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The Partisanship of Financial Regulators

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We analyze the partisanship of Commissioners at the SEC and Governors at the Federal Reserve Board. Using recent advances in machine learning, we identify partisan phrases in Congress, such as "red tape" and "climate change," and observe their usage among regulators. Although the Fed has remained relatively nonpartisan throughout our sample period (1930–2019), we find that partisanship among SEC Commissioners rose to an all-time high during the 2010-2019 period, driven by more-partisan Commissioners replacing less-partisan ones. Partisanship at the SEC appears in both the language of new SEC rules and the voting behavior of SEC Commissioners. (*JEL* G18, G28)

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Had anyone sat through every meeting while I was on the Commission, that person could never have told which of the Commissioners were Republicans and which were Democrats.
—A. A. Sommer, Jr., SEC Commissioner from 1973 to 1976, in a 1996 speech

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Most believe that the Securities and Exchange Commission (SEC) and the Federal Reserve (Fed) should be politically independent, and for good reason. A politically motivated central bank or securities regulator can lose credibility and maximize short-term political objectives to the detriment of long-term stability.[1] For this reason, both government agencies have structures in place that are meant to immunize them from politics. At the Fed, Governors cannot be discharged for policy reasons and have 14-year terms; bank presidents are not appointed by politicians; elected officials may not serve on the Board; and funding is not dependent upon Congress. According to the Fed, this structure is meant "to ensure that its monetary policy decisions do not become subject to political pressures that could lead to undesirable outcomes."[2] At the SEC, the agency does not report to the White House; existing Commissioners cannot be removed without cause; and no more than three of its five Commissioners may belong to the same political party. According to the SEC, this is "to ensure that the Commission remains nonpartisan."[3]

Although the Fed and the SEC have institutional features that are designed to protect them from partisanship, the world around them has become increasingly partisan. Several papers find increasing polarization in congressional voting (e.g., Moskowitz, Rogowski, and Snyder 2017), while Gentzkow, Shapiro, and Taddy (2019; hereafter GST) find increasing polarization in congressional speech. The general public also has become more politically polarized in recent years. A generation ago, there was significant ideological overlap between the two major political parties. In 1994, the median Democrat (when ranked by ideology) was more liberal than just 64% of Republicans, and the median Republican was more conservative than just 70% of Democrats. Since then, the political parties have become more ideologically divided: by 2014, the median Democrat was more liberal than 92% of Republicans, and the median Republican was more conservative than 94% of Democrats. People's views about the opposing party also have become more negative: in 1994, only 16% of Democrats and 17% of Republicans had "very unfavorable" views toward the other political party. By 2014, those percentages had risen to 38% and 43%, respectively.[4]

Given the independence of the SEC and the Fed and the increasing partisanship that surrounds them, we ask three questions: (1) is there systematic evidence of political polarization among SEC Commissioners and Fed Governors, and (2) if so, is their partisanship increasing over time? (3) Is

[1] See https://www.federalreserve.gov/newsevents/testimony/kohn20090709a.htm, https://www.federalreserve.gov/faqs/why-is-it-important-to-separate-federal-reserve-monetary-policy-decisions-from-political-influence.htm, and Karmel (2016).

[2] See https://www.federalreserve.gov/faqs/about_12799.htm.

[3] See https://www.sec.gov/Article/about-commissioners.html (last accessed March 31, 2023).

[4] See the Pew Research Center (2014, 2017, 2022) polls.

there evidence that partisanship among regulators is related to their behavior, such as creating and voting on new regulation?

To address these questions, we analyze the speech of SEC Commissioners and Fed Governors from 1930 to 2019. As GST observe, Democrats and Republicans essentially speak different languages. Whereas Democrats use terms like “estate tax” and “tax break,” Republicans use terms like “death tax” and “tax reform” to describe the same phenomena. Motivated by Al Sommer’s claim in the epigraph of this paper, our measure of partisanship is the ease with which someone can guess a speaker’s party based solely on the speaker’s word choice. Specifically, we estimate the model of GST based on the speech of members of Congress and then apply the model to the speech of regulators. If partisanship exists at the SEC and the Fed, then we should expect Republican SEC Commissioners and Fed Governors to speak like congressional Republicans, and for Democratic SEC Commissioners and Fed Governors to speak like congressional Democrats. For example, if congressional Democrats in the 2010s used the term “climate change” much more frequently than congressional Republicans, and we saw Democratic SEC Commissioners also use this term disproportionately in the 2010s, this would contribute to a higher value for our partisanship measure in that decade.

We find that Fed Governors remain relatively nonpartisan with their language throughout most of our sample. For example, consider a Bayesian who forms his beliefs about the speech of Democrats and Republicans from congressional data, starting with a neutral (50-50) prior; his expected posterior belief about a Fed Governor’s political party affiliation after listening to her speak for a minute would be less than 56% in every decade. The most-partisan decade for Fed speech was the 1970s, when the Bayesian would have an expected posterior of 55.8% after listening to one minute of a Fed Governor’s speech.

While there have been periods of nonpartisanship at the SEC, language at the SEC is, on average, more partisan than the Fed. Moreover, partisanship among SEC Commissioners is rising and is at an all-time high in the most recent period. In other words, SEC Commissioners are increasingly speaking like the partisans in Congress. For example, in the most recent decade, Republicans in both Congress and the SEC talk about “regulatory burden” more often than Democrats, whereas Democrats (unlike Republicans) in both Congress and the SEC commonly say the phrases “consumer protection,” “people of color,” and “African American.” This polarization makes it easier to determine SEC Commissioners’ party affiliations by simply listening to them speak. In fact, after approximately one minute of speech, an observer who understood the speaking tendencies of congressional Republicans and Democrats in the 2010s could correctly predict a random SEC Commissioner’s political party with 62.5% accuracy. Using a model with Commissioner fixed effects, we find that this rise in partisanship at the SEC is being driven by more-partisan Commissioners replacing less-partisan ones, rather than the same Commissioners becoming more partisan over time.

In addition to the GST method, we also consider a simpler, dictionary-based approach that is more common in the finance literature (e.g., Loughran and McDonald 2011). To the extent that Democrats are more supportive of regulations than Republicans, we expect Republicans to emphasize the costs of regulation whereas Democrats will emphasize the benefits. With this in mind, we use the speech of congressional Republicans and Democrats to create a list of partisan phrases that identify regulatory costs, such as "burdensome regulation," as well as a list of phrases that identify regulatory benefits, such as "consumer protection." Using this dictionary-based approach, rather than GST, yields a similar result: SEC Commissioners disproportionately use terms that align with their political party, and these differences reached an all-time high in the most recent period.

GST's language-based measure gives rise to a natural decomposition of the source of partisanship. To better understand the drivers of partisanship over time, we use this decomposition to explore whether partisanship has increased because of (1) an increase in regulators' use of terms that are historically partisan congressional terms, (2) an increase in the congressional use of terms that are historically partisan among regulators, or (3) an increase in the use of terms that are uniquely partisan in that decade among congressional politicians and regulators. We find that all three forces contribute to the recent increase in partisanship of SEC Commissioners. For example, we find that "regulatory burden" and "compliance burden" are historically partisan phrases in Congress that Republican Commissioners use more frequently in the most recent period. Similarly, "consumer protection" and "executive pay" are historically partisan phrases in Congress that Democratic Commissioners use more often recently. On the other hand, "capital requirements" and "economic analysis," among other phrases, are historically partisan phrases in the SEC that congressional Republicans use more frequently in the most recent period. Moreover, some phrases are uniquely partisan in the most recent period at both Congress and the SEC, such as the increased use of the terms "institutional investor" and "credit default swap" among congressional Democrats and Democratic regulators.

Finally, we examine whether the partisanship that we observe in regulators' speech is related to their behavior. Specifically, we examine (1) the partisanship of rulemaking language from the Fed and SEC as reported in the Federal Register and (2) the voting behavior of SEC Commissioners and Fed Governors. Our partisanship measure positively associates with both of these real outcomes. Concerning rules that regulators write, we find that partisan language from the majority party is more likely to appear in the rules when partisanship in the governing body is higher. Concerning voting behavior, we find that SEC Commissioners are significantly more likely to dissent when a member of their same party also casts a dissenting vote. Thus, votes of approval and votes of dissent disproportionately occur together along party lines. For example, when there are two votes of dissent among the SEC's five-person Commission, 97% of the time the pair of votes come from Commissioners of the same party. Moreover, like measured partisanship at the SEC, the rate of dissenting votes has also reached an all-time high in the most recent period. Finally, dissenting votes at both the SEC and the Fed are more likely to occur when partisanship is higher, and those regulators with a greater ideological difference (as measured by their speech partisanship) are more likely to dissent.

Our paper is related to recent research that examines partisanship in financial environments. Kempf and Tsoutsoura (2021) document that credit rating analysts are more optimistic about the economy when their party is in power. Like us, several authors have used textual analysis to examine partisanship in financial settings. For example, Goldman, Gupta, and Israelsen (2020) examine whether conservative (liberal) media outlets have a more positive tone when covering firms that donate more heavily to the Republican (Democratic) party, and Luo, Manconi, and Massa (2020) examine whether the 2007 acquisition of Dow Jones & Co. by News Corporation affected the market's response to the Dow Jones Newswires. Financial economists have also applied textual analysis to examine product markets (Hoberg and Phillips 2016), central bank communication (Hansen, McMahon, and Prat 2018; Cieslak and Vissing-Jorgensen 2021), corporate culture (Grennan 2019), climate risk (Engle et al. 2020), asset market sentiment (Antweiler and Frank 2004; Tetlock 2007; García 2013; Soo 2018; Ke, Kelly, and Xiu 2019), employee expectations (Sheng 2019), financial constraints (Bodnaruk, Loughran, and McDonald 2015), subjective well-being (Hills et al. 2019), uncertainty (Baker, Bloom, and Davis 2016; Manela and Moreira 2017; Goetzman, Kim, and Shiller 2017; Hassan et al. 2019; Boudoukh et al. 2019), emerging risks (Hanley and Hoberg 2019; Bybee et al. 2019), and attitudes toward finance (Jha, Liu, and Manela 2021). See Loughran and McDonald (2020) for a review of this literature. Our study is most closely related to Gentzkow, Shapiro, and Taddy (2019), who develop the generative model of speech that we employ in our paper. However, whereas GST focus on partisanship trends within Congress, we examine partisanship trends in the SEC and the Fed. To the best of our knowledge, we are the first to measure the partisanship via speech of any regulator and the partisanship of rules published in the Federal Register.

Our paper is also related to the literature on partisanship and regulators. Havrilesky and Gildea (1992) find that Fed Board members with backgrounds in economics consistently vote in line with the economic ideology of the appointing U.S. president, whereas Board members without economic backgrounds do not. Chappell, Havrilesky, and McGregor (1993) find that partisan-appointed Fed Governors desire higher interest rates when serving under a president of the opposing party than they do when serving under an own-party president, and Havrilesky and Gildea (1995) find that a subset of Federal Reserve bank presidents votes in a manner which is consistent with the partisanship of the U.S. president who appointed them. Mehta and Zhao (2020) show that political frictions among U.S. antitrust regulators can lead to a bias in enforcement decisions. Fraccaroli, Sowerbutts, and Whitworth (2020) analyze 43 countries from 1999 to 2019 to show that reduced political independence of regulators generally harms financial stability. We believe we are the first to examine the partisanship of the speeches of Fed Governors and the first to examine any type of partisanship at the SEC.

1. Data and Methodology

1.1 Speech data

We analyze text from three U.S. governing bodies: the Securities and Exchange Commission (SEC), the Federal Reserve System (Fed), and Congress.

For the SEC, we collect all historical speeches that are publicly available, spanning a 90-year period from 1930 to 2019.[5] Prior to cleaning the text, we first convert all speeches into text files. Because many speeches are only available as pdfs, we convert the pdfs to text files using optical character recognition (OCR) software. Once speeches are in text format, we apply a similar cleaning process as GST:

1. We remove stopwords, punctuation, and numbers using Python's NLTK package.
2. We reduce the remaining words to their stems.[6]
3. We group the remaining stems into two-word phrases, also referred to as "bigrams."
4. To reduce sparsity and unnecessary computational challenges, we limit the analysis to those phrases that occur at least 30 times across all Commissioner speeches and are spoken by at least two unique speakers.[7]
5. We manually remove phrases that are likely to be procedural, names of Commissioners, and U.S. locations that may simply represent the speech location.
6. We use only those speeches that are spoken by Commissioners who belong exclusively to one of the two major U.S. political parties, Republican and Democratic. SEC Commissioner political affiliations are publicly available on the SEC's website.[8]

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5 See http://sec.gov/news/speeches.

6 More information is available at http://snowballstem.org/.

7 This restriction is similar in nature to that applied by GST but adjusted for the smaller number of speakers and volume of text in the SEC.

8 See http://sec.gov/about/sechistoricalsummary.htm. Currently, Robert J. Jackson Jr.'s party affiliation is incorrectly listed on the SEC website as an independent. We identify him as a Democrat consistent with all other sources we find, such as Michaels (2017) and Olen (2019).

After this cleaning procedure, the SEC sample contains 10,475 unique phrases spoken a total of 710,938 times. Because speech, policies, and partisan ideologies can change over time, we aggregate the text at the decade level. The sample has 123 unique decade-speakers and 3,103 unique speeches.

Our second body of text includes statements and speeches from members of the Board of Governors at the Fed spanning the same period as the SEC.[9] After employing the same cleaning process as we did with the SEC text and restricting to the same sample period (1930-2019), the Fed sample contains 17,640 unique phrases spoken a total of 1.4 million times. The sample has 129 unique decade-speakers and 4,529 unique speeches. Because Fed speakers' political party affiliations are not all publicly available, we use the political party of the appointing president when the speaker's political affiliation is unavailable from public sources.[10] We provide more detail concerning the party assignments of SEC Commissioners and Fed Governors in Internet Appendix Table A1.

The congressional text comes from the *United States Congressional Record* beginning with the 43rd Congress and continuing through the 114th Congress and is the same data used by GST.[11] The data were originally obtained from HeinOnline and are also preprocessed into bigrams, after stemming and removing noise (such as stopwords, procedural phrases, and punctuation).[12] Additionally, we apply the same frequency restrictions to the congressional text as GST. That is, across the time period we analyze, the phrase must have occurred: (1) at least 10 times in at least one congressional session, (2) in at least 10 unique speaker-sessions, and (3) at least 100 times across all sessions. The remaining congressional sample contains 443,591 unique phrases spoken a total of 228 million times. The sample has 7,990 unique decade-speakers and 23,108 unique speaker-sessions.

As a final step to measure the Congress-based partisanship of these regulators, we focus on those phrases that are common among financial regulators and Congress.[13] To illustrate, Figure 1 shows a Venn diagram of the distinct phrase counts in the various intersections of the three bodies we study. Regions A, B, and C represent the number of distinct phrases only spoken in

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9 See https://fraser.stlouisfed.org/series/3763.

10 Unlike the SEC, which has limits on the number of Commissioners allowed from one party, the Fed does not have a limit. Thus, the appointing president's political party is likely to be a strong proxy for the Fed Governors. Of the 80 unique Fed Governors who speak during our sample period, 61 have political party information available from public information sources. Of the 61 party affiliations we find, only 6 are identified as the appointing president's opposing party.

11 GST share the congressional text data with documentation at https://data.stanford.edu/congress_text. It is worth noting that the congressional text ends in 2016, while the SEC/Fed speeches continue through the end of 2019. Missing the last 3 years of congressional text should bias against finding speech similarities. However, all results are similar if we do not include the last 3 years of regulator speeches.

12 For a more detail description of the congressional data source, see section 2 of GST.

13 In the Internet Appendix, we report tests conducted on just the regulator speech, which we call "internal regulator" partisanship. For these tests, we do not require that the phrase appear in the congressional speech.

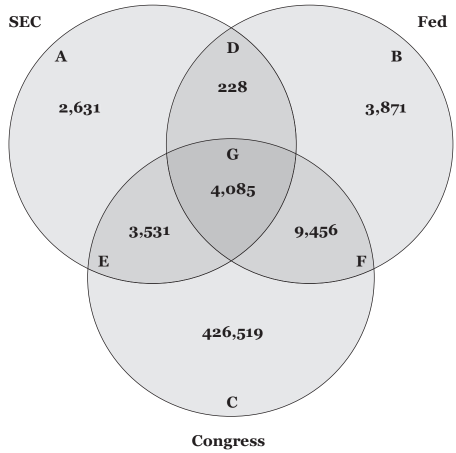

Figure 1
Unique phrase counts
We report the counts of unique phrases in the SEC, Fed, and congressional samples, and their intersections. Regions A, B, and C represent the number of unique phrases only spoken in the SEC, the Fed, and Congress, respectively. Region D represents the number of unique phrases that occur in the SEC and Fed, but not Congress. Region E represents the number of unique phrases that occur in the SEC and Congress, but not the Fed. Region F represents the number of unique phrases that occur in the Fed and Congress, but not the SEC. Finally, region G represents the number of unique phrases that occur in all three samples.

the SEC, the Fed, and Congress, respectively. Region D represents the number of distinct phrases that occur in the SEC and Fed, but not Congress. Region E represents the number of distinct phrases that occur in the SEC and Congress, but not the Fed. Region F represents the number of distinct phrases that occur in the Fed and Congress, but not the SEC. Finally, region G represents the number of distinct phrases that occur in all three samples. The samples overlap a fair amount as most of the SEC and Fed unique phrases also appear in Congress. When measuring congressional similarity in these financial regulating bodies, we analyze only those phrases that appear at the intersection with Congress.[14] For instance, when measuring congressional similarity in the SEC (Fed), we use those phrases that appear in regions E (F) and G.

Table 1 shows summary statistics for those intersecting samples across decades. Panel A displays the intersection between the SEC and Congress samples. Both samples include 7,616 distinct phrases. These phrases are spoken 552,052 times by 123 decade-speakers in 3,103 speeches at the SEC. At Congress, they are spoken 19,735,729 times by 7,930 decade-speakers in 22,937 speaker-sessions.

[14] Although it does not affect the total unique bigram counts, at the decade-party level we also require the phrase to be spoken at least once by a congressperson of the same political party in that decade. This restriction removes fewer than 1% of the decade-party bigrams.

Table 1
Summary statistics by decade

A. SEC intersecting with Congress

		SEC									Congress								
	Unique	Total Bigrams			Decade-Speakers			Speeches			Total Bigrams			Decade-Speakers			Speaker-Sessions		
Decade	Bigrams	Total	R	D	Total	R	D	Total	R	D	Total	R	D	Total	R	D	Total	R	D
1930s	4,002	19,111	4,964	14,147	13	2	11	117	18	99	779,408	275,501	503,907	1,057	416	641	2,519	821	1,698
1940s	3,860	18,237	8,027	10,210	14	4	10	80	26	54	1,005,526	478,583	526,943	1,007	418	589	2,618	1,173	1,445
1950s	4,986	39,401	33,018	6,383	16	9	7	164	138	26	1,380,918	546,722	834,196	871	380	491	2,675	1,200	1,475
1960s	4,995	26,893	10,386	16,507	13	8	5	118	46	72	2,264,315	828,251	1,436,064	871	359	512	2,720	1,065	1,655
1970s	6,918	80,197	45,399	34,798	13	9	4	351	212	139	3,438,374	1,346,925	2,091,449	917	370	547	2,691	1,030	1,661
1980s	7,063	78,815	38,265	40,550	15	7	8	318	157	161	3,171,428	1,454,864	1,716,564	789	353	436	2,697	1,151	1,546
1990s	6,606	47,188	26,985	20,203	10	6	4	277	142	135	3,367,375	1,598,947	1,768,428	905	416	489	2,701	1,295	1,406
2000s	7,317	122,652	79,378	43,274	18	10	8	759	516	243	3,101,773	1,336,510	1,765,263	806	395	411	2,701	1,325	1,376
2010s	7,035	119,558	46,937	72,621	11	6	5	919	436	483	1,226,612	575,476	651,136	707	384	323	1,615	875	740
Total	**7,616**	**552,052**	**293,359**	**258,693**	**123**	**61**	**62**	**3,103**	**1,691**	**1,412**	**19,735,729**	**8,441,779**	**11,293,950**	**7,930**	**3,491**	**4,439**	**22,937**	**9,935**	**13,002**

B. Fed intersecting with Congress

		SEC									Congress								
	Unique	Total Bigrams			Decade-Speakers			Speeches			Total Bigrams			Decade-Speakers			Speaker-Sessions		
Decade	Bigrams	Total	R	D	Total	R	D	Total	R	D	Total	R	D	Total	R	D	Total	R	D
1930s	4,989	23,402	10,853	12,549	13	6	7	122	43	79	1,029,845	367,513	662,332	1,055	414	641	2,524	820	1,704
1940s	7,169	46,661	19,576	27,085	10	3	7	241	87	154	1,522,882	729,412	793,470	1,009	418	591	2,624	1,175	1,449
1950s	8,616	62,893	22,284	40,609	13	5	8	322	105	217	1,934,766	767,698	1,167,068	874	382	492	2,680	1,203	1,477
1960s	10,552	101,948	10,433	91,515	13	3	10	431	60	371	3,701,624	1,366,286	2,335,338	872	359	513	2,721	1,065	1,656
1970s	12,005	179,852	96,840	83,012	21	9	12	667	415	252	5,019,791	1,987,863	3,031,928	917	370	547	2,691	1,030	1,661
1980s	12,806	173,184	90,534	82,650	16	9	7	584	320	264	4,701,051	2,144,070	2,556,981	789	353	436	2,698	1,151	1,547
1990s	12,700	178,866	118,140	60,726	14	7	7	689	460	229	4,966,391	2,356,029	2,610,362	905	416	489	2,701	1,295	1,406
2000s	12,618	236,638	177,921	58,717	15	10	5	886	679	207	4,167,388	1,796,471	2,370,917	806	395	411	2,701	1,325	1,376
2010s	10,799	142,307	65,783	76,524	14	8	6	587	299	288	1,557,049	727,558	829,491	707	384	323	1,615	875	740
Total	**13,541**	**1,145,751**	**612,364**	**533,387**	**129**	**60**	**69**	**4,529**	**2,468**	**2,061**	**28,600,787**	**12,242,900**	**16,357,887**	**7,934**	**3,491**	**4,443**	**22,955**	**9,939**	**13,016**

We report the counts of unique two-word phrases (bigrams), total phrases, decade-speakers, and units of observation (speeches at the SEC/Fed and speaker-sessions at Congress) for the two samples of text. Panel A (B) shows these summary statistics for the SEC (Fed) sample that intersects with Congress.

Similarly, panel B shows the intersection between the Fed and Congress samples. The intersection between these two samples provides a larger corpus as 13,541 distinct phrases overlap. At the Fed, these phrases are spoken 1,145,751 times by 129 decade-speakers in 4,529 speeches. At Congress, they are spoken 28,600,787 times by 7,934 decade-speakers in 22,955 speaker-sessions.

1.2 Measuring partisanship

1.2.1 Dictionary-based approach. Before utilizing the GST model, we start with a simpler dictionary-based exercise to illustrate partisanship within a particular topic. Specifically, we identify a list of phrases that refer to regulatory costs, such as "burdensome regulation," as well as a list of phrases that refer to regulatory benefits, such as "consumer protection."[15] If the political parties differ in their support for regulation, we should see noticeable differences in their tendencies to refer to regulatory costs versus regulatory benefits, with the party more supportive of (opposed to) regulations being relatively more likely to discuss the benefits (costs) of regulation. Moreover, we can observe how these potential partisan differences evolve over time.

Specifically, we count the number of times that each party uses terms associated with regulatory benefits and regulatory costs in each decade t, and we define *RelativeBenefits* as the frequency at which each political party $P \in \{D, R\}$ discusses regulatory benefits relative to regulatory costs:

$$RelativeBenefits_t^P = \frac{Number\ of\ benefit\ bigrams\ spoken_t^P}{Number\ of\ benefit\ bigrams\ spoken_t^P + Number\ of\ cost\ bigrams\ spoken_t^P}. \quad (1)$$

Once we calculate *RelativeBenefits* for each decade-party, we then compute the absolute value of the difference across parties to represent the dictionary-based partisanship for each decade t:

$$DBpartisanship_t = \left| RelativeBenefits_t^R - RelativeBenefits_t^D \right|. \quad (2)$$

If Republicans and Democrats use the phrases in each list at similar relative frequencies, then this difference will be close to zero. However, if each party speaks distinctly using only opposite lists, then *DBpartisanship* will be close to one.

Figure 2 plots the *DBpartisanship* measure in each decade for the SEC and the Fed. We see that the SEC has been increasingly partisan in their use of regulatory phrases across our sample period with the highest measure of *DBpartisanship* occurring in the 2010s. At the Fed, the values are generally

[15] These phrases are listed in Appendix Table A2.

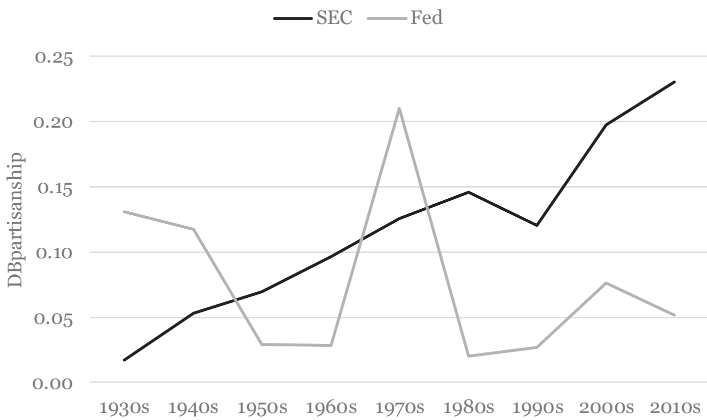

Figure 2
Dictionary-based partisanship
We plot the time series of a dictionary-based measure of partisanship detailed in Equation (2). To calculate it, we define a list of regulatory costs and benefits phrases (detailed in Internet Appendix Table A2) by manually searching the top-100 most-partisan phrases (based on GST's methodology) in each decade at both regulatory bodies. Then, we calculate the relative use of regulatory benefits phrases versus regulatory costs, or *RelativeBenefits,* detailed in Equation (1). Finally, dictionary-based partisanship is the absolute value of the difference in *RelativeBenefits* across parties.

lower than the SEC with the maximum value occurring in the 1970s. Still, the highest measure of *DBpartisanship* occurs in the most recent decade at the SEC, indicating that partisan differences in the discussion of regulatory costs/benefits at the SEC is currently at an all-time high.

In Internet Appendix Figure A1, we present more detailed graphs that disaggregate the frequency of Democratic and Republican regulators' use of phrases referring to regulatory costs and regulatory benefits. Since the 1990s, we observe a consistent deviation across parties at the SEC for Republicans (Democrats) to favor regulatory cost (benefit) phrases.

1.2.2 GST approach. In the remainder of this section, we generalize the dictionary-based measure of partisanship by employing the model of GST, which allows us to analyze the full corpus of regulator speeches without having to manually select partisan phrases. That is, we follow GST and define partisanship as the accuracy at which an observer, who has a neutral prior and who understands the speech-generating process modeled by GST, could guess a speaker's party based solely on observing the speaker's choice of a single phrase. Specifically, we adopt the leave-out estimator from GST to address a potential finite sample bias that arises in high-dimensional settings, such as ours. However, we make one notable change by defining the partisanship of a phrase completely out-of-sample by using only the congressional text to define partisan phrases and applying those definitions to the regulatory bodies.

We start with the congressional text for defining the partisan nature of the phrases. The observed text is represented by phrase counts c_{ijs}, which equals the number of times that speaker i spoke phrase j in Congressional session s. The total phrase count for a speaker i in session s is denoted by $m_{is} = \sum_j c_{ijs}$. For each political party $P \in \{D, R\}$, each phrase j, and each decade t, let q_{tj}^P be defined by

$$q_{tj}^P = \frac{\sum_{i \in P,\ s \in t} c_{ijs}}{\sum_{i \in P,\ s \in t} m_{is}}, \tag{3}$$

where "$i \in P$" denotes the event that speaker i belongs to political party P, and "$s \in t$" denotes the event that session s occurred in decade t. Note that q_{tj}^R represents the proportion of Republicans' speech in decade t that phrase j comprises, and q_{tj}^D represents the analogous statistic for Democrats' use of phrase j in decade t. Let $\boldsymbol{q}_t^P$ (where $P \in \{D, R\}$) denote the vector whose elements consist of the values q_{tj}^P for all phrases j. In other words, $\boldsymbol{q}_t^P$ is a vector with J_t elements, where J_t is the total number of distinct phrases spoken in decade t, and the elements of $\boldsymbol{q}_t^P$ sum to one.

If $\boldsymbol{q}_t^D$ and $\boldsymbol{q}_t^R$ are close to one another, Republicans and Democrats speak a similar language, whereas if they are far apart, Republicans and Democrats exhibit partisanship in their speech. Hence, to measure partisanship, one simply has to determine whether the vectors $\boldsymbol{q}_t^D$ and $\boldsymbol{q}_t^R$ are close together or far apart.

Let ρ_{tj} be defined as

$$\rho_{tj} = \frac{q_{tj}^R}{q_{tj}^R + q_{tj}^D}. \tag{4}$$

As noted by GST, ρ_{tj} is the posterior belief that an observer with a neutral prior assigns to a speaker being Republican if the speaker chooses phrase j in decade t.[16] The notation here varies slightly from section 4.2 of GST (2019) because they apply the methodology in-sample while we focus on an out-of-sample approach. When applying this measure in-sample, it is important that the unit of observation be left out of the ρ_{tj} calculations. However, the out-of-sample approach allows us to define the partisanship of a phrase j in each decade t without leaving out any speech because these definitions will be applied to an entirely unique body of text with different speakers. Thus, all of the regulators are inherently "left out" because they are not part of the congressional sample.

In Figure 3, we validate that the congressional samples that intersect with the SEC (panel A) and Fed (panel B) exhibit the same pattern that GST document. We plot the internal congressional partisanship measure using the in-sample leave out approach from GST at the decade level. Across both samples, we see relatively low partisanship (around 0.503–0.505) until the 1990s when the measure increases to 0.507 (0.511) for panel A (panel B). It then continues to rise to 0.510 (0.514) in the 2000s for panel A (panel B) and is strongest at

[16] Technically, ρ_{tj} is the plug-in estimator for the posterior belief of such an observer.

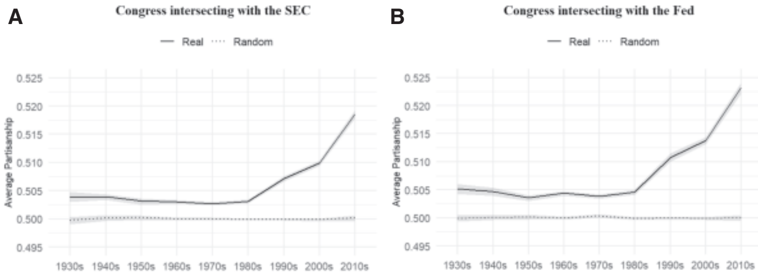

Figure 3
Internal congressional partisanship validation
We plot the GST leave-out estimator for congressional partisanship using the congressional samples that intersect with the SEC (panel A) and the Fed (panel B). In each graph, we plot the average partisanship using actual party affiliations as "real" (the solid line) and random party affiliations as "random" (the dotted line). For the random assignments, each speaker-session's party is randomly assigned using the probability that a speaker-session is Republican in that given decade. The shaded regions around both lines represent a pointwise confidence interval consistent with Politis, Romano, and Wolf (1999). More specifically, we subsample 20% of the speaker-sessions without replacement 100 times, and for each subsample k, we compute the partisanship estimate, π_t^k. Similar to GST, let τ_k be the number of speaker-sessions in the kth subsample and τ be the number of speaker-sessions in the full sample. Also, define $(Q_t^k)_{(b)}$ to be the bth order statistic of $Q_t^k = \sqrt{\tau_k}(\pi_t^k - \frac{1}{100}\sum_{l=1}^{100}\pi_t^l)$. Then, the confidence interval on the partisanship estimate is $(\pi_t - \frac{(Q_t^k)_{(90)}}{\sqrt{\tau}}, \pi_t - \frac{(Q_t^k)_{(11)}}{\sqrt{\tau}})$.

0.519 (0.523) in the 2010s. Although these subsamples do not reach the same level of partisanship compared to the maximum reported by GST when using the full congressional sample (roughly 0.535), it is noteworthy that the same pattern exists even when restricting to only those phrases that are also spoken by financial regulators.

To see which phrases drive the increase in congressional partisanship in the 1990s, 2000s, and 2010s, we report the top-30 most-partisan phrases in these decades for each party in Table 2. Panel A (panel B) shows the list using the congressional sample that intersects with the SEC (Fed). We also show the predicted number of times each phrase will appear per 100,000 phrases for each party in Congress. To generate this list of phrases, we run the congressional partisanship test 7,616 (13,541) times for panel A (panel B), one time for each unique phrase in the sample. Each time we remove the phrase of interest and then rank them based on the reduction in partisanship when removing it from the sample.[17]

In all three decades, partisan Democratic topics in Congress that are also spoken by both regulatory bodies include diversity ("affirmative action" and "people of color," among other phrases), civil liberties ("civil rights," and "voting rights," among other phrases), and consumer/investor protection ("Wall Street reform" and "protect consumers," among other phrases). On the other hand, partisan Republican topics that are also spoken by regulators tend to focus on tax structure ("tax code," "tax burden," and "intern revenue," among

[17] As GST note, the phrase-level partisanship measure they propose is not valid with a leave-out estimator. Instead, we use a more computationally intensive procedure that captures the same idea.

Table 2
Congressional partisan phrases

A. SEC

1990s						2000s						2010s					
Republican	#R	#D	Democrat	#R	#D	Republican	#R	#D	Democrat	#R	#D	Republican	#R	#D	Democrat	#R	#D
privat properti	179	58	insur compani	99	286	natur gas	570	213	african american	107	370	red tape	132	24	climat chang	148	835
american peopl	2408	1709	civil right	257	425	tax rate	261	72	civil right	208	475	intern revenu	128	37	african american	68	414
tax code	324	149	vote right	32	86	privat properti	89	25	insur compani	193	430	feder regul	141	39	vote right	31	293
tax rate	201	71	american worker	163	279	save account	140	40	credit card	128	356	regulatori burden	97	13	civil right	142	426
save account	184	75	affirm action	35	78	properti right	84	32	insur industri	30	110	natur gas	436	220	oil compani	68	284
properti right	135	66	invest futur	30	62	state line	72	26	street reform	2	36	busi owner	297	147	million american	486	894
save invest	60	17	million american	274	410	econom growth	302	182	vote right	92	163	burdensom regul	56	6	insur compani	159	354
govern control	48	14	need invest	10	35	limit govern	32	5	million american	360	579	nation defens	353	198	protect public	32	124
feder regul	108	48	make invest	22	53	govern control	46	8	privat account	3	40	govern regul	81	18	need invest	13	87
govern reform	72	37	million peopl	193	274	soviet union	140	80	peopl color	2	21	properti right	79	23	invest futur	17	80
govern regul	66	25	safeti net	62	126	busi owner	177	111	fiscal polici	27	78	econom freedom	18	2	special interest	120	259
status quo	192	111	consum protect	47	81	tax code	201	114	senior citizen	120	236	privat properti	70	25	make invest	33	89
regulatori burden	46	14	insur industri	20	64	regulatori burden	26	6	consum protect	63	120	complianc cost	37	7	global economi	55	123
full disclosur	39	19	oil compani	32	89	solv problem	230	136	fail provid	16	46	limit govern	62	13	safeti net	100	202
govern mandat	31	7	need help	123	193	across border	95	38	protect consum	32	78	save account	76	21	import invest	7	36
busi owner	102	56	industri nation	28	62	red tape	45	16	adequ fund	34	74	lower cost	142	56	street reform	6	52
privat sector	547	396	intern communiti	76	124	unintend consequ	75	28	equal opportun	21	56	cost regul	44	7	consum protect	48	130
red tape	37	14	outsid counsel	4	14	continu success	50	24	affirm action	8	31	check balanc	82	22	protect consum	28	87
tax reform	81	44	public invest	4	25	save invest	31	8	econom crisi	32	68	increas cost	145	70	invest america	14	57
fraud abus	104	65	turn back	81	127	job growth	85	58	need invest	15	42	regulatori environ	30	3	come togeth	361	587
cost regul	22	5	global economi	50	86	feder incom	39	18	secur privat	3	19	govern mandat	23	2	nation institut	74	168
econom freedom	21	6	import invest	5	19	support adopt	15	6	check balanc	41	86	regulatori reform	48	10	secur fund	27	70
regulatori relief	27	9	invest america	11	26	foreign countri	105	63	make invest	32	61	across border	74	29	social econom	7	27
real world	60	36	credit card	91	148	govern regul	34	14	independ commiss	9	35	govern control	44	6	cop beat	1	24
flexibl act	27	11	cop beat	9	25	tax polici	120	53	invest futur	16	41	held account	97	49	turn back	60	130
secur interest	119	74	nation problem	26	35	believ govern	71	15	access capit	14	30	feder regist	31	9	peopl color	2	20
burdensom regul	14	3	polit system	35	66	rais cost	34	12	provid adequ	26	51	enterpris system	35	5	invest need	9	36
nation secur	656	502	corpor america	17	34	line item	30	13	corpor interest	3	20	state line	59	23	progress made	39	91
busi men	23	7	deposit insur	45	71	growth rate	42	17	multin corpor	5	20	creat environ	61	16	econom recoveri	99	189
regulatori cost	10	2	econom interest	19	44	fanni mae	89	37	import invest	6	24	foreign polici	177	93	goldman sach	5	31

(*Continued*)

Table 2
(Continued)

B. Fed

1990s						2000s						2010s					
Republican	#R	#D	Democrat	#R	#D	Republican	#R	#D	Democrat	#R	#D	Republican	#R	#D	Democrat	#R	#D
tax increas	409	116	african american	16	71	tax increas	431	69	african american	79	275	rais tax	376	84	middl class	224	822
rais tax	243	74	insur compani	67	194	rais tax	276	41	civil right	155	353	nation debt	293	103	climat chang	117	656
feder debt	210	32	minimum wage	145	394	natur gas	424	159	insur compani	143	320	intern revenu	101	29	african american	54	325
balanc budget	1483	962	civil right	175	288	increas tax	147	29	credit card	95	265	feder regul	111	30	minimum wage	49	343
govern spend	145	44	trade deficit	44	126	tax rate	194	54	middl class	70	186	regulatori burden	77	10	student loan	136	492
tax code	220	101	unemploy benefit	33	82	govern spend	121	27	oil compani	76	216	tax increas	353	102	unemploy insur	44	236
higher tax	79	15	deficit reduct	166	287	higher tax	82	12	insur industri	23	82	govern spend	199	52	civil right	112	334
tax burden	110	37	invest educ	8	43	save account	104	30	unemploy benefit	54	167	balanc budget	644	333	unemploy benefit	43	172
increas tax	132	51	unemploy rate	34	85	feder spend	76	22	unemploy insur	23	106	energi product	147	35	reduc deficit	90	263
tax spend	60	13	american worker	111	189	increas spend	100	31	minimum wage	138	310	natur gas	345	172	tax credit	166	357
feder spend	128	52	trade agreement	87	153	properti right	62	24	trade deficit	25	111	revenu servic	73	19	invest educ	5	61
tax rate	136	48	invest futur	21	42	govern program	89	30	trade polici	22	80	busi owner	235	116	insur compani	126	278
increas spend	101	36	health safeti	70	124	lower tax	52	15	card compani	11	63	nation defens	279	155	million american	384	702
save account	125	51	farm worker	5	16	spend much	77	26	invest educ	5	41	debt crisi	104	24	health safeti	36	105
properti right	91	45	unemploy insur	11	41	entitl program	60	11	lost job	53	137	reduc spend	127	29	protect public	25	98
lower tax	53	12	unemploy worker	6	25	state line	53	19	budget surplus	12	47	feder spend	132	40	need invest	11	68
spend increas	54	19	increas minimum	27	78	tax burden	64	21	record profit	3	30	govern regul	64	14	invest futur	13	62
govern program	86	37	need invest	7	24	increas suppli	45	13	energi effici	61	124	properti right	63	18	deficit reduct	116	238
reduc tax	50	17	make invest	15	36	limit govern	24	4	budget deficit	56	119	increas spend	100	18	faith credit	13	59
high tax	19	2	medicar medicaid	60	108	govern control	34	6	lose home	10	45	govern program	86	31	full faith	13	58
save invest	41	12	privat insur	16	43	soviet union	104	59	secur trust	39	85	complianc cost	29	5	roll back	33	92
american peopl	1634	1158	unemploy compens	33	60	entitl spend	37	5	increas minimum	22	73	limit govern	49	10	communiti across	46	123
size scope	13	2	trade polici	36	69	energi product	69	31	racial ethnic	5	23	energi cost	74	27	program help	50	130
spend program	67	28	insur industri	14	43	growth govern	14	1	farm worker	6	22	save account	60	17	natur disast	44	119
feder tax	82	39	consum protect	32	55	increas domest	33	9	civil war	84	154	lower cost	113	44	infrastructur invest	11	50
feder regul	73	33	safeti net	42	85	regulatori burden	19	4	fiscal polici	20	58	avail act	43	19	colleg univers	36	83
govern control	33	9	wage worker	4	24	govern take	62	22	american communiti	18	45	red line	46	11	privat insur	25	70
govern tax	23	5	invest nation	9	21	across border	70	28	fail provid	12	35	cost regul	35	6	make invest	26	70
govern take	54	24	health insur	252	393	tax spend	33	9	foreclosur crisi	3	20	check balanc	65	18	colleg student	32	79
govern regul	45	17	program help	44	77	foreign sourc	46	18	chang direct	8	27	oil natur	50	14	higher educ	92	214

We report the 30 most-partisan Republican and Democratic phrases within Congress occurring in the 1990s, 2000s, and 2010s that are also spoken at the SEC (panel A) and the Fed (panel B). Similar to GST, we also report the predicted number of times each phrase is said per 100,000 phrases spoken by Republicans and Democrats. To generate this list of phrases, we run the congressional partisanship test 7,616 (13,541) times for the congressional sample that intersects with the SEC (Fed). Each time we remove the phrase of interest to determine its influence on the overall partisanship measure. The phrases are then ranked based on the reduction in partisanship when removing it from the sample, and they are assigned a party based on the relative frequency in each party.

other phrases) and the cost of regulation ("red tape" and "regulatory burden," among other phrases).

In Internet Appendix Figure A2, we estimate the internal regulator partisanship at the SEC and Fed by applying the GST in-sample leave-out estimator only to each regulator's speech. While this is a natural extension of GST, we note important differences in results based on the level that the leave-out procedure is applied. When applied at the speech level (panel A), we see higher levels of partisanship in both regulatory bodies than we do at Congress. However, when applying the leave-out procedure at the speaker level, we no longer find significant levels of partisanship. This difference occurs because a few speakers repeat polarizing phrases.[18] Therefore, we prefer the out-of-sample Congress-based measure of regulator partisanship because the partisan phrases are defined using only congressional text with a sufficiently large number of different speakers. Moreover, because the phrases are defined completely out-of-sample, speaker-level idiosyncrasies should be unlikely to affect our results.[19]

Next, we calculate the phrase frequencies for each regulatory body's text just as before in the congressional sample. That is, for each speech i in decade t in the SEC and Fed text, we also calculate $\boldsymbol{q}_i^P$, which is a vector with J_t elements, where J_t is the total number of distinct phrases spoken in decade t. Each element of the vector $\boldsymbol{q}_i^P$ equals the portion of the speech that is comprised of the corresponding phrase, and the elements of $\boldsymbol{q}_i^P$ sum to one.[20]

To calculate Congress-based regulator partisanship, it is important to note that the $\boldsymbol{q}_i^P$ frequencies in the following equation consist only of regulator speech, while the elements of $\boldsymbol{\rho}_t$ are defined using only congressional speech. We follow GST in defining partisanship in decade t as

$$\pi_t = \frac{1}{2}\frac{1}{|R_t|}\sum_{i\in R_t}\boldsymbol{q}_i^R\cdot\boldsymbol{\rho}_t + \frac{1}{2}\frac{1}{|D_t|}\sum_{i\in D_t}\boldsymbol{q}_i^D\cdot\left(1-\boldsymbol{\rho}_t\right), \tag{5}$$

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[18] To understand why we expect measured internal regulator partisanship to be higher when we only leave out a single speech (as opposed to all of a speaker's speeches), consider a speaker, say, a Republican, who talks about "death taxes" (a polarizing phrase that refers to "estate taxes") every time that she gives a speech. Suppose further that she is the only speaker who ever uses this phrase. If we only remove individual speeches in our leave-out estimator, the party affiliation for each of this speaker's speeches can be easily predicted by the GST methodology. To see why, note that when one of her speeches is being analyzed, the sample of speeches that this speech is compared to will include all of her other speeches, each of which contains the phrase "death tax." Because none of the other Commissioners ever uses the phrase "death tax," the posterior belief that the speaker is a Republican after hearing the phrase "death tax" will be very high. If, on the other hand, we remove all of her speeches when examining one of her speeches, the methodology will have a difficult time identifying her as a Republican, because all of her (many) other speeches that refer to "death taxes" will be excluded from the sample. Thus, to the extent that polarizing phrases are often repeated by the same speaker, the leave-out methodology will generally lead to larger estimated values of partisanship when we only "leave out" the specific speech being analyzed (as opposed to excluding that speaker's entire corpus of speeches). Additionally, the regulator samples have relatively few speakers compared to Congress, so their partisan phrases could potentially be related to speaker idiosyncrasies.

[19] We list the most-partisan internal regulator phrases in Appendix Table A3.

[20] Note that one minor difference in computing $\boldsymbol{q}_i^P$ for the regulator text is that the unit of observation occurs at the speech level, while the congressional text occurs at the speaker-session level.

where R_t and D_t denote the set of Republican and Democratic regulatory speeches i in decade t. Recall that in the definition above, $\boldsymbol{\rho}_t$ is a vector of elements, each element corresponding to a single phrase; specifically, each element in the vector corresponds to the posterior probability that an observer with a neutral prior would place on a speaker being a Republican if the speaker chose to use phrase j. With this Congress-based regulator partisanship, whether a given phrase is considered Republican or Democratic is based on congressional speech (rather than the speech of the regulators). Hence, this measure captures the extent that financial regulators sound like congressional politicians in their own party.

To gain better intuition about this measure of partisanship, consider the extreme case where Democrats use the same language as Republicans in both Congress and the SEC. In this case, $\boldsymbol{\rho}_t$ would be a vector of 0.5's, the dot products in (3) would both yield 0.5 because the phrase probabilities sum to one, and therefore partisanship π_t would be 0.5; that is, we expect the posterior to equal the neutral prior. By contrast, consider the opposite extreme case where Democrats use language that is entirely distinct from Republicans. In that case, $\boldsymbol{\rho}_t$ would be a vector of ones and zeros, the dot products in (3) would both be one, and therefore partisanship would be one as well; that is, we expect to know for certain the correct party affiliation of i after any single phrase is uttered.

1.3 Inference and validation

To gauge how sampling variance affects our inference from each sample, we follow GST and report subsampling-based 90% confidence intervals in all figures. Moreover, we conduct a random permutation exercise, where we randomize party affiliations 100 times and report the average. Together, these measures convey the statistical significance of the plotted series, that is, how much the partisanship estimates and confidence intervals differ from the random assignment benchmark. When there is a deviation between the estimated confidence interval and the random assignment confidence interval, we can reject the null hypothesis that financial regulators are not partisan.[21]

2. Congress-Based Regulator Partisanship

2.1 Main results

We plot the Congress-based regulator partisanship of the SEC (panel A) and Fed (panel B) in Figure 4. At the Fed, we observe four decades (the 1950s, 1960s, 1970s, and 1990s) that have statistically significant partisanship at the

[21] From Table 1, we observe that regulator text tends to increase over time. To analyze the relationship between the amount of text and partisanship, we simulate a consistent number of speeches and bigrams per speech in each decade and report the Congress-based regulator partisanship measures in Appendix Figure A3. We find that our point estimates are not affected by text volume, but the confidence intervals are affected. That is, less text is associated with larger confidence intervals.

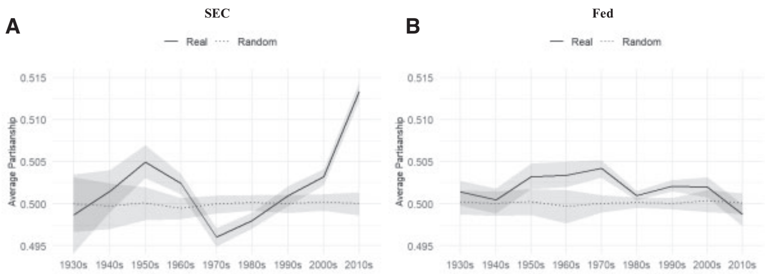

Figure 4
Congress-based regulator partisanship
We plot the average Congress-based regulator partisanship, π_t, in the SEC (panel A) and Fed (panel B) as detailed in Section 1.2. In each graph, we plot the average partisanship using actual party affiliations as "real" (the solid line) and random party affiliations as "random" (the dotted line). For the random assignments, we repeat the procedure 100 times and report the average. Each speech's party is randomly assigned using the probability that a speech is Republican in that given decade. The shaded regions around both lines represent a pointwise confidence interval consistent with Politis, Romano, and Wolf (1999). More specifically, we subsample 20% of the speeches without replacement 100 times, and for each subsample k, we compute the partisanship estimate, π_t^k. Similar to GST, let τ_k be the number of speeches in the kth subsample and τ be the number of speeches in the full sample. Also, define $(Q_t^k)_{(b)}$ to be the bth order statistic of $Q_t^k = \sqrt{\tau_k}(\pi_t^k - \frac{1}{100}\sum_{l=1}^{100}\pi_t^l)$. Then, the confidence interval on the partisanship estimate is $(\pi_t - \frac{(Q_t^k)_{(90)}}{\sqrt{\tau}}, \pi_t - \frac{(Q_t^k)_{(11)}}{\sqrt{\tau}})$.

10% level.[22] However, the economic magnitudes are small. The decade with the highest partisanship at the Fed, the 1970s, only reaches a partisanship value of 0.504. This means that an observer who understood the speaking tendencies of congressional Republicans and Democrats in the 1970s could correctly predict a random regulator's political party with 50.4% accuracy after hearing a single phrase, barely above the neutral prior of 50%. Moreover, we see that the most recent decades show no significant evidence of partisanship and even a declining trend since the 1990s.[23]

Although the Fed shows little partisanship, the SEC exhibits an increasing pattern since the 1970s with a significant increase in the 2000s and most notably in the 2010s. It is worth noting the 1950s and 1960s show slight significance as well, albeit with a much wider confidence interval and less distance from the random assignment benchmark. Still, the strongest decade (2010s) reaches 0.513 and is statistically significant well below the 10% level as the "random"

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[22] Note that the confidence interval of the "real" line does not overlap with the confidence interval of the "random" line.

[23] It is possible that our analysis of the Fed suffers from an attenuation bias because the party affiliations of the Governors are not all publicly available. The party affiliations that we use in our main analysis are based on public information searches, and when we are unable to find a Governor's party affiliation, the Governor is an independent, or there are discrepancies across the sources that we find from these searches, we use the appointing president's party as the Governor's partisan affiliation. In Appendix Figure A4, we test the different party definitions at the Fed. In panel A, we drop independents and those that are found to have multiple parties (instead of assigning the appointing president's party), and in panel B we ignore our manual searches and always use the appointing president's party. The results are similar across all definitions. In all tests, no decade at the Fed shows a partisanship measure above 0.504, and we observe a declining trend since the 1990s.

series shows the largest deviation. This means that an observer who understood the speaking tendencies of congressional Republicans and Democrats in the 2010s could correctly predict a random regulator's political party with 51.3% accuracy after hearing just a single phrase. Note that this 51.3% accuracy is almost as large as the likelihood that an observer who understood the speaking tendencies of congressional Republicans and Democrats in the 2010s could correctly predict a random *Congressperson's* political party using the same phrases (51.9%, reported in Figure 3). Thus, congressional partisanship appears to be spilling over to the SEC, although the severity of the partisanship at the SEC is slightly less than it is in Congress.

While our primary measure of partisanship is the average probability that an observer would correctly predict a speaker's party affiliation after hearing just a single phrase, it is natural to ask how this probability changes as the observer hears more speech. To examine this, we repeat a procedure from GST that allows us to compute the updated expected posterior after multiple phrases. That is, we run 1,000 Monte Carlo simulations in which each regulator speech is simulated by randomly choosing with replacement 100 times from the multinomial distribution MN(100, q_{itj}), where q_{itj} is the frequency phrase j is said during speech i in decade t. Recall from Equation (4) that ρ_{tj} is the posterior belief that an observer with a neutral prior assigns to a speaker being Republican if the speaker chooses phrase j in decade t. Note, q_{tj}^{P} is the frequency phrase j is said amongst party P in decade t at Congress. For a given regulator speech i, the expected posterior that a speaker is a Republican after the jth phrase in the sequence of speech is calculated as

$$\rho_{itj+1} = \frac{\rho_{itj} * q_{tj+1}^{R}}{\rho_{itj} * q_{tj+1}^{R} + \left(1 - \rho_{itj}\right) * q_{tj+1}^{D}}. \tag{6}$$

Note that ρ_{t0} starts at 0.5 when no phrases are heard ($j = 0$). Next, we average across the simulated speeches for each party to determine the average expected posterior of determining the true party affiliation after the jth phrase for decade t. The updating procedure in Equation (6) tells us the new posterior belief that an observer assigns to a speaker being Republican, so for Democrats, we average 1-ρ to determine the ability to recognize a Democrat correctly. Therefore, we calculate the partisanship of speech after the jth phrase in decade t as

$$\pi_{tj} = \frac{1}{2}\frac{1}{|R_t|}\sum_{i \in R_t} \rho_{itj} + \frac{1}{2}\frac{1}{|D_t|}\sum_{i \in D_t} \left(1 - \rho_{itj}\right), \tag{7}$$

where R_t and D_t denote the set of Republican and Democratic regulatory speeches i in decade t.[24]

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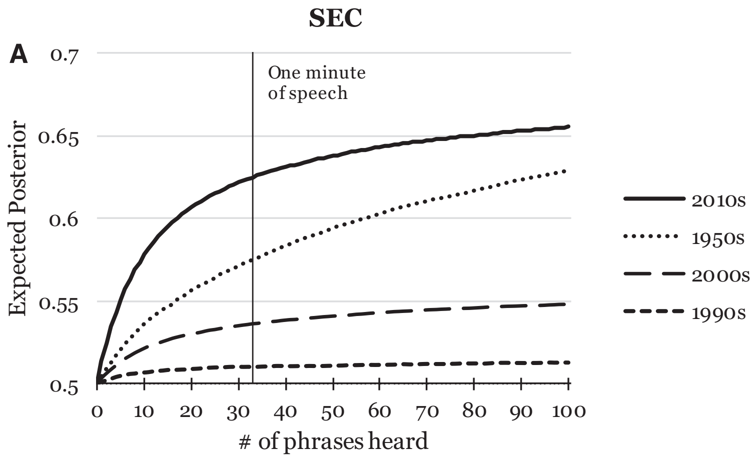
[24] This equation is similar to Equation (5), except the $\boldsymbol{q}_i^{P}$ frequencies are omitted because each frequency is essentially applied during the simulations of random multinomial draws. Since we are calculating the expected posterior up to that point of each new phase, the realized frequencies sum to one for each phrase.



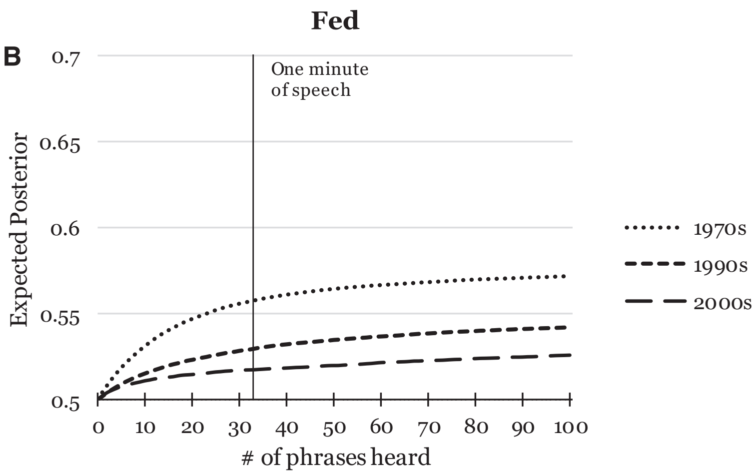


Figure 5
Expected posterior updating
We repeat a procedure from GST that allows us to compute the updated expected posterior after multiple phrases. Specifically, we run 1,000 Monte Carlo simulations in which each regulator speech is simulated by randomly choosing with replacement 100 times from the multinomial distribution MN(100, q_{itj}), where q_{itj} is the frequency phrase j is said during speech i. That is, using the partisan phrase definitions from Congress, we plot the expected posterior of assigning the true party, π_{tj}, across speeches in the SEC (panel A) and Fed (panel B) after the jth phrase as defined in Section 2.1. The vertical line in each graph represents the GST estimate of the number of preprocessed phrases (33) uttered in one minute of speech.

Figure 5 plots the expected posterior average across speeches for given decades and varying lengths of speech. As a benchmark, we also chart the GST estimation of approximately one minute of preprocessed congressional speech at 33 phrases. After this cutoff point at the SEC (panel A), the expected posterior in the 1990s only increases to around 0.510 on the speaker's true party, only slightly above the neutral prior of 0.5. In the 2000s, however, this value increases to 0.536, and in the 2010s, it climbs even further to 0.625, the highest predictability at either regulating body. This means that after approximately one minute of speech, an observer who understood the speaking tendencies of congressional Republicans and Democrats in the 2010s could correctly predict a random SEC Commissioner's political party with 62.5% accuracy. Before the 1990s, the highest predictability of speaker party affiliation at the SEC occurs in the 1950s with an expected posterior of 0.575 after approximately one minute of speech. At the Fed, we see that additional phrases help increase the expected posterior to a lesser extent. The maximum expected posterior of 0.558 occurs after approximately one minute of speech in the 1970s.

2.2 Partisan phrases

Not all phrases contribute equally to partisan predictability. Table 3 reports the top-10 most-partisan phrases for each party in each decade for the SEC (panel A) and the Fed (panel B). We also show the predicted number of times each phrase will appear per 100,000 phrases for each party in the financial regulating body of interest. Similar to Table 2, we generate this list of phrases by running the Congress-based regulatory partisanship test 7,616 (13,541) times for the SEC (Fed), each time removing the phrase of interest and then ranking them based on the reduction in partisanship when it is removed from the sample.

The most-partisan Democratic phrases in the 2010s at the SEC are "Wall Street reform" and "protect investors." More generally, the top partisan phrase lists suggest that Republican regulators favor less regulation than Democrats. For example, SEC Democrats emphasize investor and consumer protection, while SEC Republicans emphasize the regulatory burden and unintended consequences of policy intervention. However, phrase tendencies do vary across time. For example, in the 1950s, SEC Republicans are more likely than Democrats to talk about protecting investors.

Panel B for the Fed sample suggests that Fed Republicans currently talk about business owners and worry about inflation expectations, which are topics more often discussed by congressional Republicans than Democrats. Fed Democrats, by contrast, often mention aggregate demand and unemployment.

2.3 Robustness

In Figure 6, we test the robustness of the main results by aggregating the $\boldsymbol{q}_i^P$ frequencies to the decade-party level and decade-speaker level.[25] Because the partisan values for each bigram are defined entirely through Congress, the only impact from varying levels of aggregation comes from the weighting of frequencies in the regulatory body's text.

[25] Recall, the main results in Figure 4 estimate these frequencies at the speech level.

Table 3
Congress-based regulator partisan phrases

A. SEC

1930s						1940s						1950s					
Republican	#R	#D	Democrat	#R	#D	Republican	#R	#D	Democrat	#R	#D	Republican	#R	#D	Democrat	#R	#D
broker dealer	927	304	polit democraci	0	226	invest trust	897	137	secur holder	623	1401	broker dealer	669	110	invest compani	1687	3791
secur violat	181	42	reorgan proceed	40	247	profession manag	75	0	benefici owner	0	59	public investor	621	204	american gas	27	345
secur busi	383	247	trust institut	0	212	integr system	573	147	compani system	648	1479	adequ disclosur	164	47	consid independ	3	533
public util	2176	749	local region	0	141	capit structur	747	578	invest communiti	0	39	protect investor	518	298	averag investor	18	141
public account	403	49	basic econom	0	78	public util	1208	1185	financi communiti	50	147	regist secur	203	47	account profess	85	251
account principl	282	42	trade privileg	20	92	secur sold	137	49	investor need	0	39	account principl	173	78	firm account	3	235
standard busi	81	7	social econom	0	205	million share	75	0	regist secur	25	137	trade exchang	142	47	compani share	42	313
independ public	141	0	local enterpris	0	106	life insur	3177	313	averag investor	0	69	secur sold	236	16	code profession	0	16
subsidiari compani	463	14	human be	0	99	trust invest	249	10	busi commiss	0	49	civil liabil	164	78	number corpor	12	31
associ invest	81	7	secur legisl	60	212	util financ	100	39	account present	0	39	exchang act	1311	815	corpor manag	88	141
1960s						1970s						1980s					
Republican	#R	#D	Democrat	#R	#D	Republican	#R	#D	Democrat	#R	#D	Republican	#R	#D	Democrat	#R	#D
stock certif	154	24	secur industri	453	951	individu investor	335	109	corpor govern	148	376	full disclosur	342	86	independ director	63	185
transfer agent	135	18	secur regist	87	254	transfer agent	394	14	invest advis	258	425	exchang act	1103	626	corpor communiti	29	133
invest advis	549	285	hear examin	10	273	member firm	101	63	corpor account	90	560	audit standard	282	126	account profess	243	476
target compani	193	0	regulatori problem	39	97	negoti rate	48	29	account profess	366	595	settlement system	199	2	leverag buyout	78	163
act invest	154	30	concern account	10	18	hot issu	57	29	account control	44	161	ultim born	73	0	prepar financi	21	64
secur transact	385	164	fund sharehold	0	73	materi fact	159	66	american corpor	48	161	institut investor	402	150	public investor	50	91
corpor secretari	173	18	interest investor	39	73	institut custom	35	9	intern audit	15	121	trade system	267	35	financi regul	5	44
financi communiti	250	115	account corpor	10	24	compani secur	73	34	secur act	714	730	investor corpor	76	2	safeti net	18	59
turnov rate	164	121	general secur	0	61	attract investor	29	3	regul secur	97	144	compani advis	55	0	public compani	222	321
purchas share	135	36	benefici owner	19	79	equiti capit	126	29	account mechan	2	43	audit account	55	10	corpor offic	55	69
1990s						2000s						2010s					
Republican	#R	#D	Democrat	#R	#D	Republican	#R	#D	Democrat	#R	#D	Republican	#R	#D	Democrat	#R	#D
electron trade	167	49	sale practic	44	337	unintend consequ	165	16	municip secur	84	585	regulatori regim	537	160	street reform	119	310
capit rule	293	74	investor protect	374	629	capit format	234	159	investor protect	469	783	regulatori burden	109	7	protect investor	490	726
cost capit	289	124	invest advis	233	470	intern control	873	548	order flow	33	231	econom analysi	530	116	reform consum	117	299
execut compens	193	69	municip debt	0	59	tender offer	60	25	retail investor	208	298	report compani	166	98	credit default	6	118
public investor	67	59	trade account	15	20	regulatori regim	188	162	secur firm	81	268	capit format	1057	741	default swap	6	121
effect capit	26	10	disclosur document	93	287	fanni mae	44	2	access fee	50	104	busi capit	207	107	consum protect	128	307
feder regulatori	82	10	custom order	26	139	govern regul	82	30	trade strategi	18	65	complianc burden	40	3	institut investor	213	419
nonpubl inform	93	20	investor interest	85	396	regulatori burden	59	32	peopl color	0	42	regulatori respons	62	26	execut pay	47	96
regulatori scheme	211	59	fund sharehold	11	173	complianc cost	39	12	intern account	135	224	remov refer	62	25	exchang act	848	1024
econom growth	237	10	investor confid	156	322	investor get	64	14	materi inform	77	240	capit requir	183	56	relat materi	17	33

(*Continued*)

Table 3
(Continued)

B. Fed

1930s						1940s						1950s					
Republican	#R	#D	Democrat	#R	#D	Republican	#R	#D	Democrat	#R	#D	Republican	#R	#D	Democrat	#R	#D
nation debt	138	8	help achiev	0	48	inflationari forc	230	81	individu farm	0	229	inflat inevit	108	30	restraint program	9	431
secur corpor	46	0	use credit	92	518	econom world	10	4	relat currenc	5	11	monetari unit	76	7	supervisori agenc	94	241
govern busi	28	16	general credit	18	438	shortterm rate	337	63	improv program	10	281	increas product	547	106	discount rate	229	613
entir economi	46	0	deposit liabil	74	159	capit valu	77	4	credit problem	36	85	farm product	229	62	credit polici	256	485
privat credit	267	32	result effort	0	56	increas reserv	490	148	rest economi	10	100	farm oper	238	2	merger consolid	27	241
privat enterpris	396	40	technic skill	0	16	asset held	56	7	stabil fund	15	48	financi manag	58	2	compani legisl	27	79
balanc budget	470	8	repres feder	46	191	budgetari surplus	220	15	rise incom	5	37	creep inflat	121	81	credit control	45	384
budgetari deficit	147	0	borrow general	0	56	balanc budget	174	30	war product	128	255	sustain growth	135	44	banker associ	193	224
privat expenditur	64	0	advanc member	46	271	shortterm govern	215	92	year labor	0	11	secur regist	36	30	treasuri feder	31	71
rate spend	46	0	increas deposit	92	104	fiscal monetari	148	26	increas incom	66	155	govern spend	85	17	general credit	63	229

1960s						1970s						1980s					
Republican	#R	#D	Democrat	#R	#D	Republican	#R	#D	Democrat	#R	#D	Republican	#R	#D	Democrat	#R	#D
farm lend	125	8	time deposit	441	753	central banker	70	25	credit card	61	825	gold standard	129	21	monetari credit	15	144
million check	19	7	supervisori agenc	67	130	rate inflat	356	131	demand deposit	207	351	credit card	657	505	state usuri	3	38
farm debt	115	4	gradual rise	0	4	econom expans	223	77	deposit rate	19	104	trade compani	393	42	high interest	103	244
borrow lender	134	13	demand deposit	288	403	wage rate	96	19	central citi	5	67	fund rate	218	53	specul activ	3	25
farm product	220	7	merger act	0	95	wage increas	160	29	discount rate	65	247	export trade	276	47	inflationari forc	8	48
get back	29	8	discount rate	201	381	busi cycl	107	40	thrift industri	7	34	secreci act	62	0	demand deposit	51	241
increas product	412	31	thrift institut	0	125	result inflat	39	5	save loan	123	248	fix exchang	44	10	time inflationari	0	16
assum respons	29	8	conveni need	0	42	monetari expans	100	37	electron transfer	20	76	openmarket oper	17	0	fight inflat	29	97
farm mortgag	105	2	foreign credit	0	114	busi firm	211	52	loan associ	108	187	privat sector	225	114	central banker	30	48
econom cycl	38	7	truth lend	0	93	consum leas	50	6	capit outflow	21	92	intern monetari	139	62	credit restraint	12	52

1990s						2000s						2010s					
Republican	#R	#D	Democrat	#R	#D	Republican	#R	#D	Democrat	#R	#D	Republican	#R	#D	Democrat	#R	#D
central plan	119	0	fund rate	84	407	inflat expect	463	114	predatori lend	20	227	refer rate	68	0	aggreg demand	50	188
intern control	183	49	insur compani	65	168	natur gas	150	32	fiscal polici	87	261	communiti banker	258	80	feder fund	626	1303
econom growth	419	128	unemploy rate	124	283	intern control	291	77	aggreg demand	123	320	busi owner	222	25	asset purchas	306	517
govern regul	67	8	merger acquisit	26	156	econom review	89	36	capit ratio	47	179	debt manag	24	3	fire sale	27	191
currenc circul	13	0	credit standard	36	76	crude oil	119	20	nation save	75	290	household busi	251	102	mortgag servic	32	118
rate return	130	51	safeti net	467	502	econom growth	409	262	function regul	22	85	feder debt	74	17	street reform	46	101
deposit insur	444	436	cra rate	17	64	monetari econom	71	22	trade deficit	20	128	regulatori environ	38	8	asset manag	18	77
deriv transact	33	7	acceler inflat	7	36	econom activ	459	179	infrastructur invest	3	34	central banker	79	57	full employ	108	208
real asset	23	0	full employ	3	147	fanni freddi	57	5	social secur	97	485	econom outlook	322	263	larg institut	32	91
increas capit	55	13	credit need	58	135	cash flow	100	32	us last	65	240	financi futur	21	3	insur compani	20	124

We report the 10 most-partisan Republican and Democratic phrases by decade using the Congress-based regulator partisanship measure as detailed in Section 1.2 for the SEC (panel A) and the Fed (panel B). Similar to GST, we also report the predicted number of times each phrase is said per 100,000 phrases spoken by each party. To generate this list of phrases, we run the Congress-based regulator partisanship test 7,616 (13,541) times for the SEC (Fed). Each time we remove the phrase of interest to determine its influence on the overall partisanship measure. The phrases are then ranked based on the reduction in partisanship when removing it from the sample, and they are assigned a party based on the relative frequency in each party.

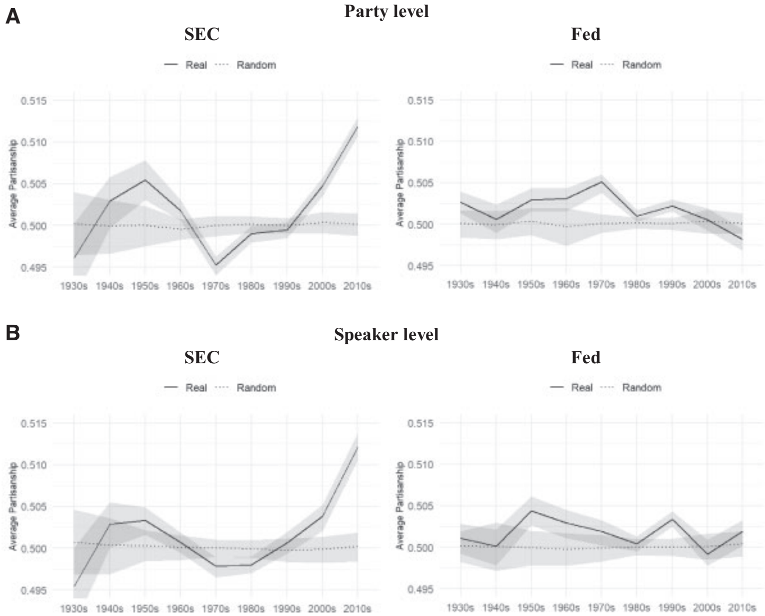


Figure 6
Robustness
We plot the same tests as Figure 4, the average Congress-based regulator partisanship, π_t, as detailed in Section 1.2 with varying aggregation levels for the q_i^P frequencies. Recall that the main results use the speech level frequencies. In panel A (panel B) we report the average partisanship when the q_i^P frequencies are aggregated to the decade-party (decade-speaker) level. In each graph, we plot the average partisanship using actual party affiliations as "real" (the solid line) and random party affiliations as "random" (the dotted line). For the random assignments, we repeat the procedure 100 times and report the average. Each speech's party is randomly assigned using the probability that a speech is Republican in that given decade. The shaded regions around both lines represent a pointwise confidence interval consistent with Politis, Romano, and Wolf (1999). More specifically, we subsample 20% of the speeches without replacement 100 times, and for each subsample k,we compute the partisanship estimate, π_t^k. Similar to GST, let τ_k be the number of speeches in the kth subsample and τ be the number of speeches in the full sample. Also, define $(Q_t^k)_{(b)}$ to be the bth order statistic of $Q_t^k = \sqrt{\tau_k}(\pi_t^k - \frac{1}{100}\sum_{l=1}^{100}\pi_t^l)$. Then, the confidence interval on the partisanship estimate is $(\pi_t - \frac{(Q_t^k)_{(90)}}{\sqrt{\tau}}, \pi_t - \frac{(Q_t^k)_{(11)}}{\sqrt{\tau}})$.

In panel A, we see a similar pattern to the main results when aggregating at the decade-party level. However, the decade-speaker aggregation in panel B has some important differences. Most notably, partisanship at the SEC in the 1950s and 1960s is no longer statistically significantly at the 10% level as the point estimates are reduced and the confidence intervals overlap with the "random" confidence intervals. Similarly, at the Fed, partisanship in the 1960s and 1970s is no longer statistically significant either. In fact, the only decades with statistical significance in all robustness tests at the SEC (Fed) are the 2000s and 2010s (1990s). Moreover, across all robustness specifications, the decade with the highest level of partisanship across both regulating bodies is the 2010s at the SEC, which never drops below 0.512.

2.4 Partisanship decomposition

In this section, we decompose the average partisanship estimates from the previous section to gain a better understanding of what drives the changes in partisanship that we observe over time. Recall that we apply partisan definitions from one sample to the speech frequencies of another sample. In other words, one sample is used to define partisan phrases, and another is the test sample. Therefore, it is possible that changes in average partisanship across time could be driven by changes in congressional speech, regulator speech, or both.

Let $\tilde{x}_t = x_t - \tilde{x}$ be the deviation of a variable, x in decade t from its average across all decades. We decompose the elements of our partisanship measure, $\boldsymbol{q}_t^P$ and $\boldsymbol{\rho}_t$, in a similar manner. We detail the steps of the decomposition in Internet Appendix B, After applying the decomposed terms to Equation (5) and rearranging, we get the following components of Congress-based regulator partisanship:

$$\pi_t = \pi_0 + \pi_t^{\rho} + \pi_t^{q} + \pi_t^{\rho q}, \tag{8}$$

where

$$\pi_0 = \frac{1}{2}\left[\overline{\boldsymbol{q}}^R \cdot \overline{\boldsymbol{\rho}} + \overline{\boldsymbol{q}}^D \cdot (1 - \overline{\boldsymbol{\rho}})\right], \tag{8a}$$

$$\pi_t^{\rho} = \frac{1}{2}\left[\overline{\boldsymbol{q}}^R \cdot \tilde{\boldsymbol{\rho}}_t + \overline{\boldsymbol{q}}^D \cdot (-\tilde{\boldsymbol{\rho}}_t)\right], \tag{8b}$$

$$\pi_t^{q} = \frac{1}{2}\left[\tilde{\boldsymbol{q}}_t^R \cdot \overline{\boldsymbol{\rho}} + \tilde{\boldsymbol{q}}_t^D \cdot (-\overline{\boldsymbol{\rho}})\right], \tag{8c}$$

$$\pi_t^{\rho q} = \frac{1}{2}\left[\tilde{\boldsymbol{q}}_t^R \cdot \tilde{\boldsymbol{\rho}}_t + \tilde{\boldsymbol{q}}_t^D \cdot (1 - \tilde{\boldsymbol{\rho}}_t)\right]. \tag{8d}$$

The first component in Equation (8), detailed in line (8a) as π_0, is simply a constant term computed using the average ρ value for each phrase across decades in Congress and the average q frequencies for each party across decades in the regulator's text. In practice, we find that the value of π_0 is very close to 0.5 in both bodies of text. Thus, the remaining terms drive the deviations from the neutral prior of 0.5. The second term, detailed in line (8b) as π_t^{ρ}, is the component of partisanship that varies across time due to variation in the congressional use of terms that are historically partisan among regulators. The third term, detailed in line (8c) as π_t^{q}, varies across time due to changes in regulators' use of terms that are historically partisan in Congress. Finally, the fourth term, detailed in line (8d) as $\pi_t^{\rho q}$, varies across time due to the use of terms that are uniquely partisan in the given decade.

We report the components of the decomposition for the SEC (panel A) and the Fed (panel B) in Figure 7. For ease of interpretation, the constant term

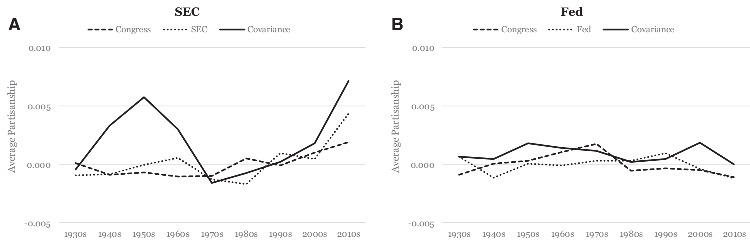


Figure 7
Partisanship decomposition
We plot the components of average partisanship at the SEC (panel A) and Fed (panel B) as detailed in Equation (8) and Section 2.4. We omit the first component in Equation (8), detailed in line (8a) as π_0, because it is simply a constant term. We find that the value of π_0 is very close to 0.5 in both bodies of text. The remaining three components π_t^ρ, π_t^q, and $\pi_t^{\rho q}$ are denoted as Congress, SEC/Fed, and Covariance, respectively. The "Congress" line represents the component of partisanship that varies across time due to variation only due to changes in congressional use of terms that are historically partisan among regulators. The "SEC/Fed" line represents the partisanship component that varies only due to changes in regulators' use of terms that are historically partisan in Congress. Lastly, the "Covariance" line represents the component of partisanship that varies across time due to both bodies of speech.

is omitted because it is the same in all decades and very close to 0.5. The remaining components of π_t^ρ, π_t^q, and $\pi_t^{\rho q}$ are denoted as Congress, SEC/Fed, and Covariance, respectively. In most decades, the average partisanship is predominately driven by the covariance term, $\pi_t^{\rho q}$. Thus, most of the time partisanship in a given decade is driven by unique phrases in that decade that Congressional Republicans and Democrats speak disproportionately which are also spoken disproportionately by party-matched regulators. This is consistent with language, topics, and technology changing over the decades so that partisan speech by those in Congress and financial regulators would surround new phrases each decade. For example, "climate change" and "credit default swap," among other phrases, are partisan according to Table 3 but could only occur in later decades as CDS were first created in the 1990s and the first Congressional hearing on climate change occurred in 1988.

However, at the SEC, we see that all three components are responsible for the recent increase in partisanship in the 2000s and 2010s. Specifically, in the 2010s at the SEC, we observe that the increase in Congress-based regulator partisanship is strong among all three components.

Looking back at the list of the most-partisan phrases in Table 3, we can determine how specific phrases influence these components. For instance, "regulatory burden" and "compliance burden" ("consumer protection" and "executive pay") are historically Republican (Democratic) phrases in Congress that Republican (Democratic) Commissioners use more frequently in the 2010s. Conversely, "capital requirements" and "economic analysis," among other phrases, are historically Republican phrases in the SEC that congressional Republicans use more frequently in the 2010s. Finally, some phrases are uniquely partisan in the 2010s at both Congress and the SEC, such as the higher

Table 4
Commissioner turnover and partisanship trends at the SEC

	All years		1990 - 2019	
DV: π_t	(1)	(2)	(3)	(4)
Year	0.0002***	0.0003	0.0009***	−0.0003
	(7.67)	(0.87)	(9.07)	(−0.80)
Speaker FE	No	Yes	No	Yes
Observations	3,103	3,099	1,955	1,955
R-squared	0.017	0.297	0.035	0.275

We examine the effects of SEC Commissioner turnover on the time trend in partisanship at the SEC. The sample consists of speeches given by SEC Commissioners. In columns 1 and 2, the sample consists of every speech given by an SEC Commissioner during the entire time period (1930–2019). In columns 3 and 4, the sample consists of speeches given between 1990 and 2019. The dependent variable is the value of Congress-based regulator partisanship for each speech. From Equation (5), this speech-level partisanship measure is $\boldsymbol{q}_i \cdot \boldsymbol{\rho}_t$ for each speech, i, when spoken by a Republican and $\boldsymbol{q}_i \cdot (1-\boldsymbol{\rho}_t)$ for each speech, i, when spoken by a Democrat. Recall that $\boldsymbol{q}_i$ is a vector of frequencies for each bigram spoken in the speech in which the sum of all frequencies equals one. Additionally, $\boldsymbol{\rho}_t$ is a vector of elements, each corresponding to the posterior probability that an observer with a neutral prior would place on a speaker being a Republican if the speaker chose to use the given phrase, defined using the congressional text of the given decade. The independent variable of interest is the year of the speech. In columns 2 and 4, we include Commissioner fixed effects. Standard errors are heteroscedasticity robust. t-statistics are reported in parentheses. $^*p<.1$; $^{**}p<.05$; $^{***}p<.01$.

frequency of Democrats saying "institutional investor" and "credit default swap." Jointly, these components show that the recent growth in Congress-based regulator partisanship at the SEC is driven by an increase in phrases historically partisan in Congress, historically partisan in the SEC, and recently partisan at both bodies simultaneously.

2.5 Where did the rise in SEC partisanship come from?

Partisanship can rise in a regulatory body for two reasons. On the one hand, there could be a *within-person* effect, whereby a regulatory body becomes more partisan because the typical person becomes more partisan over time while serving as a regulator. On the other hand, the effect could be generated *across-person*, whereby less-partisan regulators are replaced by more-partisan ones.

To examine which of the mechanisms described above is behind the rise in partisanship at the SEC documented in Figures 4–6, we conduct regressions with and without Commissioner fixed effects, and report the results in Table 4. The sample consists of all speeches by SEC Commissioners during the entire sample period (columns 1 and 2) and the years 1990–2019, when the SEC exhibited a dramatic rise in partisanship (columns 3 and 4). The dependent variable is the Congress-based regulator partisanship of each speech.[26] In column 1, the only independent variable is the year that the speech was given.

[26] From Equation (5), this speech-level partisanship measure is $\boldsymbol{q}_i \cdot \boldsymbol{\rho}_t$ for each speech, i, when spoken by a Republican and $\boldsymbol{q}_i \cdot (1-\boldsymbol{\rho}_t)$ for each speech, i, when spoken by a Democrat. Recall that $\boldsymbol{q}_i$ is a vector of frequencies for each bigram spoken in the speech in which the sum of all frequencies equals one. Additionally, $\boldsymbol{\rho}_t$ is a vector of elements, each corresponding to the posterior probability that an observer with a neutral prior would place on a speaker being a Republican if the speaker chose to use the given phrase, defined using the congressional text of the given decade.

We see that the time trend is positive ($\beta=0.0002$) and statistically significant (t-stat$=7.67$). In column 2, we control for differences in Commissioners' partisanship by including Commissioner fixed effects. When those controls are included, the coefficient is no longer statistically significant (t-stat$=0.87$).

In columns 3 and 4, we consider the sample of speeches given between 1990 and 2019, when the increase in partisanship at the SEC is particularly pronounced (Figures 4–6). In column 3, we see that the coefficient of year is positive ($\beta=0.0009$) and statistically significant (t-stat$=9.07$), consistent with the rise in partisanship over the most recent three decades at the SEC. However, when we include Commissioner fixed effects, the coefficient of year is actually negative ($\beta=-0.0003$), although the estimate is not statistically significantly different from zero (t-stat$=-0.80$). Moreover, the F-test for the Commissioner fixed effects all equaling zero is large and highly significant ($F(28, 1925)=35.71$, $p<.0001$), which is consistent with the notion of substantial heterogeneity in Commissioners' partisanship. Because the significant time trend in partisanship completely disappears when controlling for Commissioner fixed effects, we conclude that the SEC has become more partisan because less-partisan Commissioners are being replaced by more-partisan ones and not because Commissioners are becoming more partisan as they sit on the Commission. These findings suggest that the ultimate source of rising partisanship at the SEC is the nomination/confirmation process in the executive and legislative branches whereby more partisan Commissioners are being selected and approved over time.[27]

Having established the substantial heterogeneity in Commissioners' partisanship and that the increase in partisanship at the SEC is driven by less-partisan Commissioners being replaced by more-partisan ones, we next examine whether Commissioners' partisanship is correlated with observable characteristics. This analysis mirrors work in corporate finance which investigates whether certain manager characteristics are related to their style of management (Bertrand and Schoar 2003; Fee et al. 2013; Mullins and Schoar 2016; Schoar and Zuo 2016, 2017; Janke et al. 2019; Fenizia 2022; Limodio 2021).

Specifically, we estimate each Commissioner's partisanship by conducting the regression reported in column 2 of Table 4, and we use each Commissioner's fixed effect as our measure of the Commissioner's partisanship. We

[27] While it may seem worthwhile to analyze data on the Congressional confirmation votes of SEC Commissioners and Fed Governors, unfortunately, most of these votes are conducted via "voice votes" where there is no official tally of the yeas and nays. In these votes, members supporting a nomination simply say "yea," while those who oppose say "nay." (For more information on voice votes, see https://www.senate.gov/about/powers-procedures/voting.htm.) If there is doubt about which side has the most votes, a "division" can be requested whereby the votes are officially tallied. While it might seem reasonable to conjecture that the regulators who are confirmed via a voice vote are confirmed nearly unanimously, this need not be the case. For example, suppose one party has a strong majority in Congress, and everyone knows that the regulator has unanimous support among the majority party's congresspeople. In this scenario, there would be no reason for members of the minority party to request a division even if the minority party was unanimously opposed to the regulator's confirmation.

Table 5
Commissioner partisanship and observable characteristics

DV: Commissioner's estimated partisanship (fixed effect from Table 4, column 2)	(1)	(2)	(3)	(4)	(5)	(6)
Male	0.0047					0.0048
	(0.87)					(0.96)
Political background		−0.0026				−0.0022
		(−0.67)				(−0.56)
Lawyer			0.0032			0.0015
			(0.76)			(0.36)
MBA				−0.0016		−0.0012
				(−0.23)		(−0.16)
Graduate degree in economics					−0.0109*	−0.0097*
					(−1.92)	(−1.68)
Observations	90	90	90	90	90	90
R-squared	0.009	0.006	0.007	0.001	0.032	0.046

We examine the relationship between SEC Commissioners' partisanship and observable characteristics of the Commissioners. The sample consists of the 90 SEC Commissioners who gave speeches between 1930 and 2019. The dependent variable is the estimated partisanship of the Commissioner, as measured by the Commissioner's estimated fixed effect from the regression in column 2 of Table 4. *Male* is an indicator for the Commissioner's gender; *Political background* is an indicator for the Commissioner having worked for a congressperson or president prior to being appointed to the SEC; *Lawyer* is an indicator for the Commissioner having a background in law; and *MBA* (*Graduate degree in economics*) is an indicator for the Commissioner having an MBA (a graduate degree in economics). Standard errors are heteroscedasticity robust. t-statistics are reported in parentheses. *$p<.1$; **$p<.05$; ***$p<.01$.

then regress Commissioners' partisanship onto their gender, an indicator for whether the Commissioner had prior experience working for the president or a member of Congress, and indicators for whether they earned graduate degrees in law (JD), business (MBA), or economics (masters or PhD) prior to joining the Commission. We report the results of these regressions in Table 5.

In columns 1–5, we regress partisanship onto each of the indicators separately, and in column 6, we regress partisanship onto all six indicators simultaneously. We find no significant evidence that partisanship is correlated with gender, political background, law degrees, or MBAs, and weak evidence that Commissioners who have graduate degrees in economics are less partisan than others. Overall, these findings suggest that while there is substantial heterogeneity in Commissioners' partisanship, and more-partisan Commissioners have recently been replacing less-partisan ones, Commissioners' partisanship is mostly uncorrelated with observable characteristics, such as the Commissioners' gender, educational background, and work experience.

3. Implications of Partisanship

3.1 Rulemaking language

Having documented that SEC Commissioners' speech has become significantly more partisan in recent decades, we now examine whether partisanship affects the text that ultimately gets written by SEC Commissioners and Fed

Governors in the Federal Register. We hypothesize that the majority party in each regulating body has significant power over the rule making activity of the regulating body and that the influence of the majority party on the language in the agency's published text should increase when partisanship is high. In other words, we ask two questions: (1) Does the text that gets written by regulators sound like Democratic (Republican) members of Congress when Democrats (Republicans) comprise a majority of the regulatory body, and (2) Is the effect increasing in the partisanship of the regulators' speeches?

To answer these questions, we collect the SEC and Fed text from the daily Federal Register (hereafter referred to as "Register text"). The Register text at the SEC and Fed include notices, proposed rules, and finalized rules/regulations. The Register text is available for most of our sample period dating back to 1938. We perform a similar cleaning procedure to the Register text as with the speeches. Once the Register text is in digital text format, we remove noise (stopwords, punctuation, numbers, etc.), stem and group the text into two-word phrases or bigrams, limit the analysis to those phrases that occur at least 100 times across the entire sample, and intersect the resultant phrases with the phrases that occur in the congressional text.[28] Recall that when we analyzed the partisanship of regulators' speeches, we assigned each speech to a political party based on the speaker's party affiliation. When analyzing the Register text, we assign a given day of text to the political party that comprises a majority of the agency on the given day. If a day has no majority (because of an even split of Republican and Democrat Commissioners or Governors), then that day is omitted.[29] The final SEC (Fed) Register text contains 33,208 (8,317) unique phrases that occur a total of 10,483,646 (2,837,744) times across 13,702 (10,815) days.

We calculate Congress-based Register partisanship, further denoted as *RegisterPartisanship*, by using Equation (5) described in Section 1.2. However, in this setting, i is a given day of Register text (instead of a given speech), and the party affiliation of the Register text is the majority party represented in that regulating body on that day. Thus, when measuring *RegisterPartisanship*, whether a given phrase is considered Republican or Democratic is based on congressional speech, and *RegisterPartisanship* captures the extent that the Register text sounds like congressional politicians in a particular party (the

[28] The Register text is much larger than the speeches, so we use the total count threshold of 100 from GST to avoid unnecessary computational challenges. The results presented in this section are nearly identical if we use the speech count threshold of 30 occurrences.

[29] At the SEC (Fed), there are 17,833 (11,105) days of Register text before dropping days without a majority party of Commissioners (Governors), and thus, 4,131 (290) or approximately 23.2% (2.6%) are days without a majority party. At the SEC, the even split is caused by an independent Commissioner for 2,474 of the 4,131 no-majority days. We perform several robustness tests for these omitted days in Appendix Table A4. We find that the results shown in this section are similar statistically and economically when including the days without a majority party of regulators and assigning a party to the Register text on these days using (1) the current president's political party, (2) the party indicated by the speech of independent regulators, or (3) a combination of the two.

Table 6
Partisanship and the register text of regulators

	SEC			Fed		
DV: *RegisterPartisanship*$_t$	(1)	(2)	(3)	(4)	(5)	(6)
π_t	0.2002***	0.1222***	0.1054**	0.2280***	0.1951***	0.1984***
	(4.96)	(2.96)	(2.58)	(3.15)	(2.73)	(2.69)
π_{t-1}		0.1042**	0.0586		0.2998***	0.2935***
		(2.33)	(1.25)		(4.02)	(3.75)
π_{t-2}			0.0382			0.1559**
			(0.81)			(2.01)
Observations	596	484	401	826	796	768
R-squared	0.053	0.047	0.040	0.016	0.046	0.062

We analyze the relationship between partisanship and the text published in the Register of the SEC/Fed. The dependent variable is *RegisterPartisanship*, and the independent variables are one contemporaneous and up to two lagged measures of average Congress-based regulator partisanship, π_t, where t indexes months. We collect the Register text from the Federal Register and define *RegisterPartisanship* similar to Congress-based regulator partisanship. That is, we use Equation (5) from Section 1.2, except that i is a given day of Register text (instead of a given speech), and the party affiliation of the Register text is the majority party represented in that regulating body on that day. If a day has no party majority (because of an even split of Commissioners or Governors), then that day is omitted when calculating *RegisterPartisanship*. From Equation (5), the daily value of *RegisterPartisanship* is $\boldsymbol{q}_i \cdot \boldsymbol{\rho}_t$ for each day, i, when the majority party is Republican and $\boldsymbol{q}_i \cdot (1-\boldsymbol{\rho}_t)$ for each day, i, when the majority party is Democrat. Recall that $\boldsymbol{q}_i$ is a vector of frequencies for each bigram that appears in the day of Register text in which the sum of all frequencies equals one. Additionally, $\boldsymbol{\rho}_t$ is a vector of elements, each corresponding to the posterior probability that an observer with a neutral prior would place on the text being a Republican if the speaker chose to use the given phrase, defined using the congressional text of the given decade. To calculate the monthly measure of *RegisterPartisanship*, we average the daily values within the given month. Similarly, the monthly measures of Congress-based regulator partisanship are calculated as the average value across speeches within the given month. Standard errors are heteroscedasticity robust. t-statistics are reported in parentheses. $*p<.1$; $**p<.05$; $***p<.01$.

majority party at the regulating body). A measure of one (zero) indicates that the Register text uses only phrases from the majority (minority) party, while 0.5 indicates an equal balance or no partisanship.

We first test for evidence of partisanship in the text written by the regulators; that is, we test whether *RegisterPartisanship* exceeds 0.5. From Equation (5), we calculate the daily value of *RegisterPartisanship* as $\boldsymbol{q}_i \cdot \boldsymbol{\rho}_t$ for each day, i, when the majority party is Republican and $\boldsymbol{q}_i \cdot (1-\boldsymbol{\rho}_t)$ for each day, i, when the majority party is Democrat. Recall that $\boldsymbol{q}_i$ is a vector of frequencies for each bigram that appears in the day of Register text in which the sum of all frequencies equals one. Additionally, $\boldsymbol{\rho}_t$ is a vector of elements, each corresponding to the posterior probability that an observer with a neutral prior would place on the text being a Republican if the speaker chose to use the given phrase, defined using the congressional text of the given decade. We find that the average daily value of *RegisterPartisanship* is 0.5067 (0.5019) at the SEC (Fed), and that the difference from the null of 0.5 is statistically significant (t-stat$=$32.68 and t-stat$=$5.83, respectively), confirming that the text written by each regulatory body sound like the members of Congress who belong to the political party that controls the regulatory body.

Next, we examine whether *RegisterPartisanship* is increasing in the partisanship of the regulators' speeches. In Table 6, the dependent variable is *RegisterPartisanship,* and the independent variables are one contemporaneous and up to two lagged measures of average Congress-based regulator partisanship, π_t, where t indexes months. To calculate the monthly measure of *RegisterPartisanship,* we average the daily values within the given month. Similarly, the monthly measures of Congress-based regulator partisanship are calculated as the average across speeches within the given month. The speech-level measure of Congress-based regulator partisanship is calculated the same as the daily measure of *RegisterPartisanship,* except that i is each regulator speech instead of a day of Register text and the party used is the speaker's party affiliation instead of the majority party. That is, using Equation (5), the speech-level partisanship measure is $\boldsymbol{q}_i \cdot \boldsymbol{\rho}_t$ for each speech, i, when spoken by a Republican and $\boldsymbol{q}_i \cdot (1-\boldsymbol{\rho}_t)$ for each speech, i, when spoken by a Democrat.

At both the SEC and the Fed, we observe a positive contemporaneous relationship between regulator partisanship and register partisanship. No matter the number of lags included, the relationship at the SEC (columns 1–3) remains statistically significant with the contemporaneous coefficient ranging from 0.1054 to 0.2002 (t-statistics range from 2.58 to 4.96). Regarding economic magnitudes, our results suggest that roughly 10.54%–20.02% of the partisanship reflected in regulator speech is likely to spill over into the language of their Register text during the same month. Although the lagged coefficients are also positive, their magnitudes are significantly lower than the contemporaneous coefficient at the SEC. At the Fed (columns 4–6), we find similar contemporaneous coefficients (ranging from 0.1951 to 0.2280) and statistical significance (t-statistics range from 2.69 to 3.15). However, we also observe that the lagged coefficients at the Fed are similar in economic and statistical significance to the contemporaneous coefficient, suggesting a more persistent relationship.[30]

Because the party affiliation of the Register text for a given day is defined as the majority party represented in that regulating body, the positive relation we document between Register partisanship and regulator partisanship means that the Register text of the regulators are more likely to sound like the majority party when partisanship is higher. In other words, not only do regulator speeches sound like the politicians in the regulator's party, but also this partisan language is more likely to appear in the Federal Register.

Having documented the positive relationship between Register partisanship and speech partisanship, we next analyze the granularity of the Register text categories that are available. The Register text includes notices, proposed

30 Appendix Table A5 tests the robustness of the aggregation level used in Table 6. While more frequent levels of aggregation, such as monthly, create a larger sample, each observation is also more likely to be measured with noise since they are based on fewer days (for *RegisterPartisanship*) or speeches (for Congress-based regulator partisanship). Additionally, when analyzing the relationship between *RegisterPartisanship* and Congress-based regulator partisanship, lower levels of aggregation may cause missing observations when Register text and speeches do not occur in the same time period. For these reasons, we also report the results for Table 6 using quarterly and yearly aggregation in Appendix Table A5. Across all levels of aggregation, we find a strong, positive contemporaneous relationship between *RegisterPartisanship* and Congress-based regulator partisanship, which indicates that the text written by regulators are more likely to sound like the majority party when partisanship is higher.

rules, and finalized rules, and we can recover these classifications via XML tags that began on January 3, 1995.[31] In Table 7, we analyze the relationship between Congress-based regulator partisanship and the *RegisterPartisanship* of these categories. Specifically, we run a linear regression on the unbalanced panel in which the unit of observation is month-year-category. The dependent variable is monthly *RegisterPartisanship*. The independent variables are monthly Congress-based regulator partisanship (π_t), an indicator for proposed or finalized rules (written as *Rule*), an indicator for finalized rules (written as *Final rule*), and/or interactions for each of the rule indicators with π_t.

In Table 7 column 1, we verify the relationship documented in Table 6 for this subsample period (post-1995) by including only Congress-based regulator partisanship, π_t, as the independent variable. We observe the same positive relationship from Table 6 with similar magnitudes at both regulating bodies, indicating that the Register text overall is more likely to sound like the majority party when partisanship is higher, even for this subsample period. In column 2, we include only *Rule* as the independent variable. We observe a strong positive coefficient at both regulating bodies. This coefficient indicates that proposed rules and finalized rules together have higher partisan values than notices (the omitted category) at the SEC and Fed, and this difference is statistically significant at the 1% level. In column 3, we include *Rule* and *Final rule* as independent variables. Thus, the coefficient for *Rule* becomes the partisanship difference between notices and proposed rules while the coefficient for *Final rule* is the difference between final rules and proposed rules. At the SEC, we observe that the text of proposed rules is significantly more partisan than notices, but the difference between proposed and finalized rules is insignificant. However, at the Fed, the difference between notices and proposed rules is insignificant, while the text of final rules is significantly higher than proposed rules. In columns 4 and 5, we add Congress-based regulator partisanship to the specifications from columns 2 and 3, respectively. We see that even after controlling for the regulator partisanship of the given month, the same relationships hold regarding the relative partisanship of the Register text categories. In columns 6 and 7, we add month-year fixed effects to the specifications from columns 2 and 3, respectively. Once again, we observe that even after controlling for month-year fixed effects, the same relationships hold regarding the relative partisanship of the Register text categories.

In columns 8–11 of Table 7, we test the influence of regulator partisanship on the relative value of partisanship across Register text categories by analyzing interactions of Congress-based regulator partisanship, π_t, with each of the rules category indicators. Columns 10 and 11 include month-year fixed effects. Across all specifications at both regulating bodies, these interactions are

31 These categories existed for some periods before 1995, when the Federal Register is available in PDF only, but because that categorization occurs in the table of contents and not near the actual text, there is substantial noise in the classification of categories via OCR.

Table 7
Partisanship and the register text of regulators by category

A. SEC

DV: *RegisterPartisanship*$_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
π_t	0.0919**			0.0908**	0.0908**			−0.0019	−0.0019		
	(2.36)			(2.32)	(2.32)			(−0.13)	(−0.13)		
rule		0.0039***	0.0042***	0.0039***	0.0042***	0.0040***	0.0044***	−0.0692**	−0.0533	−0.0693**	−0.0551
		(3.43)	(2.98)	(3.40)	(2.96)	(3.58)	(3.13)	(−2.23)	(−1.07)	(−2.27)	(−1.12)
final rule			−0.0006		−0.0006		−0.0008		−0.0294		−0.0253
			(−0.36)		(−0.36)		(−0.44)		(−0.56)		(−0.48)
*rule**π_t								0.1457**	0.1146	0.1462**	0.1189
								(2.36)	(1.15)	(2.41)	(1.19)
*final rule**π_t									0.0575		0.0489
									(0.55)		(0.47)
Month-Year FEs	No	No	No	No	No	Yes	Yes	No	No	Yes	Yes
Observations	453	453	453	453	453	453	453	453	453	453	453
R-squared	0.014	0.019	0.019	0.033	0.033	0.444	0.444	0.041	0.042	0.452	0.453

B. Fed

DV: *RegisterPartisanship*$_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
π_t	0.2405***			0.2416***	0.2371***			0.1762**	0.1762**		
	(3.23)			(3.23)	(3.20)			(2.24)	(2.24)		
rule		0.0057***	0.0009	0.0058***	0.0011	0.0054***	0.0023	−0.0487	−0.0316	−0.0700	−0.0607
		(3.67)	(0.42)	(3.68)	(0.49)	(3.42)	(1.08)	(−0.92)	(−0.43)	(−1.33)	(−0.84)
final rule			0.0081***		0.0079***		0.0050**		−0.0209		−0.0093
			(3.15)		(3.10)		(2.10)		(−0.24)		(−0.11)
*rule**π_t								0.1087	0.0651	0.1503	0.1258
								(1.03)	(0.44)	(1.44)	(0.88)
*final rule**π_t									0.0574		0.0283
									(0.33)		(0.16)
Month-Year FEs	No	No	No	No	No	Yes	Yes	No	No	Yes	Yes
Observations	648	648	648	648	648	648	648	648	648	648	648
R-squared	0.017	0.012	0.026	0.029	0.043	0.627	0.632	0.030	0.044	0.629	0.633

We analyze the relationship between partisanship and the categories of the text published in the Register of the SEC/Fed. The unit of observation is month-year-category. The three categories are notices, proposed rules, and finalized rules. The dependent variable is monthly *RegisterPartisanship*, which is defined similar to Congress-based regulator partisanship. That is, we use Equation (5) from Section 1.2, except that i is a given day of Register text (instead of a given speech), and the party affiliation of the Register text is the majority party represented in that regulating body on that day. If a day has no party majority, then that day is omitted when calculating *RegisterPartisanship*. To calculate the monthly measure of *RegisterPartisanship*, we average the daily values within each month. Similarly, the monthly measure of Congress-based regulator partisanship, π_t, is calculated as the average across speeches within the given month. The independent variables are π_t, an indicator for proposed or finalized rules (denoted as *Rule*), an indicator for finalized rules (denoted as *Final rule*), and/or interactions for each of the rules indicators with π_t. Columns 6, 7, 10, and 11 include month-year fixed effects. Standard errors are clustered at the month-year level. t-statistics are reported in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

positive; however, they are only statistically significant at the SEC when aggregating proposed and finalized rules together. This result indicates that the relatively higher partisanship of proposed and finalized rules is even higher when regulator speech partisanship is high. In other words, the proposed and finalized rules are disproportionately more likely to be influenced by regulator partisanship compared to notices in the Register text.

3.2 Voting activity

For rules to be passed, they must be voted on. Having established that Congress-based regulator partisanship is likely to spill over into the rules of regulators, we now examine whether partisanship is related to regulators' voting behavior. Our data on SEC Commissioner voting activity consists of the votes on the Commission's decisions, orders, rules, or similar actions between April 2006 and December 2019. This sample consists of 45,369 votes placed by 21 Commissioners for 10,200 distinct decisions, orders, rules, etc.[32] Our data on Fed Governor voting activity consist of their votes at FOMC meetings between 1936 and 2019.[33] This sample consists of 5,152 votes placed by 76 Governors in 805 FOMC meetings.

The majority of the votes in both agencies are unanimous: in the SEC, 95.8% of the votes are unanimous, and 81.0% of the Fed's FOMC votes are unanimous. A natural question is whether dissenting votes are related to partisanship. To answer this, we examine how a voter's propensity to dissent is related to the votes cast by other voters in her own party and in the opposing party. Specifically, if partisanship and dissenting votes are related, a voter's propensity to dissent should be increasing in the number of dissenting votes cast by other voters in her own party and decreasing in the number of dissenting votes cast by voters in the opposite party. We consider the sample of all votes cast by Commissioners at the SEC and Fed Governors at the FOMC but exclude the Chairs' votes for two reasons. First, the Chair has enormous influence over the items that are brought up for a vote.[34] Consistent with this idea, during our sample period, no SEC Chair ever casts a dissenting vote. Second, for most of our sample period, the SEC Chair was an independent.[35] Removing

32 *Sources*: https://www.sec.gov/foia/foia-votes.shtml (for the 2006–2015 period) and https://www.sec.gov/about/commission-votes.shtml (for the 2016–2019 period).

33 *Source*: https://www.stlouisfed.org/fomcspeak/history-fomc-dissents.

34 According to former SEC Commissioner Luis Aguilar (2015), "Matters are often voted 'by seriatim,' which means that these matters are being circulated to each Commissioner's office in turn, Commissioner-by-Commissioner, for his or her vote. The Chair typically votes last, but given that the Chair decides whether to circulate a seriatim in the first instance, it is reasonable to assume the Chair will approve it." Aguilar further writes, "It is important to understand that the Chair alone determines the Commission's agenda, as well as the content of the recommendations [that SEC Commissioners are] asked to vote on."

35 Mary Schapiro served as Chair from January 2009 through December 2012; Mary Jo White served from April 2013 through January 2017; and Jay Clayton served from May 2017 through the end of our sample period. All three of these Chairs are independents, so we cannot examine whether they are more or less likely to dissent when other Commissioners from their party or the opposite party dissent.

Table 8
Dissenting votes and partisanship

	SEC		Fed	
DV: *Dissent*	(1)	(2)	(3)	(4)
DissentOwnParty	0.4540***	0.4279***	0.1497***	0.1073***
	(14.31)	(13.07)	(5.63)	(3.65)
DissentOtherParty	−0.0055**	−0.0317***	0.0600***	0.0050
	(−2.12)	(−9.19)	(3.30)	(0.21)
Year FE	No	Yes	No	Yes
Observations	35,534	35,534	4,347	4,347
R-squared	0.153	0.169	0.055	0.087

We regress an indicator for a regulator, i, casting a dissenting vote, denoted as *Dissent*, onto *DissentOwnParty* and *DissentOtherParty*, which are indicators for another regulator in i's party and i's opposing party, respectively, casting a dissenting vote. The sample in columns 1 and 2 consists of all votes placed on decisions, orders, and rules by non-Chair SEC Commissioners, and columns 3 and 4 consist of all FOMC votes by non-Chair Fed Governors. Columns 2 and 4 contain year fixed effects. Standard errors are clustered by the rule/decision that is being voted on. t-statistics are reported in parentheses. $*p<.1$; $**p<.05$; $***p<.01$.

the Chairs reduces our SEC sample from 45,369 to 35,534 observations and our Fed sample from 5,152 to 4,347 observations.

To formally examine the relation between partisanship and dissenting votes, we use regressions. Our dependent variable is an indicator for the voter casting a dissenting vote. We have two independent variables of interest: an indicator for there being any dissents cast by members of the voter's own party, and an indicator for there being any dissents cast by members of the opposite party. In column 1 of Table 8, we consider the sample of SEC Commissioner votes. The coefficient for *DissentOwnParty* is positive and highly significant, both economically and statistically: the probability of a Commissioner dissenting is 45.4 percentage points higher (t-stat = 14.31) when another Commissioner in her party casts a dissenting vote. Conversely, the coefficient of *DissentOtherParty* indicates that a Commissioner is significantly less likely to dissent ($\beta = -55$ bps, t-stat = −2.12) when a Commissioner in the opposite party casts a dissenting vote. In column 2, we include year fixed effects and obtain qualitatively similar results.

A less parametric approach is to simply examine the composition of dissents whenever two SEC Commissioners dissent: when two Commissioners dissent, do they tend to belong to the same party, or is it common for one Republican and one Democrat to dissent together?[36] There are 93 instances in which 2 Commissioners dissent. Of these 93 instances, in only 3 instances does a Democrat dissent along with a Republican.[37] Taken together, these results strongly suggest that SEC Commissioners' voting behavior is partisan in that a Commissioner is significantly more (less) likely to dissent when a member of her (the opposite) party casts a dissenting vote.

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[36] In our sample, three or more dissents never occur. The Commission consists of five Commissioners, so if three or more were to dissent, the rule would not pass and we would not be able to observe the data point.

[37] In 27 instances, 2 Democrats dissent, and in 63 instances, 2 Republicans dissent.

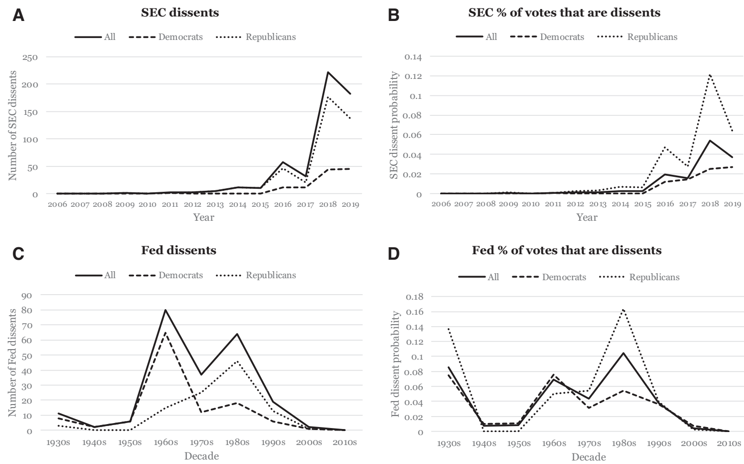

Figure 8
Dissent activity by year
We plot the number of dissenting votes at the SEC (panel A), the percentage of votes at the SEC that are dissents (panel B), the number of dissenting votes by Governors at Fed FOMC meetings (panel C), and the percentage of Governors' FOMC votes that are dissents (panel D). We report the dissenting activity for all regulators, Democratic regulators, and Republican regulators. We aggregate the dissenting activity by year in the SEC sample and by decade for the FOMC sample.

In columns 3 and 4, we repeat the regressions on the sample of the Fed's FOMC votes. As in the SEC, the probability that a Governor casts a dissenting vote rises when another Governor from her party casts a dissenting vote ($\beta =$ 15.0%, t-stat =5.63). However, in contrast to the SEC, the probability that a Fed Governor dissents also rises whenever a Governor from the opposite party casts a dissenting vote ($\beta =$6.0%, t-stat =3.30), suggesting that at the Fed, the FOMC decisions that provoke dissenting votes are controversial for nonpartisan reasons. When we include year fixed effects (column 4), the positive coefficient of *DissentOwnParty* remains statistically significant, while the coefficient of *DissentOtherParty* becomes statistically insignificant (t-stat =0.21).

After establishing that dissenting votes, especially at the SEC, are associated with partisanship, we now examine possible trends in the frequency of dissenting votes over time. Figure 8 plots the number of SEC dissents (panel A) and the percentage of SEC votes cast (panel B) that are dissents. There was just one dissent (in 2009) between 2006 and 2010. The years 2011–2019 saw a dramatic increase in the dissenting activity: the number of dissenting votes ranged from 2 to 12 per year between 2011 and 2015, and then it increased significantly further (ranging from 32 to 221 dissents per year) between 2016 and 2019. The percentage of votes that are dissents (panel B) follows a similar pattern.

In panels C and D, we report the results for dissenting votes at the Fed's FOMC meetings. The number of dissents is greatest in the 1960s and the 1980s, and the percentage of votes that are dissents (panel D) is high in these two decades as well as the 1930s.

Next, we examine possible links between a regulator's propensity to cast a dissenting vote and the partisanship of her speech, specifically, the distance between the ideology of her speech and the speech of the rest of the regulators (and/or the Chair of the agency). We form two different measures for a regulator's ideology, one based on the similarity of her speech to Congressional Democrats/Republicans, and the other based on the dictionary-based approach whereby we count the relative frequency with which she speaks about regulatory costs versus regulatory benefits.

We focus on the ideological distance between a regulator and the other regulators voting on the given issue for two reasons. First, consider the SEC, which typically has five Commissioners serving at a time. Suppose there are three extremely partisan Democrats, and two nonpartisan Republicans. In this scenario, the (nonpartisan) Republicans are more likely to dissent than the (partisan) Democrats, because the SEC would be dominated by extremely partisan Democrats who might pass rules that are exactly what partisan Democrats would want to pass. Second, for most of our SEC sample period, the Chair (who is the most powerful member of the Commission) is an independent. How closely a regulator's ideology aligns with the Chair's ideology should be related to the likelihood the regulator dissents, and it would not be possible to capture this effect if we simply focused on a regulator's partisanship. It is worth emphasizing that though our independent variable of interest is a measure of ideological distance, the ideological distance between regulators increases as a regulatory body becomes more partisan.

Our first ideological measure is based on GST's congress-based regulator partisanship measure. Formally, let a regulator, i's, *DemSimilarity* be defined as

$$DemSimilarity_i = \begin{cases} \pi_i & \text{if } i \text{ is a Democrat} \\ 1-\pi_i & \text{if } i \text{ is a Republican} \end{cases}, \tag{9}$$

where π_i is regulator i's partisanship, computed as the average partisanship across each of i's speeches. Thus, a highly partisan Democrat (Republican) would have a *DemSimilarity* score close to one (zero), whereas a Democratic (Republican) regulator who speaks like Congressional Republicans (Democrats) would have a *DemSimilarity* score close to zero (one). In other words, *DemSimilarity* simply captures how similar a regulator's speech is to Congressional Democrats' (vs. Republicans') speech.

Let i's *IdeologicalDistance* be defined as the difference between i's *DemSimilarity* and the average *DemSimilarity* of the other regulators casting votes on the given rule:

$$IdeologicalDistance_i = \left| DemSimilarity_i - \frac{1}{N-1}\sum_{j \neq i} DemSimilarity_j \right|, \quad (10)$$

where N is the number of regulators voting on the given issue. Because the Chair of the agencies has significant power over the agencies' ultimate decisions, we also define a measure for the ideological distance between a regulator and the Chair:[38]

$$IdeologicalDistanceChair_i = \left| DemSimilarity_i - DemSimilarity_{chair} \right|. \quad (11)$$

In addition to these two measures of ideological difference, we also create measures based on the dictionary-based approach.[39] Specifically, we calculate the *RelativeBenefits,* detailed in Equation (1), for each speaker. Recall that *RelativeBenefits* is the frequency at which the speaker discusses regulatory benefits relative to regulatory costs. Thus, our dictionary-based measures of ideological distance are then defined as

$$DBIdeologicalDistance_i = \left| RelativeBenefits_i - \frac{1}{N-1}\sum_{j \neq i} RelativeBenefits_j \right|, \quad (12)$$

$$DBIdeologicalDistanceChair_i = \left| RelativeBenefits_i - RelativeBenefits_{chair} \right|. \quad (13)$$

To the extent that one party generally supports regulation and the other party generally opposes it, these measures also capture partisanship of the regulators.

In column 1 of Table 9, we regress an indicator for an SEC Commissioner casting a dissenting vote onto the ideological distance between her and the other Commissioners voting on the issue. We include rule fixed effects to control for time and the issue that is being voted on. The coefficient of *IdeologicalDistance* is positive ($\beta = 0.0021$) and statistically significant (t-stat $= 2.93$), indicating that a one-standard-deviation increase in *IdeologicalDistance* is associated with a 21-bps increase in the likelihood a regulator casts a dissenting vote, which represents a 14.2% increase relative to the dependent variable's average value (1.48%).[40] In column 2, we consider the ideological distance between

[38] An alternative approach would be to ignore Congressional speech and simply use GST's methodology to directly compute the distance between a regulator's speech and the other regulators' speech. However, this approach would capture differences in the regulator's speech that may be unrelated to their partisanship. Because partisanship is the focus of our paper, we do not analyze ideological distance in that manner.

[39] See Appendix Table A2 for the list of these bigrams.

[40] We normalize each of the four independent variables presented in Table 9 so that they have a mean of zero and unit standard deviation.

Table 9
Regulators' speech and their propensity to dissent

	SEC				Fed			
DV: *Dissent*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IdeologicalDistance	0.0021***				0.0061*			
	(2.93)				(1.84)			
IdeologicalDistance Chair		0.0032***				0.0081**		
		(6.33)				(2.57)		
DBIdeologicalDistance			0.0087***				0.0059	
			(15.36)				(1.40)	
DBIdeologicalDistance Chair				0.0062***				0.0091**
				(13.54)				(2.37)
Observations	35,534	34,482	35,534	34,482	4,284	4,284	4,113	4,113
R-squared	0.387	0.387	0.390	0.389	0.271	0.272	0.267	0.268

We regress an indicator for a regulator casting a dissenting vote onto measures of the ideological difference between her and the other regulators (columns 1, 3, 5, and 7) and the Chair (columns 2, 4, 6, and 8). Columns 1, 2, 5, and 6 rely on the GST methodology to measure the extent that a regulator's speech is similar to Congressional Democrats' speech versus Congressional Republicans' speech. Columns 3, 4, 7, and 8 use the dictionary-based approach that counts the relative frequency with which regulators speak about regulatory benefits as opposed to regulatory costs. See Equations (9)–(13) for formal definitions of the independent variables. Columns 1–4 consider votes placed on decisions, orders, and rules by non-Chair SEC Commissioners, and columns 5–8 consist of all FOMC votes by non-Chair Fed Governors. The number of observations in columns 2 and 4 is less than the number in columns 1 and 3 because the SEC Chair does not participate in every vote. The number of observations in columns 7 and 8 is less than the number of observations in 5 and 6 because three Fed Governors (Ernest Draper, James Vardaman, Jr., and Joseph A. Broderick) do not speak of regulatory costs or benefits, so their dictionary-based ideology is undefined. In all the regressions, we include fixed effects for the rule/decision being voted on. We normalize each of the four independent variables so that they have zero mean and unit standard deviation. Standard errors are clustered by the rule/decision that is being voted on. t-statistics are reported in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

the Commissioner and the Chair of the SEC. Here, the coefficient is more significant both economically ($\beta = 0.0032$, or 21.6% of the dependent variable's average value) and statistically (t-stat = 6.33). In columns 3 and 4, we consider the ideological distance measures based on the dictionary-based approach. We find a much stronger relation between dissenting activity and ideological difference: a one-standard-deviation increase in ideological difference is associated with an 87-bps (62-bps) increase in the probability of dissenting when the ideological distance is measured from the rest of the Commission (the Chair of the SEC). These results are also statistically more significant (t-stats = 15.36 and 13.54, respectively).

In columns 5–8, we repeat the analysis for the sample of the Fed's FOMC votes. We find that the coefficients are not all statistically different from zero, possibly because of the relatively small sample of Fed FOMC votes. Given the low presence of dissenting votes at both the SEC and the Fed, we verify that our results in Tables 7 and 8 are robust to alternative methods that account for the very low presence of dissents using Poisson pseudo-maximum likelihood regressions. We report these results in Internet Appendix Tables A6 and A7.

Summarizing, we find that (1) dissenting votes at the SEC appear to be partisan in that a Commissioner is more (less) likely to dissent when a Commissioner from her own (the opposite) party dissents, (2) dissenting votes at the SEC have risen dramatically over the last 15 years, coinciding with the increase in the partisanship of SEC Commissioners' speech, and (3) SEC Commissioners and Fed Governors are most likely to dissent if their speech suggests their ideology differs greatly from the other regulators and/or the chair. Regarding (3), we emphasize that the ideological distance between regulators increases as the regulatory body becomes more partisan, so this finding suggests that dissenting activity should rise as the body becomes more partisan, which is exactly what we see in the SEC.

4. Conclusion

The Federal Reserve and SEC have institutional features that are designed to shield them from the effects of partisanship. In recent decades, these safeguards have been put to the test as the U.S. political landscape has become significantly more polarized. Have the Fed and SEC been affected by this increased polarization? We address this question by comparing the speech of Fed Governors and SEC Commissioners to the speech of congressional Republicans and Democrats.

Following the methodology developed by GST, we examine whether Republican (Democratic) regulators speak like Republican (Democratic) congresspeople. With this approach, the Federal Reserve appears to be largely immune from the increased partisanship in American society. However, the SEC seems to have been affected, as there has been a significant increase in its partisanship in the 2010s relative to earlier decades. This effect is driven by more-partisan Commissioners replacing less-partisan ones.

An examination of the most-partisan phrases suggests that the increased partisanship at the SEC might affect not only the Commissioners' speech but also their regulatory philosophies. For example, the most-partisan Democratic phrases in the 2010s are "Wall Street reform" and "protect investors." More generally, the most-partisan phrases suggest that Republican regulators favor less regulation than Democrats. For example, SEC Democrats emphasize investor and consumer protection, while SEC Republicans emphasize regulatory burdens and the unintended consequences of policy intervention. These differences have grown over time and were at their highest levels in the 2010s.

Consistent with the ideas above, we find that partisanship at these regulatory bodies is not restricted to their speech but extends to their governing activity. We find that rules are more likely to sound like the partisan language of the majority party in the regulatory body when the partisanship of their speeches is greater. Additionally, we document a dramatic increase in partisan voting behavior at the SEC between 2006 and 2019, whereby (1) dissenting activity increases substantially, and (2) the dissenting votes disproportionately occur along party lines. Finally, we connect these voting results to our speech data by showing that dissents at both regulatory bodies are more likely to be cast by regulators whose speech is ideologically dissimilar from the other regulators' speech and the Chair's speech. Because our measures of ideological difference among regulators rises as partisanship increases, these results help explain why the increase in dissenting votes at the SEC has coincided with the increase of partisan speech at the SEC.

Although we focus on the partisanship of Fed Governors and SEC Commissioners, our approach of using congressional speech to examine the partisanship of noncongressional speech can be applied more broadly. For example, researchers can use this methodology to examine whether the United States Supreme Court or state/local governments also have become more partisan over time. More generally, many government entities were designed to be immune from partisan influence, and the approach here can be used to evaluate whether the rise in partisanship in American society has spilled over into these entities. We leave such investigations to future research.

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