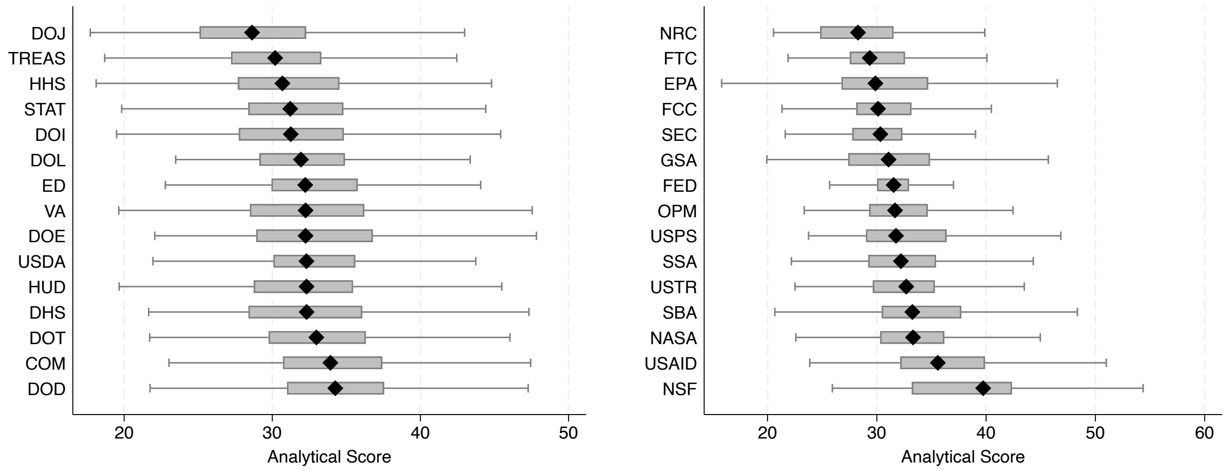
Figure 4 shows the distribution of analytical information within and across agencies. It is clear that the amount of within-agency variation still exceeds the amount of across-agency variation for both the executive departments and other agencies.[10]

Legislator-Witness Interactions

To test the effect of partisan incentives on witnesses' information sharing with members of Congress, we aggregate the data obtained from hearing transcripts by legislator-witness pairs. In this pair-

[10]There are 55 non-executive department agencies in our sample. For illustrative purposes, in panel (b) we plot the distribution of analytical information scores for the 15 agencies with the highest number of bureaucrats testifying in hearings.

Figure 4: Analytical Score Distributions By Agencies



(a) Executive Department

(b) Other

Notes: The bars' ranges indicate the minimum and maximum values, the boxed area indicates the interquartile range, and the red squares indicates each agency's median analytical score.

level dataset, the unit of observation is a pair of a legislator and a witness who interacted in a House committee hearing, and it covers the period 1997-2014. We define that an interaction occurred if a member statement is immediately followed by a witness statement.[11] We compute the average analytical score measured based on a witness's testimonies for each pair.

In total, we have 61,802 pairs of bureaucratic witness-member observations and 87,216 pairs of non-bureaucratic witness-member observations from 6,686 hearings. For bureaucratic witnesses, on average, we have nine pairs of witness-member interactions per hearing, ranging from 1 to 102. On average, in a given hearing, two bureaucrats were invited as witnesses and seven members asked them questions. For non-bureaucratic witnesses, on average, we have 11 pairs of witness-member interactions per hearing, ranging from 1 to 131. On average, four non-bureaucrat witnesses were invited and five members asked them questions.

[11] Since witnesses speak only when they are given a chance to speak, most witnesses' statements are preceded by a member's statement. This feature facilitates analyzing dyadic interactions between a member and a witness in a hearing.

The Effect of Partisan Alignment on Information Sharing

In this section, we empirically examine how incentives underlying the partisan alignment between Congress and the executive branch, as well as the type of bureaucrat, drive the amount of analytical information that bureaucrats share. Using the pair-level data, we estimate the following regression:

$$\begin{aligned} \text{Analytical Information}_{bmh} &= \beta_1 \text{President Out-Partisan}_m \\ &+ \beta_2 \text{Member Question}_{bmh} + \Gamma X_{bmh} + \alpha_a + \alpha_c + \alpha_i + \alpha_p + \varepsilon_{bmh} \end{aligned} \tag{3}$$

where the subscripts indicate bureaucrat b, member m, hearing h, agency a, committee c, issue i, and president p. The unit of observation is bureaucrat-member pair conditional on a member asking at least one question of a bureaucrat in a given hearing. The outcome variable *Analytical Information*$_{bmh}$ is the average analytical score of bureaucrat b's testimony in response to member m's question in hearing h.[12] To capture partisan misalignment at the member-bureaucrat level, we use the *President Out-Partisan* variable, which equals 1 if the questioning member's party affiliation is different from the party of the president and equals 0 otherwise. We also include an interaction term between *President Out-Partisan* and *Political Appointee* variable to see whether the partisan dynamics are more salient when politicallly appointed bureaucrats interact with the president's out-partisan members.

Crucially, members' statements preceding a witness's testimony can shape the witness's response, and the manner in which legislators ask questions can be correlated with the variables that capture the partisan alignment. To account for this, we measure various features of members' questioning styles (*Member Question*). Due to the public nature of congressional hearings, sometimes legislators may intend to use a hearing to send political messages and gain media attention rather than to elicit analytical information from a witness. Thus, first, we address this underlying incentive of legislators by controlling for the grandstanding score, which was constructed to measure

[12] We trimmed the observations with an outlier value of the outcome measures below 1% and above 99%. Including these outliers does not change the results.

the intensity of political messages conveyed in each statement that members made in committee hearings (Park 2021).[13]

Legislators' grandstanding incentives, however, may not necessarily preclude the exercise of their duty to check facts; they may pursue both at the same time (e.g. Eldes, Fong, and Lowande 2024). Therefore, to add another control for legislators' intent when they interact with a witness, we also measure members' incentive to seek information by counting the number of keywords that are indicative of analytical information in member statements. We use the analytical keywords introduced in Ban, Park, and You (2023).

We also measure and control for the sentiment in members' questions using `pysentimiento`, which is a Python package that provides a pre-trained BERT-based sentiment classifier (Pérez, Giudici, and Luque 2021). For each analyzed statement, `pysentimiento` generates three continuous scores for each statement: positive, neutral, and negative. Finally, we measure the number of words in each member's question because the length of questions may correlate with our measures of members' questioning tone. As these measures were constructed for each member statement, we compute the average values of these measures for each legislator-witness pair in a hearing. Table A1 in the Appendix shows the mean value for each variable that captures the questioning styles of members.

X_{bhm} includes various bureaucrat-level, member-level, and hearing-level control variables (e.g., the number of witnesses in a hearing). To capture the partisan characteristics of a bureaucrat, we include the *Political Appointee* variable which is coded as 1 if a bureaucrat is a political appointee requiring Senate confirmation (PAS).[14] We also note whether a questioning member is a committee chair or a ranking member, the member's majority party status, and their legislative effectiveness

[13] The operational definition of grandstanding includes 1) denouncing or praising a person or an institution, 2) taking a position on a policy (which includes a subjective interpretation of a policy-relevant situation), or 3) asking questions designed to attack or embarrass a witness. The study defines non-grandstanding statements as those that 1) offer an objective description of a policy-relevant situation or 2) question a witness a question for the purpose of fact-finding or obtaining an expert opinion. The score was constructed using a crowd-sourced supervised learning method at the statement level and ranges from 0 to 100.

[14] Among 3,409 political appointees who appeared in hearings in our dataset, 73% are PAS. 24% are political appointees without Senate confirmation required (PA) and 3% are Schedule C (excepted service nonpermanent) appointees. For robustness, we also run the regression with defining the *Political Appointee* including all types of political appointees and the results are presented in A3 in the Appendix. These results are similar to the main results.

score from Volden and Wiseman (2014). Also, we include the members' ideological extremism, measured by the absolute difference between a member's DW-NOMINATE score and the decade-level median DW-NOMINATE score for each party.[15]

Given the way that hearings are structured, the order in which bureaucrats answer members' questions can also affect the amount of analytical information bureaucratic witnesses share with the committee. For example, suppose the first question to a witness comes from a member of the president's party, and suppose the bureaucrat, in response to that question, gives all the analytical information she prepared to share. The next question might come from a presidential out-partisan member. There may be little analytical information left to share. This situation raises the possibility of a correlation between analytical information and how many questions have already been asked. To address this issue, we extract the information about the order of each member-witness dyad that appears in each hearing (*Dyad Order*) as well as the order of the first dyadic member-witness interaction for each witness in a given hearing (*Witness Response Order*). In the regression, we control for the order of when the witness response is provided.[16]

We include bureaucrats' agency fixed effects (α_a) to control for agency-specific characteristics. We also include issue fixed effects (α_i) based on major issue codes from the Policy Agenda Project (Baumgartner and Jones 2015) and committee fixed effects (α_c). To control for time-trend, we include president fixed effects (α_p).[17] ε_{bmh} is clustered at the hearing-level. Appendix Table A2 presents the summary statistics on the variables included in the regression analysis.

[15] Using the absolute distance from zero to measure a legislator's ideological extreme is inappropriate because the scale 0 is a latent variable and it has no substantive meaning. Instead, we use a global average over multiple years for each party and treat a further deviation from the global average as more extreme. We use a decade (10 years) to calculate a global mean and calculate the absolute distance between a legislator's DW-NOMINATE score and the median of the legislator's party at the decade-level to measure the legislator's ideological extremism.

[16] Figures A4 and A5 in the Appendix show the average analytical information by the variables *Dyad Order* and *Witness Response Order*.

[17] In some regressions, we use the *Divided Government* variable that varies at the Congress level; to estimate the effect of this variable while controlling for time trend, we use president fixed effects. Using the Congress fixed effect when we do not need to estimate the *Divided Government* variable produces similar results.

Bureaucratic Witnesses and Provision of Analytical Information

First, we examine how partisan alignment affects the information sharing between bureaucratic witnesses and members of Congress at the pair level. Table 2 presents the results of estimating equation (3) for legislative hearings and oversight hearings. Columns (1) and (4) show the results without including members' questioning styles.[18] Across both types of hearings, partisan misalignment between members of Congress and bureaucrats affects the amount of analytical information that bureaucrats share during hearings. Overall, bureaucrats provide less analytical information when they interact with legislators who are president out-partisan. This pattern is more pronounced when political appointees are responding to a member who is an out-partisan of the president in oversight hearings. Compared to legislative hearings, bureaucratic agencies may be on political defense more so in oversight hearings, when Congress tends to examine the performance of a bureaucratic agency and discuss the potential problems or corrections that the agency needs to make in its implementation of government programs and policies. It is unsurprising, then, that the behavior of political appointees with out-partisans is more robust in oversight hearings.

As discussed previously, the negative association between partisan misalignment and the provision of analytical information by bureaucrats could be driven by legislators' questioning styles. As Table A1 in the Appendix shows, under divided government, president out-partisan members ask less analytical questions and their tone is more negative. These patterns of questioning styles also could influence how much analytical information bureaucratic witnesses share during their testimonies. Columns (2) and (5) show the results when we include the variables that capture members' questioning styles. The results show that members' questioning styles are indeed correlated with the amount of analytical information in bureaucrats' testimonies. When members ask questions with higher grandstanding scores or a more negative tone, bureaucrats tend to provide less analytical information. In contrast, when members ask questions that have a more positive tone, more analytical words, and more words in total, bureaucrats' testimonies tend to include

[18] We understand that variables of members' questioning styles are post-treatment, but we include these in subsequent regressions in order to control for members' behavior.

more analytical information.[19] The member-witness order (*Dyad Order*) has a consistently negative sign, suggesting that less analytical information is shared by bureaucratic witnesses as the hearing progresses.[20]

It is interesting to note that even after controlling for members' questioning styles, the coefficient on the variable *President Out-Partisan* is negative and statistically significant, although the magnitude of the coefficients becomes slightly smaller. Of course, the set of control variables for the members' questioning styles may not fully capture members' intentions. However, the result could suggest that bureaucrats may control the amount of analytical information they share with committee members depending on whether they interact with president co-partisan or president out-partisan legislators. The results in Table 2 also show that bureaucrats' testimonies contain significantly more analytical information when they are questioned by the committee chair and ranking member. In addition, bureaucrats' statements contain more analytical information in hearings held at the subcommittee level as opposed to the full committee level, which are hearings that feature more witnesses.

Although we include agency-, issue-, and committee-fixed effects to control for the selection issues, the frequency of bureaucratic invitations and the types of bureaucrats who are invited could be different under divided vs. unified governments (Ban, Park, and You 2023). In addition, the identity of the bureaucrats who receive questions from president co-partisan members vs. president out-partisans could be different. To address this potential selection problem, we exploit our pair-level data, which allows us to estimate equation (3) with witness-hearing fixed effects. We examine how the same witness in a given hearing responds differently to different members.[21] By including witness-hearing fixed effects, we are unable to measure the effect of some variables that do not vary at the witness-hearing level such as political appointee, but this exercise is the most rigorous estimation of how bureaucrats respond to partisan misalignment with politicians in hearings. We

[19] The reference category is the share of neutral tone.

[20] If we instead include the variable *Witness Response Order* to capture the effect of the response order within a witness, we also observe a negative coefficient and including this variable does not change the main result. Table A4 in the Appendix.

[21] A unique witness ID is assigned at the witness-hearing level. If the same bureaucrat appeared in different hearings, the bureaucrat is assigned different witness IDs.

use the same specification as before, but with witness-hearing fixed effects. Because we examine within-bureaucrat variation in a given hearing, we do not include other fixed effects. Columns (3) and (6) of Table 2 show the results. We see consistent results from the specifications including witness-hearing fixed effects: The same bureaucrat's response contains a lower level of analytical information when she responds to members who are president out-partisans and this effect is more salient when the bureaucrat is a political appointee appearing in oversight hearings.[22]

In terms of the substantive effect, each bureaucrat provides 4.6% less analytical information when questioned by members who are president out-partisans and this reduction increases to 7.2% when political appointees interact with president out-partisans in hearings.[23] Given that 12,704 bureaucrats were invited to congressional hearings during the period of our study (1997-2014), and 27% of them were Senate-confirmed political appointees, at the aggregate level, this is a significant reduction in the amount of analytical information that bureaucrats share with members of Congress.

Additional Analyses of Bureaucratic Witnesses

In this section, we provide additional analyses of bureaucratic witnesses and the interbranch flow of analytical information in hearings that may enhance our understanding of the dynamic interactions between legislators and bureaucrats. Our analyses in this section parse how differences across bureaucrats—such as the types of their agencies or how ideologically close their agencies are to the president—and differences across issues and committees—such as the issue polarization and types of committees—moderate the effect of partisan alignment on the analytical information shared.

First, we conduct separate analyses for bureaucrats who come from the executive departments and other agencies. Because executive departments are subject to more direct executive control by the president, who can hire and fire department heads and other political appointees at will,

[22]In Appendix Table A5, we further confirm that the negative coefficient on the interaction term *President Out-Partisan x Political Appointee* is more salient under divided government when president out-partisan legislators are the majority party members in Congress.

[23]This calculation is based on the results in Column (4) of Table 2. Given the mean outcome measure of analytical information of 33.5, the coefficients on the variables *President Out-Partisan* and *President Out-Partisan* $\times$ *Political Appointee* indicate the reduction of 3.1% (-1.556/33.5) and 5.5% ((-1.556-0.886)/33.5).

Table 2: Bureaucratic Witnesses' Provision of Analytical Information

	Legislative			**Oversight**		
	(1)	(2)	(3)	(4)	(5)	(6)
President Out-Partisan	-1.404***	-1.221***	-1.188***	-1.556***	-1.299***	-1.162***
	(0.142)	(0.132)	(0.155)	(0.162)	(0.150)	(0.167)
Political Appointee	0.0382	-0.437*		0.477*	-0.124	
	(0.211)	(0.199)		(0.218)	(0.198)	
President Out-Partisan X	-0.407	-0.163	-0.0851	-0.886***	-0.451*	-0.628*
Political Appointee	(0.233)	(0.215)	(0.255)	(0.240)	(0.222)	(0.247)
Majority Party	-0.189	-0.198	-0.109	-0.180	-0.0363	-0.0481
	(0.132)	(0.122)	(0.144)	(0.144)	(0.134)	(0.146)
Committee Chair	3.504***	3.263***	2.487***	3.825***	3.753***	2.615***
	(0.186)	(0.171)	(0.209)	(0.209)	(0.191)	(0.214)
Ranking Member	0.0874	0.323	-0.0987	1.053***	1.454***	0.924***
	(0.261)	(0.243)	(0.291)	(0.256)	(0.238)	(0.271)
Ideological Exstreme	-1.862***	-0.487	-0.441	-2.576***	-1.282**	-0.698
	(0.436)	(0.412)	(0.473)	(0.463)	(0.426)	(0.472)
LES	-0.0776	-0.0643	-0.0884	-0.0112	-0.0220	-0.0366
	(0.0422)	(0.0391)	(0.0470)	(0.0460)	(0.0415)	(0.0446)
Subcommittee	0.385	0.491**		1.367***	1.514***	
	(0.200)	(0.184)		(0.221)	(0.200)	
Referral Hearing	-0.402	-0.567**		-0.337	-0.497	
	(0.222)	(0.208)		(0.362)	(0.334)	
Number of Witness	0.126***	0.112***		0.115***	0.128***	
	(0.0218)	(0.0202)		(0.0224)	(0.0227)	
Dyad Order	-0.171***	-0.137***	-0.239***	-0.0779***	-0.0641***	-0.185***
	(0.0115)	(0.0103)	(0.0162)	(0.0101)	(0.00904)	(0.0129)
Grandstanding Score		-0.126***	-0.102***		-0.105***	-0.0832***
		(0.00798)	(0.00959)		(0.00825)	(0.00926)
Share of Positive Tone		6.838***	5.686***		6.353***	5.106***
		(0.265)	(0.319)		(0.287)	(0.325)
Share of Negative Tone		-1.574***	-0.653		-1.259**	-0.939*
		(0.372)	(0.445)		(0.384)	(0.426)
Analytical Word Count		0.167***	0.164***		0.154***	0.136***
		(0.0175)	(0.0218)		(0.0176)	(0.0204)
(ln) Number of Legislator Words		1.794***	1.767***		1.772***	1.902***
		(0.150)	(0.184)		(0.167)	(0.189)
Agency, Committee, Issue, President FEs	✓	✓		✓	✓	
Witness-Hearing FE			✓			✓
Mean Outcome Measure	33.3	33.3	33.3	33.5	33.5	33.5
N	30117	30117	30117	27401	27401	27401
adj. R^2	0.098	0.190	0.325	0.112	0.202	0.333

Notes: $*$ p<0.05, $**$ p<0.01, $***$ p<0.001. Standard errors are clustered at the hearing-level.

the partisan dynamics for political appointees may differ between executive departments and other agencies. Table A6 in the Appendix shows that a statistically significant negative relationship for the interaction term, *President Out-Partisan* X *Political Appointee*, is observed only among executive department bureaucrats in oversight hearings.[24]

Second, our main analysis focuses on the partisan alignment between Congress and the president, and we assume that bureaucrats are under the control of the president. However, bureaucratic agencies exhibit various ideological leanings (Richardson, Clinton, and Lewis 2018), and individual bureaucrats have their own partisan leanings (Spenkuch, Teso, and Xu 2023). This implies that some executive agencies are more aligned with the president than others depending on the partisanship of the president. We use the measure for the agency ideology from Richardson, Clinton, and Lewis (2018) to capture the partisan alignment between the president and the agency. Specifically, we divide agencies into those aligned and misaligned with the president in terms of ideology and examine whether the partisan dynamics of analytical information provision are more salient for bureaucrats from presidentially aligned agencies.[25] Table A8 in the appendix shows that bureaucrats from agencies that are aligned with the president are less likely to provide analytical information to president out-partisan committee members.

Third, we examine whether the effect of partisan alignment on bureaucrats' provision of analytical information varies by issue polarization and committee type. A full discussion of these heterogeneous effects can be found in Appendix Section C. Overall, we find that bureaucrats provide significantly less analytical information when they appear in hearings that address highly polarized issues. Moreover, the negative effect of partisan misalignment is larger in prestigious and policy committees than in constituent service committees (Deering and Smith 1997).

Overall, the additional analyses in this section show that when the partisan nature of the legislator-bureaucrat alignment is more salient—such as when the bureaucrat is from an agency

[24] Table A7 in the Appendix presents the result when we classify the EPA as part of the executive department, given the president's control over the agency. The main results do not change.

[25] Based on the measure of agency ideology developed by Richardson, Clinton, and Lewis (2018), we label agencies as Democratic-leaning if the ideology is below the median (-.1256831). These agencies are coded as aligned with the Democratic president. For Republican presidents, we coded these agencies as aligned with the president if the agency's ideology is above the median ideology.

more closely aligned ideologically with the president or when the issue is highly polarized—the effect of facing an out-partisan legislator on the amount of analytical information shared is stronger.

Placebo Test: Non-Bureaucratic Witnesses

Finally, we examine whether these partisan misalignment effects are unique to bureaucrats or are shared by other witnesses as well. Are non-bureaucratic witnesses, who are not employed in the executive agencies, affected by the interbranch relationship between the legislative and executive branches? As a "placebo" test, we perform the same analysis on all other non-bureaucratic witnesses.[26] In total, we have 87,261 pairs of interactions between committee members and non-bureaucratic witnesses for the period 1997-2014.

We measure the analytical score for all other witnesses, create a pair-level dataset for non-bureaucratic witnesses, and run the same specification as in equation (3). Table 3 presents the regression results for non-bureaucratic witnesses.[27] There are no statistically significant effects of the variable *President Out-Partisan* on the sharing of analytical information by non-bureaucratic witnesses. This is in stark contrast to the previous results for bureaucratic witnesses, where the same variable has statistically significant, negative effects. Overall, this placebo test suggests that the interbranch relationship has a unique effect on the behavior of *bureaucratic* witnesses in sharing analytical information with committee members.

Partisan Dynamics and Collective Information Acquisition

In the previous sections, we show that bureaucratic witnesses provide less analytical information in their testimony when they respond to questions from members of the president's own party. We also show that we do not find a similar partisan dynamic when it comes to non-bureaucratic witnesses. These results speak to information transmission at the pair level between two individuals—

[26] We exclude congressional staff, members of Congress, or affiliates of congressional organizations to focus on non-governmental witnesses.

[27] With non-bureaucratic witnesses, we include witness type FEs (16 different types, such as corporations, nonprofits, and think tanks and academics) instead of agency FEs. A full regression result is provided in Appendix Table A9.

Table 3: Non-Bureaucratic Witnesses' Provision of Analytical Information

	Legislative			Oversight		
	(1)	(2)	(3)	(4)	(5)	(6)
President Out-Partisan	-0.169	-0.0362	0.0577	-0.176	-0.158	-0.103
	(0.106)	(0.146)	(0.218)	(0.159)	(0.216)	(0.310)
Witness Type, Issue, Committee, President FEs	✓			✓		
Witness-Hearing FE		✓	✓		✓	✓
Bureaucrat Appeared in Hearing			✓			✓
Mean Outcome Measure	35.3	35.3	35.9	35.5	35.5	35.9
N	52217	52217	27401	28168	28168	14265
adj. R^2	0.222	0.350	0.352	0.232	0.359	0.359

Notes: $*$ p<0.05, $**$ p<0.01, $***$ p<0.001. Standard errors are clustered at the hearing-level. Columns (3) and (6) present the results for the hearings where non-bureaucratic witnesses appeared along with at least one bureaucratic witness.

a legislator and a witness. However, given the public nature of hearings and the fact that members can observe how their colleagues, from both parties, interact with all witnesses in a hearing, this raises the question of how hearings serve members of Congress in the *collective acquisition of information* and how partisan dynamics affect this process. Even if bureaucratic witnesses provide less analytical information to members who are presidential out-partisans, if these legislators are more actively engaged in hearings by asking more questions of non-bureaucratic witnesses under divided government, this may generate more analytical information for Congress at the aggregate level.

To address this question, we created a hearing-level dataset that included the total number of question-answer pairs between a member and a witness (i.e., which captures how actively members engage with witnesses) and the total amount of analytical information weighted by the number of words from witness testimony. We also created these variables separately for bureaucratic and non-bureaucratic witnesses.

We use the presence of divided government as a measure of partisan alignment between the legislative and executive branches at the aggregate hearing level. Under divided government, when the two branches are represented by opposing parties with different electoral and partisan incentives, the flow of policy-relevant information may be hampered by strategic interactions between legislators and bureaucrats. Divided government presents a more difficult policymaking environment, as politicians between the legislature and the executive have opposing leverage and face institutional impediments in the branch their party does not control. This challenging institutional environment has been the basis for theoretical arguments explaining the complications that divided government brings to policymaking (Coleman, 1999; Howell et al., 2000).

Using our hearing-level data, we run a regression that examines how divided government correlates with collective information gathered at the hearing level. Table 4 presents the results.[28] First, during divided government, members of Congress asked more questions of witnesses, primarily driven by president out-partisan members. Specifically, presidential out-partisan members engage in more questioning of both bureaucratic and non-bureaucratic witnesses under divided government compared to presidential co-partisan members. Second, we find that divided government is not correlated with total analytical information from testimony at the hearing level. While the total analytical information from bureaucratic witnesses is lower under divided government, this negative effect is offset by the analytical information coming from non-bureaucratic witnesses. The fact that out-partisan members ask more questions, especially of non-bureaucratic witnesses, drives the results. Members who are co-partisan with the president ask significantly fewer questions under divided government—maybe partly because they are the minority party in the House—explain the reduction in the overall transmission of analytical information from both bureaucratic and non-bureaucratic witnesses. These two effects cancel each other out, and thus we find that divided government is not correlated with the aggregate level of analytical information transmitted by witnesses through hearings.

Overall, this set of results highlights how partisan dynamics differentially affect Congress's ability to acquire analytical information at the individual and collective levels. Although the partisan misalignment reduces the transmission of analytical information between bureaucratic witnesses and out-partisan members at the pair-level, the presence of non-bureaucratic witnesses and

[28] The detailed analysis by witness type is presented in Tables A10 and A11 in the Appendix.

increased questioning by out-partisan members during divided government leads to no discernible effect on the transmission of analytical information at the aggregate level. Our findings provide a nuanced understanding of the effect of divided government on information transmission in hearings.

Table 4: Divided Government and Information Transmission at the Aggregated-Level

	No. Question-Answer Pair			**Analytical Information**		
	(1) Total	(2) Co-Partisan	(3) Out-Partisan	(4) Total	(5) Bureaucrat	(6) Non-Bureaucrat
Divided Government	2.813***	-2.974***	5.787***	-4.419	-51.82**	47.40
	(0.365)	(0.344)	(0.424)	(27.44)	(17.90)	(23.49)
Issue, Committee, President FEs	✓	✓	✓	✓	✓	✓
Mean Outcome Measure	16.8	7.7	9.1	1,450.3	247.5	336.3
N	10753	10753	10753	10753	10753	10753
adj. R^2	0.423	0.354	0.449	0.461	0.220	0.452

Notes: $*$ p<0.05, $**$ p<0.01, $***$ p<0.001. The unit of observation is hearing. Standard errors are clustered at the committee-level. Control variables (oversight hearing, subcommittee, referral hearing, number of witness) are included but not presented here.

Conclusion

In democracies, the people who make the laws are not those who implement the laws. This division of labor results in disparities in the levels of knowledge and expertise between legislators and bureaucrats. Information about policy implementation and its costs and consequences is gained through on-the-ground working experience in the bureaucracy; legislators must rely on searching for and acquiring that information. Compared to members of Congress, bureaucrats are closer to policy implementation, and thus gain more expertise and specialized information. Scholars have documented and theorized about the informational advantage held by bureaucrats, but the question of what affects the exchange of information between bureaucrats and Congress has remained unanswered, especially empirically.

Using a new dataset that provides—for the first time—the federal agency affiliation, appointment type, and agency-level characteristics for each bureaucrat who testified in Congress over the span of decades of congressional history, we find that partisan dynamics exert a nuanced influence on the transmission of analytical information during congressional hearings. At the pair level between an individual bureaucrat and legislator, bureaucratic witnesses offer less analytical information when questioned by members of the president's party, a pattern not observed with non-bureaucratic witnesses. At the hearing level, divided government prompts increased engagement from members of the president's opposing party, who ask more questions, thereby compensating for the reduced input from bureaucratic witnesses. Consequently, the overall level of analytical information transmitted in hearings remains stable despite these partisan influences. This understanding reveals that while individual interactions between members and witnesses are affected by partisanship, the collective acquisition of information in Congress is maintained through the dynamics of questioning under divided government.

Our research and new data provide a refreshed foundation for continued work on the inter-branch relationship between bureaucrats and Congress. As we show, the partisan alignment between Congress and bureaucrats has important implications for the information that members of Congress collect through hearings. Congress relies heavily on information provided by the executive branch to make policy decisions with far-reaching consequences—especially concerning complex scientific issues facing society today, such as climate change or pandemic response. Thus, understanding what affects information sharing within government—between bureaucrats, one of Congress's best sources of policy information, and Congress—is paramount.

This study also sets the stage for future work to further disentangle the individual incentives of bureaucrats. Our findings suggest that, on average, misalignment leads bureaucrats to provide less information to legislators, an effect that may reflect strategic considerations on the part of bureaucrats. Future work would be well-positioned to examine the motivations for this behavior and whether the motivations are driven by policy preferences, career incentives, or personal ideology.

Future research should also examine how the effect of partisan misalignment on the provision of analytical information from bureaucrats through hearings might affect politicians' other choices for acquiring information from the executive branch. For example, Congress has the statutory authority to request a variety of reports from the executive branch, ranging from descriptive reports documenting agency activities to studies and evaluations on emerging issues such as artificial intelligence (Egar 2020). A fruitful extension of this study would be to examine various legislative tools available to Congress to access executive branch information, and how the partisan alignment between the two branches of the government affects the choice of tool or channel.

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Part

Appendix

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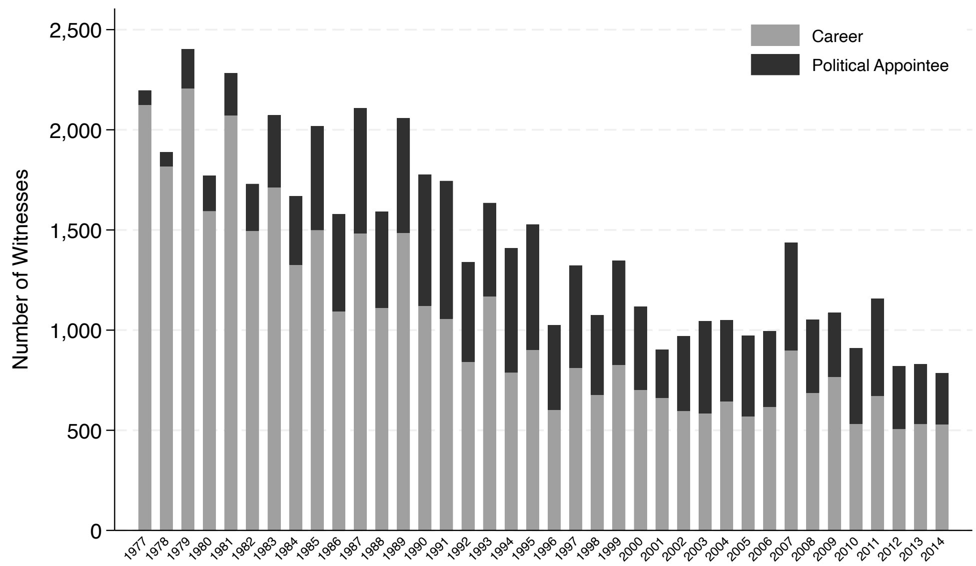
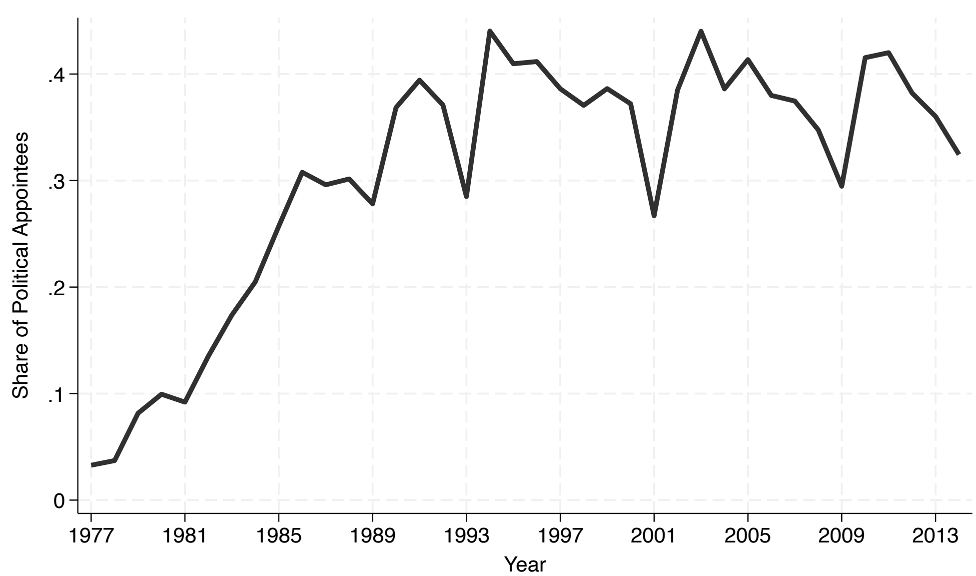
A Additional Figures

Figure A1: Types of Bureaucratic Witnesses Over Time



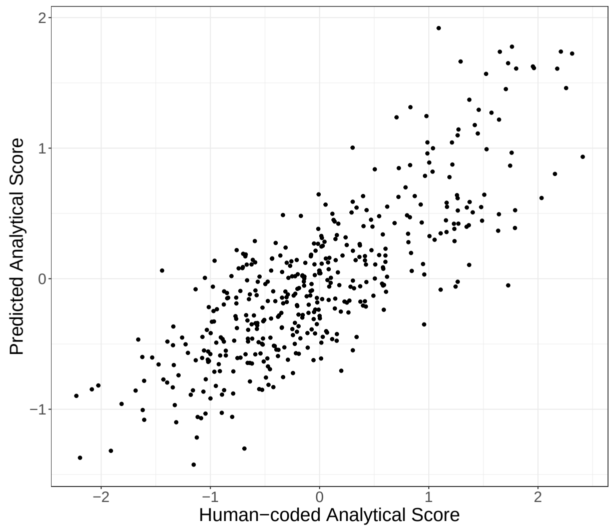
Notes: The figure shows the number of career vs. political appointees among bureaucratic witnesses for the period 1977-2014 in the House hearings. We combine the executive departments and other agencies.

Figure A2: Share of Political Appointees Over Time



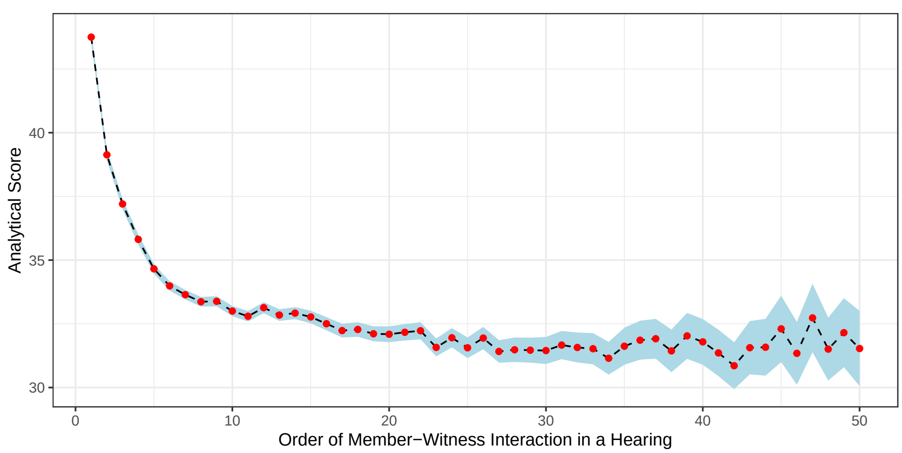
Notes: The figure shows the share of political appointees among bureaucratic witnesses for the period 1977-2014 in the House hearings. We combine the executive departments and other agencies.

Figure A3: Validation of the Final Ensemble Model



Notes: The graph shows how our final model predicts the human-coded labels of the validation set that was set aside. The Pearson correlation coefficient between the human-coded labels and the model predictions is 0.81, and the Root Mean Squared Errors (RMSE) is 0.53.

Figure A4: Analytical Information and the Order of Member-Witness Pair



Notes: We counted the order of each member-witness dyad that appeared for the first time in each hearing. The horizontal axis shows the order of these pairs in our data. The vertical axis is the average analytical score of witness testimonies for the corresponding member-witness pair order. Because there are fewer observations as the order number increases, the confidence interval widens significantly, making the computed average scores less reliable. Therefore, we censored the horizontal axis at 50. The graph shows that there is greater transmission of analytical information at an earlier stage in each hearing.

Figure A5: Analytical Information and the Order of Witness Response

Notes: We counted the order of dyadic member-witness interactions for each witness in a given hearing. For example, if a witness interacted with three legislators, we order the three pairs based on which interaction occurred earlier in a hearing. The horizontal axis shows the order of these pairs in our data. The vertical axis is the average analytical score of witness testimonies for the corresponding member-witness pair order. Because there are fewer observations as the order number increases, the confidence interval widens significantly, making the computed average scores less reliable. Therefore, we censored the horizontal axis at 20. The graph suggests that witnesses tend to provide more analytical information in response to questions posed by legislators with whom they interacted earlier in the given hearing session.

B Additional Tables

Table A1: Summary Statistics of the Members' Questioning Styles

	Divided		**Unified**	
Variable	Co-Partisan	Out-Partisan	Co-Partisan	Out-Partisan
Grandstanding Score	44.8	42.9	43.4	45.5
Positive Tone Share	0.28	0.24	0.29	0.24
Neutral Tone Share	0.56	0.58	0.57	0.58
Negative Tone Share	0.16	0.18	0.14	0.18
Analytical Word Count	5.9	4.8	5.4	6.0
Word Count	131	109	123	133
N	14,716	23,088	14,115	9,883

Notes: The numbers indicate the mean value for each variable. Unit of observation is at member-bureaucrat-hearing level.

Table A2: Summary Statistics of the Variables at the Pair Level

Variables	N	Mean	SD	Min	Max
Panel A: Bureaucratic Witness Analysis					
Analytical Score	61802	33.48	9.33	12.96	64.61
Number of Word (Witness)	61802	152.01	155.21	11.00	2603.00
Political Appointee	61802	0.35	0.48	0.00	1.00
President Out-Partisan	61802	0.53	0.50	0.00	1.00
Majority	61802	0.60	0.49	0.00	1.00
Committee Chair	61802	0.16	0.36	0.00	1.00
Ranking Member	61802	0.06	0.24	0.00	1.00
Ideological Extremism (Member)	61802	0.16	0.13	0.00	1.01
LES	61802	1.20	1.63	0.00	18.69
Dyad Order	61802	11.49	10.89	1	138
Witness Response Order	61802	5.11	4.87	1	52
Grandstanding Score	61802	43.91	11.99	6.12	93.11
Share of Positive Tone	61802	0.26	0.28	0.00	0.99
Share of Neutral Tone	61802	0.57	0.25	0.00	0.98
Share of Negative Tone	61802	0.17	0.18	0.00	0.98
Analytical Word Count (Member)	61802	5.38	5.81	0.00	106.00
Number of Word (Member)	61802	121.79	120.98	10.00	1679.00
Subcommittee	61802	0.63	0.48	0.00	1.00
Referral Hearing	61802	0.10	0.29	0.00	1.00
Number of Witness	61802	5.64	4.49	1.00	76.00
Panel B: Non-Bureaucratic Witness Analysis					
Analytical Score	87261	35.44	11.03	11.80	67.59
Number of Word (Witness)	87261	212.15	238.15	10.00	3564.00
President Out-Partisan	87261	0.53	0.50	0.00	1.00
Majority	87261	0.65	0.48	0.00	1.00
Committee Chair	87261	0.26	0.44	0.00	1.00
Ranking Member	87261	0.06	0.24	0.00	1.00
Ideological Extremism	87261	0.17	0.13	0.00	1.01
LES	87261	1.46	1.90	0.00	18.69
Dyad Order	87261	13.77	11.82	1	151
Witness Response Order	87261	2.73	2.32	1	36
Grandstanding Score	87261	42.30	13.50	3.05	94.08
Share of Positive Tone	87261	0.30	0.32	0.00	0.99
Share of Neutral Tone	87261	0.56	0.29	0.00	0.98
Share of Negative Tone	87261	0.14	0.19	0.00	0.98
Analytical Word Count (Member)	87261	4.48	6.06	0.00	317.00
Number of Word (Member)	87261	106.85	124.58	8.00	4817.00
Subcommittee	87261	0.71	0.45	0.00	1.00
Referral Hearing	87261	0.19	0.39	0.00	1.00
Number of Witness	87261	7.99	9.43	1.00	127.00

Notes: Unit of observation is bureaucrat-politician pair in a given hearing conditional on at least one interaction. The data covers the hearings in the House of Representatives for 1997-2014.

Table A3: Bureaucratic Witnesses' Provision of Analytical Information: Including All Political Appointees

	Legislative			Oversight		
	(1)	(2)	(3)	(4)	(5)	(6)
President Out-Partisan	-1.266***	-1.118***	-1.084***	-1.432***	-1.184***	-1.085***
	(0.150)	(0.140)	(0.165)	(0.167)	(0.153)	(0.172)
Political Appointee	0.123	-0.271		0.640**	0.0996	
	(0.199)	(0.187)		(0.216)	(0.197)	
President Out-Partisan X	-0.658**	-0.382	-0.305	-1.061***	-0.663**	-0.729**
Political Appointee	(0.223)	(0.206)	(0.244)	(0.232)	(0.215)	(0.238)
Committee, Issue, President FEs	✓	✓	✓	✓	✓	✓
Agency FE	✓	✓		✓	✓	
Witness-Hearing FE			✓			✓
Member Question Controls		✓	✓		✓	✓
Mean Outcome Measure	33.3	33.3	33.3	33.5	33.5	33.5
N	30117	30117	30117	27401	27401	27401
adj. R^2	0.098	0.190	0.325	0.112	0.203	0.333

Notes: $*$ p<0.05, $**$ p<0.01, $***$ p<0.001. Standard errors are clustered at the hearing-level. Member- and hearing-level control variables are included in the regression but not presented in the table. The *Political Appointee* variable includes all types of political appointees: PAS, PA, and C.

Table A4: Controlling for the Order of Witness Response

	Legislative			Oversight		
	(1)	(2)	(3)	(4)	(5)	(6)
President Out-Partisan	-1.345***	-1.185***	-1.183***	-1.438***	-1.183***	-1.151***
	(0.141)	(0.131)	(0.155)	(0.162)	(0.149)	(0.167)
Political Appointee	0.448*	-0.0934		0.775***	0.155	
	(0.213)	(0.198)		(0.218)	(0.196)	
President Out-Partisan X	-0.369	-0.111	-0.0759	-0.876***	-0.413	-0.625*
Political Appointee	(0.229)	(0.211)	(0.254)	(0.240)	(0.221)	(0.247)
Witness Response Order	-0.374***	-0.356***	-0.336***	-0.254***	-0.276***	-0.265***
	(0.0282)	(0.0282)	(0.0285)	(0.0171)	(0.0158)	(0.0177)
Committee, Issue, President FEs	✓	✓	✓	✓	✓	✓
Agency FE	✓	✓		✓	✓	
Witness-Hearing FE			✓			✓
Member Question Controls		✓	✓		✓	✓
(ln) Mean Outcome Measure	33.3	33.3	33.3	33.5	33.5	33.5
N	30117	30117	30117	27401	27401	27401
adj. R^2	0.103	0.199	0.320	0.119	0.214	0.331

Notes: $*$ p<0.05, $**$ p<0.01, $***$ p<0.001. Standard errors are clustered at the hearing-level. Member- and hearing-level control variables are included in the regression but not presented in the table.

Table A5: Bureaucrat's Provision of Analytical Information: Divided vs. Unified Government

	Divided	**Unified**
	(1)	(2)
President Out-Partisan	-0.867***	-1.085***
	(0.198)	(0.297)
President Out-Partisan X Political Appointee	-0.855**	-0.276
	(0.292)	(0.444)
Controls	✓	✓
Witness-Hearing FE	✓	✓
Mean Outcome Measure	33.1	34.5
N	19108	9041
adj. R^2	0.352	0.285

Notes: The sample is oversight hearings in the House. $*$ p<0.05, $**$ p<0.01, $***$ p<0.001. Standard errors are clustered at the hearing-level. Member- and hearing-level control variables are included in the regression but not presented in the table.

Table A6: Bureaucrats from the Executive Departments vs. Other

	Executive Department		**Other**	
	(1) Legislative	(2) Oversight	(3) Legislative	(4) Oversight
President Out-Partisan	-1.156***	-1.113***	-1.298***	-1.336***
	(0.178)	(0.186)	(0.301)	(0.309)
President Out-Partisan X Political Appointee	-0.128	-0.682*	0.0200	-0.536
	(0.297)	(0.288)	(0.483)	(0.465)
Controls	✓	✓	✓	✓
Witness-Hearing FE	✓	✓	✓	✓
Mean Outcome Measure	33.4	33.7	33.1	33.2
N	23045	21201	7072	6200
adj. R^2	0.326	0.327	0.321	0.355

Notes: $*$ p<0.05, $**$ p<0.01, $***$ p<0.001. Standard errors are clustered at the hearing-level. Member- and hearing-level control variables are included in the regression but not presented in the table.

Table A7: Bureaucrats from the Executive Departments vs. Other - Treating the EPA as the Executive Department

	Executive Department		**Other**	
	(1) Legislative	(2) Oversight	(3) Legislative	(4) Oversight
President Out-Partisan	-1.175***	-1.096***	-1.221***	-1.420***
	(0.174)	(0.183)	(0.323)	(0.320)
President Out-Partisan X Political Appointee	-0.132	-0.739**	0.0260	-0.211
	(0.287)	(0.282)	(0.534)	(0.493)
Controls	✓	✓	✓	✓
Witness-Hearing FE	✓	✓	✓	✓
Mean Outcome Measure	33.4	33.6	33.3	33.4
N	23983	21949	6134	5452
adj. R^2	0.330	0.331	0.307	0.345

Notes: $*$ p<0.05, $**$ p<0.01, $***$ p<0.001. Standard errors are clustered at the hearing-level. Member- and hearing-level control variables are included in the regression but not presented in the table.

Table A8: Incorporating Agency Ideology: President Aligned vs. Not-Aligned Agencies

	Legislative	**Oversight**
	(1)	(2)
President Out-Partisan	-0.969***	-1.187***
	(0.152)	(0.166)
Political Appointee	-0.522**	-0.368*
	(0.164)	(0.158)
President-Aligned	0.298	0.00688
	(0.178)	(0.199)
President Out-Partisan X President -Aligned	-0.612**	-0.582**
	(0.207)	(0.222)
Controls	✓	✓
Agency, Issue, Committee, President FEs	✓	✓
Mean Outcome Measure	33.4	33.6
N	30117	27401
adj. R^2	0.190	0.203

Notes: $*$ p<0.05, $**$ p<0.01, $***$ p<0.001. Standard errors are clustered at the hearing-level. In all regressions, issue-, committee-, and president-fixed effects and other control variables are included.

Table A9: Non-Bureaucratic Witnesses' Provision of Analytical Information

	Legislative			Oversight		
	(1)	(2)	(3)	(4)	(5)	(6)
President Out-Partisan	-0.169	-0.0362	0.0577	-0.176	-0.158	-0.103
	(0.106)	(0.146)	(0.218)	(0.159)	(0.216)	(0.310)
Majority	0.727***	0.746***	0.779**	0.582***	0.468*	0.617
	(0.118)	(0.164)	(0.252)	(0.165)	(0.222)	(0.332)
Committee Chair	3.772***	3.174***	3.135***	4.351***	3.960***	3.481***
	(0.152)	(0.220)	(0.328)	(0.216)	(0.298)	(0.433)
Ranking Member	-0.0472	-0.675*	-0.952*	0.541*	0.110	0.106
	(0.214)	(0.299)	(0.466)	(0.263)	(0.376)	(0.571)
Ideological Extremism	-1.053**	-1.058	-0.294	-1.251*	-1.021	-1.574
	(0.403)	(0.564)	(0.869)	(0.539)	(0.742)	(1.177)
LES	0.0526	-0.0435	-0.117	0.102*	-0.0130	-0.0383
	(0.0371)	(0.0527)	(0.0830)	(0.0491)	(0.0646)	(0.0970)
Subcommittee	0.323*			0.922***		
	(0.163)			(0.210)		
Referral Hearing	-0.0486			0.305		
	(0.147)			(0.265)		
Number of Witness	0.108***			0.0759***		
	(0.0181)			(0.0124)		
Dyad Order	-0.106***	-0.302***	-0.342***	-0.0917***	-0.271***	-0.297***
	(0.00864)	(0.0171)	(0.0310)	(0.0126)	(0.0200)	(0.0373)
Grandstanding Score	-0.156***	-0.116***	-0.134***	-0.165***	-0.128***	-0.148***
	(0.00617)	(0.00865)	(0.0131)	(0.00789)	(0.0103)	(0.0156)
Share of Positive Tone	8.976***	7.258***	7.463***	8.603***	7.188***	7.458***
	(0.205)	(0.290)	(0.448)	(0.274)	(0.383)	(0.590)
Share of Negative Tone	-0.542*	-0.502	-0.929	-0.207	0.0325	0.314
	(0.277)	(0.389)	(0.630)	(0.366)	(0.519)	(0.817)
Analytical Word Count	0.0468*	0.0734*	0.00258	0.0999***	0.132***	0.0935
	(0.0218)	(0.0306)	(0.0464)	(0.0235)	(0.0320)	(0.0525)
(ln) Number of Word	0.0138***	0.0115***	0.0154***	0.0132***	0.0111***	0.0131***
	(0.00101)	(0.00140)	(0.00216)	(0.00130)	(0.00180)	(0.00296)
Witness Type, Issue, Committee, President FEs	✓			✓		
Witness-Hearing FE		✓	✓		✓	✓
Bureaucrat in Hearing			✓			✓
Mean Outcome Measure	35.3	35.3	35.9	35.5	35.5	35.9
N	52217	52217	27401	28168	28168	14265
adj. R^2	0.222	0.350	0.352	0.232	0.359	0.359

Notes: $*$ p<0.05, $**$ p<0.01, $***$ p<0.001. Standard errors are clustered at the hearing-level.

Table A10: Number of Question-Answer Pairs at the Aggregated-Level

	(1)	(2)	(3)	(4)	(5)	(6)
		Bureaucrat			**Non-Bureaucrat**	
	Total	Co-Partisan	Out-Partisan	Total	Co-Partisan	Out-Paritsan
Divided Government	1.003*	-1.007***	2.010***	1.810***	-1.967***	3.777***
	(0.400)	(0.225)	(0.301)	(0.166)	(0.253)	(0.348)
Issue, Committee, President FEs	✓	✓	✓	✓	✓	✓
Mean Outcome Measure	7.3	3.3	3.9	9.4	4.3	5.1
N	10753	10753	10753	10753	10753	10753
adj. R^2	0.275	0.260	0.271	0.349	0.296	0.358

Notes: $*$ p<0.05, $**$ p<0.01, $***$ p<0.001. The unit of observation is hearing. Standard errors are clustered at the committee-level. Control variables (oversight hearing, subcommittee, referral hearing, number of witness) are included.

Table A11: Total Amount of Analytical Information at the Aggregated-Level

	(1)	(2)	(3)	(4)	(5)	(6)
		Bureaucrat			**Non-Bureaucrat**	
	Total	Co-Partisan	Out-Partisan	Total	Co-Partisan	Out-Paritsan
Divided Government	-51.82**	-164.3***	112.5***	47.40	-495.9***	543.3***
	(17.90)	(19.48)	(18.56)	(23.49)	(62.96)	(61.35)
Issue, Committee, President FEs	✓	✓	✓	✓	✓	✓
Mean Outcome Measure	492.0	250.5	241.4	958.3	455.4	502.8
N	10753	10753	10753	10753	10753	10753
adj. R^2	0.220	0.197	0.193	0.452	0.314	0.405

Notes: The outcome is the total analytical information weighted by the number of words in the testimony at the hearing level. $*$ p<0.05, $**$ p<0.01, $***$ p<0.001. The unit of observation is hearing. Standard errors are clustered at the committee-level. Control variables (oversight hearing, subcommittee, referral hearing, number of witness) are included.

C Heterogeneous Effects

We examine whether the effect of partisan alignment on bureaucrats' provision of analytical information varies by issue polarization and types of committees. First, for issue polarization, we create a vote-based measure of issue polarization for 20 major issue areas, defined by the Comparative Agenda Project (Baumgartner and Jones 2015). Within each issue area, for each passage or amendment roll-call vote, we calculate the percentage of each party voting yea for these roll call votes and then calculate the absolute difference between these percentages. We take the mean of these absolute differences across all roll-call votes in that issue area in a given Congress to generate the issue polarization score by issue and Congress.

Then, for each Congress, we divide the issues into three groups (Bottom, Middle, and Top) based on the degree of polarization between Democrats and Republicans. We merge the Congress-specific issue polarization score to our hearing data based on the major issue code for each hearing. Then, we run separate regressions of equation (3) with witness-hearing FEs for three different groups based on the issue polarization categories. Figure A6 shows that the regression coefficients of the variable *President Out-Partisan* and bureaucrats provide significantly less analytical information when they appear in hearings that address highly polarized issues and this pattern is more salient in legislative hearings.

We also examine whether the effect of the partisan alignment varies by the types of committees. Deering and Smith (1997) divide committees into three types: (1) prestigious (Appropriations, Budget, Rules, and Ways and Means); (2) policy (Financial Services, Education and Labor, Energy and Commerce, Foreign Affairs, Judiciary, Government Oversight); and (3) constituency service (Agriculture, Armed Services, Natural Resources, Science, Small Business, and Veterans Affairs). Figure A7 shows the coefficients of the *President Out-Partisan* variable on bureaucrat's provision of analytical information across different types of committees. The negative effect of partisan misalignment is larger in prestigious and policy committees than constituent service committees and this pattern is more salient in legislative hearings.

Figure A6: Heterogeneous Effects of “President Out-Partisan” by Issue Polarization

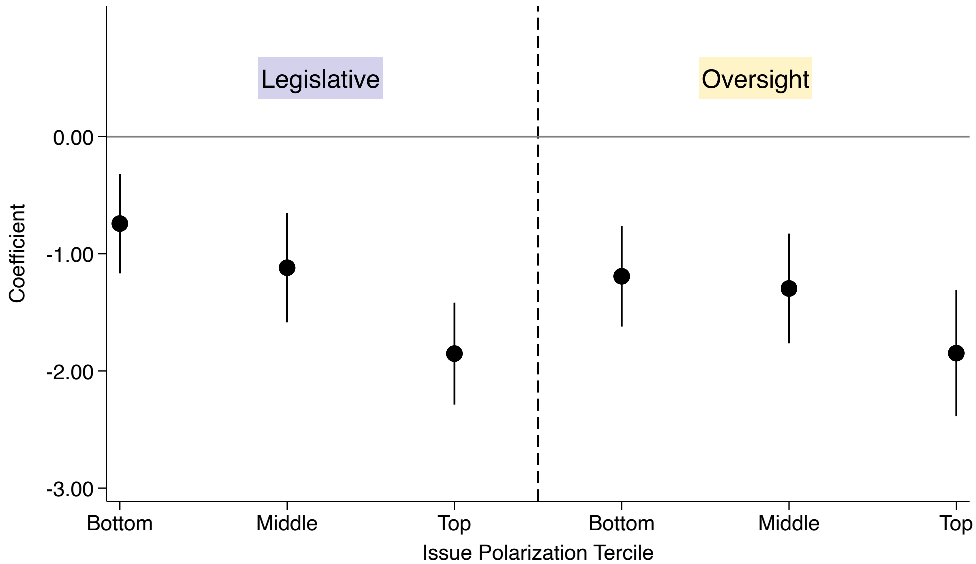
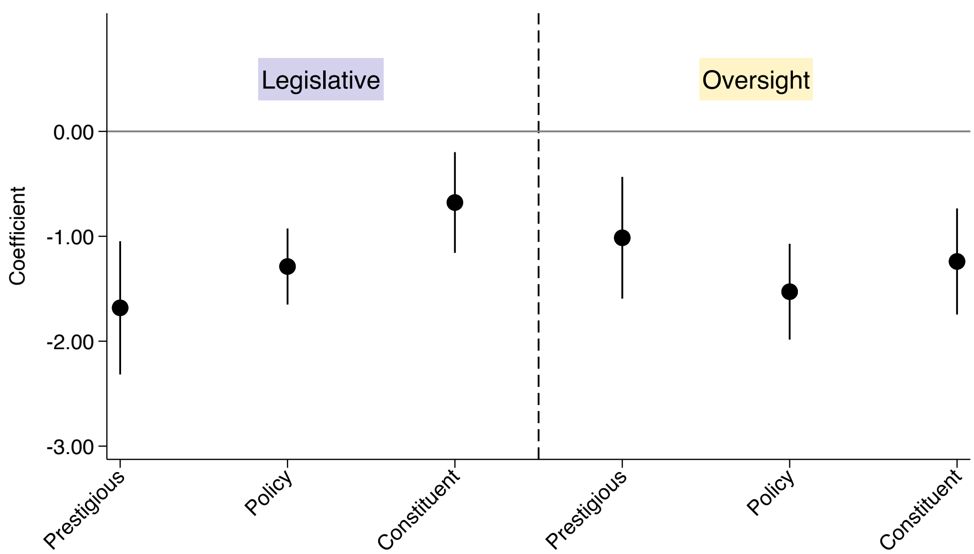


Figure A7: Heterogeneous Effects of “President Out-Partisan” by Committee Type



D Measuring Analytical Information

D.1 Coding Instructions for MTurk Workers

This task involves reading two statement excerpts made by witnesses invited to testify at congressional committee hearings held from 1997 to 2018. Researchers will use your responses to better understand the "tone" of each statement.

Your job is to read both statements and select the one that is relatively more analytical.

To give you some background knowledge, congressional committees hold hearings to collect policy-relevant information from external experts, bureaucrats, citizens or any groups that can be affected by policies that committees consider (e.g. trade associations, farmers, veterans, etc.).

In a typical hearing, witnesses give an opening statement and then answer questions that committee members ask during the Q and A session. Witness testimonies transmit various types of information to committee members (e.g. analytical information, political information on preferences of certain group of people, etc.). Our study specifically focuses on identifying and measuring analytical information that witnesses provide. To do so, you will help us by comparing two randomly selected excerpts from witness testimonies and choosing the one that sounds relatively more analytical.

We define a testimony as analytical if it contains statements that are fact-based, objective or research/data driven. In contrast, a non-analytical testimony tends to contain statements that are based on personal experience or opinion (which scholars call "ordinary knowledge" as opposed to "expert knowledge"), subjective, or normative.

Your performance will be monitored as you complete these HITs. We will reject all work done by workers who provide poor quality answers.

Do not allow your own political opinion to influence your decision. Your goal is to select the statement that other workers would also recognize as more analytical.

A statement is analytical if it is . . .
1) Fact-based
2) Verifiable (Based on research or data driven analysis)
3) Objective

(Example) Fact-based statement:

"I have over 27 years of experience in the field of community and economic development. The authority I represent has approximately 1,300 public housing units. We administer 4,600 housing choice vouchers. We manage market-rate units and two office buildings. In 2010, we opened our housing choice voucher waiting list for only 5 days and received over 6,000 applications. Our public housing waiting lists are currently at 130 percent of our total units."

(Example) Verifiable (Based on research or data driven analysis):

"The available evidence indicates that the response of individuals to increasing amounts of THC is much more variable than it is for alcohol, so with alcohol, we have a considerable body of evidence that can place risk odds at increasing levels of blood alcohol content. For example,

.08 blood alcohol content is associated with about four times the crash risk of a sober person. The average arrest is .15 THC. That's associated with about 15 times the crash risk. Beyond a– some broad confirmation that higher levels of THC are generally associated with higher levels of impairment, a more precise association of various THC levels and degrees of impairment are not yet available."

"There are several options in some of the background in the literature, everything from taking a budget level and determining what different levels of performance you can get for that same budget amount versus different levels of performance for different budget level amounts versus cost agency or even intraagency tradeoffs among requirements and budget responsibilities. So, what we need to do from a piloting standpoint is look at these and say how can we test those theories in various ways."

(Example) Objective:

"When projects are authorized, when there is a Chief's Report and the Congress authorizes a project, the economic analysis that is done on that calculates a benefit to cost ratio. And that benefit to cost ratio is based on a 3.125 discount rate."

A statement is non-analytical if it is ...

1) Opinion-based/Normative
2) Anecdotal or experiential (Based on personal experience)
3) Subjective or preferential (Revealing preferences of certain groups)
4) Procedural statements
5) All the statements that do not contain analytical information as defined earlier

(Example) Opinion-based/normative:

"We should do it this year. But we should adjust the system so that we get ready for 2017 when more money is going out than coming in, and we can do it."

(Example) Anecdotal or experiential (Based on personal experience):

"When Michael came home that night and I confronted him and was talking to him, he had eye contact like we do now. But when he was sitting on the sofa and nobody was confronting him, he was comatose. He was in the ozone. He was sitting with his mouth hanging open, staring at the door. I knew that there was something wrong with him that night. I could tell that he had taken something."

"I guess we mistakenly believed that it was a secret location, and the only people who knew about it were the EOD staff from both SFPD, the FBI and the Sheriff's Office. Unbeknownst to us, this particular individual, and I won't say too much, but was a plumber in that area and apparently had seen the officers going into that area and perhaps followed them in."

(Example) Subjective or preferential (Revealing preferences of certain groups):

"–that we try to organize that under FEHB because there has been a concern from the employees of not moving away from FEHB. From our perspective, we're okay to wait, as long as we get the savings. The savings are what's key to us. If I could put a chart up here."

(Example) Procedural statements:

"Thank you very much, Mr. Souder, and your staff for helping to deal me in today. I found out about this yesterday morning, and I'm pleased to be here. I am a former college administrator and teacher. My name is Dean, but I was one once."

In summary, consider that all statements can be placed on a continuum ranging from 0 to 100, where 0 is the most extreme non-analytical statement and 100 is the most extreme analytical statement. Some statements can be a mixture of analytical and non-analytical statements; some may be moderately analytical. Consider that these instances can be placed between the two extreme ends of the continuum.

For each HIT, you will receive two speech extracts. Your task is to read both and select which of the two statements is more analytical in the following manner:

If statement A is...	If statement B is...	Then, choose
Analytical	Non-analytical	Statement A
Analytical	Analytical	The one that is more explicitly factual/verifiable/objective
Non-analytical	Non-analytical	The one that is more explicitly opinion-based/experiential/subjective

Please read each statement carefully and judge each by the standards listed above and the information in the text. DO NOT make your judgments on your own knowledge of a person or a policy in question or on definitions of analytical and non-analytical statements different from those listed above.

Your performance will be monitored as you complete these HITs. We will reject all work done by workers who provide poor quality answers.

This training module has two parts.

In Part 1, we will provide **5 practice HITs** followed by instructions about how the statements need to be coded.

In Part 2, we will give you **5 test HITs** to complete. To receive qualification for the **Compare Witness Testimony task 2022**, you must complete **4 out of 5 of these test HITs correctly**.

D.2 Labeling Process

The sampling of the training paragraphs was a two-stage process. First, we originally planned sampling 3,300 paragraphs from the corpus of witness testimonies. To do this, we randomly selected 3,300 hearings and took only the witness testimonies. To facilitate online workers' comparison of paired paragraphs, the length of paragraphs to constitute the training set was controlled through the following process: 1) For the statements containing multiple paragraphs and more than 150 words, we divided each statement into paragraphs, but we skipped the paragraphs containing less than 50 words to keep them together with the following paragraph so it was long enough; 2) then, the paragraphs containing less than 50 words or more than 150 words were removed. From the remaining paragraphs, we randomly selected 3,300 paragraphs. Each paragraph appeared 20 times in the pair-wise comparisons generating 33,000 comparison tasks or HITs. Using the online workers' binary choices on these tasks and the `labelR` software (Carlson and Montgomery, 2017), we fit a Bradley-Terry model to generate a continuous, human-coded score or label for the 3,300 paragraphs.

However, our machine learning models fit on the random sample of the 3,000 paragraphs could not predict the rest of the 300 paragraphs well. We suspected that this is because the training set did not contain enough variation in the analytical information. Indeed, when we measure this concept using the dictionary of analytical information used in Ban, Park, and You (2023), the measurement has a highly skewed distribution with few statements scoring high. To solve this issue, we decided to repeat the labeling procedure by over-sampling the statements containing the words in their dictionary.

In the second stage, we used random-block sampling to select 1,000 paragraphs to be labeled. For the pre-processed paragraphs from the 3,300 hearings, we computed the proportion of analytical words in the dictionary. Then, we partitioned the paragraphs into four blocks based on this preliminary measurement with three cut-points: 0.05, 0.1 and 0.15. The number of blocks and the cut-points were selected to ensure that we had a high enough number of statements in the block with the highest proportion of analytical words when the equal number of statements are selected for each block. Then, we randomly selected 250 statements for each of the four blocks.

In doing so, we included statements that were labeled in the first stage so they could be used as a bridge to help the Bradley-Terry model learn the relative strength of the analytical information for the paragraphs that were labeled only in the first stage and those labeled only in the second stage. As the paragraphs labeled in the first stage were mostly populated in the blocks featuring low proportions of analytical words, we sampled 150 paragraphs of them for each of the first and second blocks. This renders 100 new paragraphs to be randomly selected for these two blocks. For the third block, we included all 66 paragraphs from those labeled in the first stage and selected 184 new paragraphs. For the fourth block with the proportion of analytical words to be greater than or equal to 0.15, all five paragraphs from those labeled in the first stage and 245 new paragraphs were included. In summary, 371 paragraphs from the first labeling process and 629 new paragraphs were labeled in the second phase.

Then, we fit a Bradley-Terry model on the combination of all the 43,000 HITs collected from the first and second phases to generate our human-coded score of the analytical information for the 3,929 paragraphs.

D.3 Learning and Predicting the Analytical Information

First, we pre-processed the corpus by lowercasing, removing stop words, and stemming. However, we decided to keep numbers as they can be an important feature of analytical information. Also, we included both unigrams and bigrams as we confirmed that the prediction performance of the model improved by including bigrams in addition to unigrams. For this test, Kernlab's support vector machine was used as it quickly fits and has relatively high prediction performance.

Second, we constructed document-level matrices using two approaches: term-document frequency (TDF) and doc2vec. For the TDF matrix, we included only the most frequent 2,000 terms due to the large size of our corpus.

Third, we randomly selected 3,500 paragraphs as a training set and held out 429 paragraphs to validate the final model. Using the paragraphs in the training set, we fit the four best performing machine learning models out of the six used in Park (2021) as our data and her data are from the same source: House hearing transcripts. The four models are support vector machine (SVM), Kernlab's support vector machine (KSVM), LASSO, and Gradient Boosting Machine (GBM). These models were fit on each of the two document matrices totaling eight models. The tuning parameters for each of the eight models were chosen through a grid search. For this, Kernlab's support vector machine was used.

Fourth, we used the `EBMAforecast` R package (Montgomery, Hollenbach, and Ward, 2012) to conduct ensemble Bayesian model averaging to reach a final model that basically aggregates all eight models by assigning weights to them to optimize the model prediction. Montgomery, Hollenbach, and Ward (2012) reports that this method achieves better model prediction than any single best machine learning model. Six models received non-zero weights. Table A12 presents the tuning parameters and weights assigned for each of the eight models.

Table A12: Machine Learning Models

Document Matrix	Model	Parameters	Weight
TDF	SVM	cost = 2	0.132
TDF	KSVM	epsilon = 0.1	0.164
TDF	LASSO	nlambda = 200	0.172
TDF	GBM	shrinkage = 0.1	0.061
Doc2vec	SVM	cost = 2	0
Doc2vec	KSVM	epsilon = 0.1	0.291
Doc2vec	LASSO	nlambda = 200	0
Doc2vec	GBM	shrinkage = 0.1	0.181

Using the final model, we predicted the score for the entire corpus and rescaled the score to range from 0 to 100.

D.4 Validation of the Measurement

This section validates the measurement statistically and substantively. First, to validate the human-coded labels substantively, below we present the five most analytical and least analytical paragraphs from the human-coded set.

D.4.1 The most analytical paragraphs (in descending order)

[1] "I can probably take that, sir. For MIDRP, there is about $430,000. For the specific on wound infections, there is $895,000. U.S. Navy wound infection research also gets money. I don't have the exact number right here. USUHS has a little over $4 million. For congressional special interest projects on wound infection, there is almost $12 million. SBIR project is about $3.7 million. Dr. Smith spoke about the Defense health programs and then war supplemental intermural projects, there is about another $2.5 million, sir."

[2] "I'm not sure I have those numbers for seven years. I can tell you that during the last two years, that number is in the range of $147 million of State money. That includes a Clean Water Management Trust Fund. We put about 6.5 percent of remaining funds after the budget is complete into a fund and that's anywhere from $40 to $50, $55 million a year. And, in addition to that, we just, of course, passed the Clean Water Responsibility Act. We've significantly increased our ag share program, working with the farmers on BMPs and so forth; so, $147 million if you total that."

[3] "Early data for cyber Monday 2017 by Adobe Analytics indicate that, collectively, shoppers spent almost $3.4 billion on online purchases, a 17 percent increase over last year. Looking at

the underlying data, over 50 percent of the virtual store visits and 40 percent of the revenue were made from tablets or smartphones, an increase of 20 percent and 41 percent respectively over last year. This could indicate that the online shopping experience is becoming more frictionless and shoppers are feeling more secure with online transactions."

[4] "The official service cost position for production is $39.8 billion. As I explained, sir, while you were out, we put together what's called an, we used the Air Force cost analysis group to develop the service cost position. The group, in doing their analysis and developing an official cost estimate for this program, estimated the cost at $40.8 billion, which included $1 billion of risk in the out years, of risk that was unidentified. Without that $1 billion for risk, the estimate is $39.8 billion."

[5] "Mr. Taylor, I believe I have an answer to your question. In 2004, the two polar icebreakers cost over $3 million in fuel costs, $3,039,000. In 2005, both the Polar Star and Krasin together cost $1,720,000 for fuel. Breaking that down, the Polar Star which had limited service during that campaign, the fuel cost was $1,057,000, and the cost of the fuel for the Krasin was $662,739."

D.4.2 The least analytical paragraphs (in ascending order)

[1] "OK. I will wrap it up there. With that, I just want to thank you. And I appreciate the opportunity to be here today. This is something I am very passionate about, and I have a lot more I want to share, but a lot of it is in my written testimony. So I appreciate the opportunity, Mr. Chairman, thank you."

[2] "I do have a problem here and I do share my colleagues' concerns with this situation in the VA. And what is the consequence for those staff that are not reporting or are not taking their duty as they should, they are not properly carrying out that responsibility, what is the consequence for them directly?"

[3] "I would say yes and amen to that. There are other things that need to happen in addition to that. I think not just middle class people are concerned about crime. All people are concerned about crime. Poor people are concerned about crime as well. I think the way Jolice Wilson talks about it is—-"

[4] "No, it is not my view of that sort at all. And I would be happy that they would be very well paid. My only perspective is that, in terms of the constitutional purpose, our focus should be on the production of output. Now, obviously, a well-compensated artist and musician class is probably important for long-run copyright output of creative works—-"

[5] "I hadn't heard that we had that problem before. You mentioned earlier the comment about the dike. I wish I could say more, and I would like to get back to the Committee on that point. Just so that I don't give you an impression that it's all OK or it's all bad, I'd rather go back and talk to my—-"

The paragraphs that received the highest scores tend to present verifiable information frequently referring to numeric figures whereas those scored the lowest points tend to be procedural statements, normative statements presenting their perspectives, or statements expressing uncertainty about a policy situation. Therefore, these two sets of paragraphs provide us with confidence that the human-coding process was conducted by closely capturing the concept that we intended to measure as described in the coding instructions.

Following the suggestions from Park and Montgomery (2024), we took an additional step to validate the human-coded scores by constructing our own coding on a 5-point scale on a random subset of 120 paragraphs that were labeled by online-workers. Then, we compared the crowd-sourced score to our 5-point scale coding to double-check if the online workers coded paragraphs in a way consistent with our conceptualization of analytical information. The Pearson correlation coefficient between the two measurements is 0.906, which provides both statistical and substantive validation of our human-coding process.

Second, we validated the analytical score predicted for the entire corpus. Below we present the ten most and least analytical statements, respectively. As some of the most analytical statements are extremely long, here, we report only those with 150 words or less.

D.4.3 The most analytical statements (in descending order)

[1] "For the joint NBC defense program, which is the program that I manage, in the area of very basic research–this is laboratory-level research for chem-bio–about $33.2 million for fiscal year 2001; in the area of applied research, $73.6 million; for advanced development programs, $46.6 million; for what we call demonstration validation of the technologies, $83.8 million; for engineering management development, which is actually putting the technologies into the widgets and doing the final operational and developmental testing, $100.8 million; and for overall management of the program, publication of doctrine, training requirements and the training base for chem-bio defense, about $23.9 million, for a total of $361.9 million for research and development. But probably more importantly, we are going to be spending $473.9 million to physically procure new equipment and putting it into the hands of the warfighters in all of those areas I discussed–detection, identification, early warning."

[2] "Congressman, Gosar, thank you. The total energy- related revenues to the Nation are nearly 100 percent. They are–well over 90 percent of the general revenue funds come from royalties, taxes, right-of-way fees, projects related to that. And Navajo Oil and Gas themselves contribute to 10 to 15 percent or more of that total revenue. The other comes from other energy companies, and our rate is rapidly increasing. I may also comment that relative to the energy delays, our very first Navajo Nation issues–what are called operating agreements, not standard BIA leases–the first operating agreement that the Council approved took over 400 days for BIA approval. The more recent one was still approximately nine months. These type of days, when the company paid out in excess of $4 million to the Nation's general fund for the rights to explore this land, are just economic–huge economic hurdles that we have to overcome."

[3] "This fiscal year we are increasing commodities to the Colombian police–aircraft parts, tools, avionics, field investigative equipment–from $7.4 million to $12.6 million. Training is at $1.5 million. Aircraft operations and so on are doubling from $4.1 million to $8 million. Military assis-

tance would involve $2.5 million in commodities, $1 million in training and $1.5 million in other programs. Judicial sector reform, we are now picking up support for this very important program of $250,000, and we're providing aviation services. We will be providing aviation programs at $14 million, and in addition, new equipment this year involving UH-1H helicopters valued at $10.8 million, Bell 212 helicopters valued at $9 million, and OV-10 Bronco aircraft valued at $84 million. So actually that is a total of $147.8 million."

[4] "Chairman Walberg, first of all, the intent of this regulation is to extend the most basic economic protections to this workforce–the minimum wage and overtime protections. Contrary to your opening statement, the department estimates that the average analyzed costs to employers to familiarize themselves with the regulation would total about $4.7 million over 10 years; and that the increase or transfer of–of transfers to home–of wages to home health care workers in the form of increased minimum wage protections would be approximately $16.1 million; the payment for time spent traveling between patients, approximately $34.7 million; and the payment of overtime premium for hours worked over 40 hour–40 hours in a work week would range between $0 and $180 million per year, on average. So consequently, the impact of this regulation is not $2.8 billion; it is actually rather modest–a modest proposal to extend significant economic protections to this workforce."

[5] "Yes, sir. So, you know, the Corps receives appropriations in different accounts: investigations, construction, and operations and maintenance. And so the numbers that you heard today are only one–they only reflect the Operations and Maintenance account. They don't reflect the Construction and the Investigations account. When you look at all appropriations across all the business lines in 2011, we had: $72.8 million allocated and spent for flood risk management; $15 million for navigation; $61.4 million for hydropower; $13.3 million for environmental stewardship; $800,000 for water supply; $21.6 million for recreation; and $87 million for environmental restoration. So that was last year's budgeted and spent amount, sir."

[6] "That would be terrific. That would be great. The last program I would like to mention real quickly is the State Drinking Water Security Responsibility. Since the events of 2001 as well as the more recent events, hurricanes, wildfires and floods, states have taken on exceptional measures to meet the security and emergency response-related needs of the drinking water community. They provided assistance, training, information and financial support to their water systems and continually work toward integrating security considerations into all aspects of their programs. The appropriated level in fiscal year 2009 was about $5 million or a little less than $100,000 per state, and states have a tough time understanding why that level has been flat-funded since 2002. And so we respectfully request $7 million in fiscal year 2010 for funding state drinking water security initiatives."

[7] "I'm not sure I have those numbers for seven years. I can tell you that during the last two years, that number is in the range of $147 million of State money. That includes a Clean Water Management Trust Fund. We put about 6.5 percent of remaining funds after the budget is complete into a fund and that's anywhere from $40 to $50, $55 million a year. And, in addition to that, we just, of course, passed the Clean Water Responsibility Act. We've significantly increased our ag share program, working with the farmers on BMPs and so forth; so, $147 million if you total that."

[8] “Another initiative provides funding for ocean conservation. In the refuge program about $400,000 will go to the Palmyra Atoll Research Consortium, and we would also put about $500,000 into the Marine Debris Campaign to help clean up. It is a very serious issue in our coastal refuges. As part of the Department’s Safe Borderlands initiative, we have requested $1 million to add six new law enforcement officers in refuges along the southwest border. This would take us from 26 to 32. Now I will turn to discussing our budget request for the Service’s programs. For the refuge system, the budget sustains the funding increase of $35.9 million that Congress approved in 2008. And given the difference between the 2008 President’s request and the 2009 President’s request, I believe that your work last year made a significant impact on OMB to help us sustain that increase.”

[9] “The President’s budget mark for the CFTC was $130 million. The House Agriculture Subcommittee for Appropriations recently gave us $135 million. As a result of their efforts, we have asked on top of the $130 for an additional $27 million, $21 million to increase our staffing levels by roughly 100 FTEs to get us up to historic levels of where we need to be. Second, the implementation of the farm bill requires us to regulate new markets, known as exempt commercial markets. This Committee helped enact this provision that will require additional staff as well. And, so we have asked for an additional $6 million on top of the $21 million for a total of $27 million.”

[10] “Yes. I have the notes of who the entities are. You have got–Health and Human Services was $811 million of the amount. Education was $530 million. The USAID was $169 million. Commerce was $15 million. Energy, $13 million. Labor, $9 million. NASA, $7 million. Then a bunch of other ones were the rest. Keep in mind, our analysis excluded things like Medicaid. It was only limited to certain grant systems, and we looked at the payment systems that were–these were payments made, so $1.6 billion of payments made related to grant programs at those specific agencies.”

D.4.4 The least analytical statements (in ascending order)

[1] “I guess I don’t know what to think of it. I was surprised by it. I believe that they are friends and–but I don’t know.”

[2] “Well, there shouldn’t be any more. There shouldn’t be any more.”

[3] “Some of it was, some of it was not. Most of it was.”

[4] “Well, there are some that are. There are some that are not.”

[5] “Of which they do very, very well. They do it very, very well.”

[6] “I do, but I don’t have that with me. But we do.”

[7] “No, no, no. I won’t do that. No. That is for you all.”

[8] “But you have to do it, and we are doing it.”

[9] “I do. I don’t have it with me, but I do.”

[10] “We did not have that here. We did not have that here.”

These examples are consistent with the features characterizing the most and least analytical paragraphs that were labeled as shown above. This suggests that our machine learning models successfully predicted the analytical scores validating our prediction process.

The statements scoring high tend to contain falsifiable statements frequently involving statistical information and explanations of where revenue and funding for the issue at hand originates.[1]

One additional aspect found here is that highly analytical statements tend to be longer than non-analytical statements, which is not the case for labeled paragraphs because their length was controlled to facilitate human coding. The relationship between the length of statements and their scores is intuitive because the statements that are too short to convey any meaningful information are likely to be evaluated as less analytical.

Finally, we take a further step to validate our final, predicted measurement for analytical information. As we did for the human-coded set, we manually constructed a 5-point scale measurement on a random subset of 120 statements in the corpus that were not labeled by assigning the highest score to the most analytical statements. The correlation coefficient between our manual coding and the analytical scores is 0.876 suggesting that the analytical score captures the concept that we intended to measure very well.

[1] One concern may be that words relating to money or financial matters may bias the measurement of the analytical score. While words relating to money or financial matters do correspond with higher analytical scores, this substantively reflects the type of information that we want to measure for the concept of analytical information—executive agencies are funded by Congress and a main source of discussion and technical information provision is on *how* agencies’ budgets are used and the financial cost and impact of their programs. As such, we do not view the correspondence between money- or financial-related words and high analytical information as a problem.