Expanding Shareholder Voice: The Impact of SEC Guidance on Environmental and Social Proposals

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Abstract

After a dramatic increase over the past decade, shareholder support for environmental and social (E&S) proposals seems to have waned. In this Article, we examine whether this recent decline is linked to a 2021 shift in the SEC's policy, which expanded the ability of shareholders to influence E&S corporate decisions. We suggest that this regulatory shift has led to an increase in "prescriptive" E&S proposals, which typically call for more aggressive but costlier E&S policies by companies. Using a combination of supervised and unsupervised machine learning techniques to identify prescriptive proposals, we find that these proposals generally receive less shareholder support and seem to be driving a substantial part of the decline in support for E&S proposals. This decline is observed among the vast majority of institutional investors, including many ESG funds. However, there is considerable heterogeneity in the magnitude of this decrease across different investor groups. By ranking investors based on their ideological preferences over E&S issues, we find that investors with more intense preferences for E&S issues are more likely to support prescriptive proposals, while those on the opposite end of this spectrum are more likely to oppose them. Our results suggest that while investors continue to vote along ideological lines on E&S issues, the financial cost of prescriptive proposals often outweigh the intensity of E&S preferences for most of them.

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1 Introduction

Shareholders of major publicly traded companies frequently employ shareholder proposals to introduce resolutions addressing environmental, political, ethical, or social issues ("E&S proposals"). Such proposals have included calls for ExxonMobil to reduce its greenhouse gas emissions, for Meta to remedy its gender pay gaps, and for Lululemon to discontinue the use of down feathers in their merchandise.

Historically, E&S proposals have generally garnered low shareholder support (He et al. (2023)), but this landscape has significantly shifted in recent years. As Tallarita (2022) indicates, the average shareholder vote in favor of E&S proposals was 18% in 2010, but it almost doubled to more than 35% by 2021. While from 2010 to 2019, a mere 1% of E&S proposals achieved majority support at annual meetings, this figure rose to 16% in 2020 and 2021.

The rising support for E&S proposals among shareholders is consistent with a number of plausible theories. For instance, investors may have become increasingly aware of the escalating risks of climate change and other E&S-related risks for their investment portfolios (Krueger et al. (2020); Ilhan et al. (2023); Bolton and Kacperczyk (2021); Ilhan et al. (2021); Bolton and Kacperczyk (2023)). Furthermore, investors may derive non-pecuniary utility from acting in a pro-social fashion (Andreoni (1990)), or may otherwise have altruistic preferences (Hart and Zingales (2017)) and are therefore willing to sacrifice pecuniary returns in order to pursue social goals (Barber et al. (2021); Hirst et al. (2023); Hart et al. (2024)). While voting has historically been viewed as a costlier alternative to simply exiting the firm (Admati and Pfleiderer (2009)), recent studies by Li et al. (2022) and Brav et al. (2022) have shown that shareholders often prefer to exercise their voting rights over divestment. Indeed, Broccardo et al. (2022) illustrate how voting may be more effective than exit in achieving "socially responsible" outcomes.

Despite this dramatic rise over the last decade, the trend has notably shifted in the opposite direction in the years 2022-2023. In Panel A of Figure 1, we plot shareholder support for E&S proposals over time, measured as the mean percentage of "votes for as a percentage of votes cast." In 2021, shareholder support for environmental proposals stood at 40.24% for environmental proposals, surpassing even that for governance proposals, which was at 35.52%. In 2022, however, the support for environmental proposals dropped to 34.00%, and further declined to 19.01% in 2023. Social proposals also saw a decrease in support, from 35.27% in 2021 to 24.51% in 2022, and then to 16.96% in 2023. Meanwhile, as Figure 1 reveals, the decline in voting support for governance proposals has been far more muted, with support decreasing from 35.52% to 26.5% between 2021 and 2023.

In this article, we examine whether the declining support for E&S proposals is linked to a recent regulatory shift that expanded the ability of shareholders to submit these proposals. Traditionally, the SEC allowed corporate management to exclude E&S proposals under the so-called "ordinary business exclusion" if they included specific goals, methods, or time-frames to accomplish the relevant policies. In November 2021, however, the SEC's Division of Corporation Finance issued a new "staff legal bulletin" (the "2021 Guidance") (SEC (2021)) that allowed the submission of such "prescriptive" proposals.[1]

Our starting position is that "prescriptive" E&S proposals ex a higher level of commitment to E&S issues compared to their non-prescriptive counterparts. For example, a non-prescriptive proposal might simply request management to issue a report detailing the company's current levels of carbon emissions and management's own assessment of the situation. In contrast, a prescriptive proposal might require management to implement a specific policy aimed at achieving a quantified reduction in carbon emissions over a specific time-frame.[2] Therefore, prescriptiveness entails a different tradeoff between an investor's pecuniary and non-pecuniary preferences. Since prescriptive proposals generally incur significantly higher implementation costs for the firm, these proposals are often supported by shareholders with more intense non-pecuniary preferences.[3] Based on these assumptions, the 2021 Guidance would have an ambiguous impact on voting support, depending on the composition of the investor voting base. For example, if the majority of investors had relatively weak pro-social preferences, one would expect to see a decrease in voting support attributable to the 2021 Guidance((Bolton et al. (2020); Curtis et al. (2021); Bebchuk and Hirst (2019); Bebchuk and Hirst (2022); Griffin (2020); Zytnick (2022)).

Reactions to whether the 2021 Guidance had an effect on the support for E&S proposals were mixed. On one hand, journalists (WSJ (2022)), legal practitioners (Posner (2022); Gibson-Dunn (2022); Gibson-Dunn (2023)), and even major institutional investors (Blackrock (2022)) have suggested that the greater "prescriptiveness" of shareholder proposals associated with the 2021 Guidance may have contributed to the decline in support for E&S proposals. On the other hand, skeptics like Morgan (2024) have argued that the 2021 Guidance has had little to no effect on voting support. Indeed, Morgan (2024) contends that the observed decrease in voting for E&S proposals was due to "a dramatic increase in anti-ESG proposals, which have proven largely unpersuasive and acted as an anchor on average vote totals," and that "the SEC's no-action process remains remarkably lop-sided in favor of [management]."

[1]See Section 3.1.

[2]See Section 10.3 for examples of these proposals.

[3]We use the terms "financial" and "pecuniary" interchangeably throughout this article, as well as the terms "pro-social" and "non-pecuniary".

To assess the effect of the SEC's policy shift on the shareholder support for E&S proposals, we employ two distinct strategies. The first strategy is to use governance proposals as a control group.[4] This strategy is based on the plausible assumption that the 2021 Guidance, which determines the excludability of proposals based on whether they raise "significant social policy issues," would primarily affect the level of prescriptiveness of E&S proposals, with minimal or no impact on governance proposals (Tallarita (2022); Gibson-Dunn (2022); Gibson-Dunn (2023)). After controlling for a wide array of variables, we observe a significant decrease in the shareholder support for E&S proposals after 2021, as compared to governance proposals.

The second strategy is to employ a mix of supervised and unsupervised machine learning methods in Natural Language Processing (NLP) to ascertain the prescriptive nature of proposals. Our supervised machine learning algorithm exploits the SEC staff's own assessment of a contested proposal's prescriptiveness before 2021. In other words, to establish whether a given proposal is prescriptive, we do not use our subjective interpretation of the pre-2021 policy; instead, we train the algorithm to recognize prescriptive proposals based on the SEC's own assessment of hundreds of contested proposals. We use proposals contested under the "ordinary business exclusion" prior to 2021 as a training dataset for Google's BERT (Bidirectional Encoder Representations from Transformers) algorithm (Liu and Lapata (2019)).[5] Assuming that the SEC is more likely to exclude highly prescriptive proposals under the "ordinary business exclusion," we then use this algorithm to classify all uncontested and withdrawn proposals from 2018 to 2021, as well as all the proposals from 2022 and 2023. Furthermore, recognizing that this classification might not capture all prescriptive proposals, in a secondary step, we adopt an unsupervised "Topic Modeling" strategy (Grootendorst (2022)) to identify additional prescriptive proposals. This approach aims to uncover clusters of proposals potentially associated with prescriptive textual elements, such as the request for the adoption of specific policies.

After adjusting for a comprehensive range of characteristics, our analysis reveals that prescriptive proposals tend to attract lower levels of shareholder support. More pertinently, by exploiting the regulatory shock created by the 2021 Guidance to induce quasi-exogenous changes in proposal prescriptiveness, we find a marked decline in support for prescriptive proposals post-2021, relative to their non-prescriptive counterparts.

To determine if the decline in support for E&S proposals might be influenced by specific shareholder groups known for their ideological stances on E&S issues, we investigate the relationship

[4] We define "governance" proposals as all shareholder proposals in our dataset that are not categorized as "environmental" or "social." This approach avoids the arbitrariness of other possible definitions for the control group.

[5] As noted in Sections 5.1 and 10.2, a portion of these proposals is reserved as a validation dataset to test the model on out-of-sample data that it has not encountered before.

between individual fund-level voting behavior and the prescriptiveness of proposals. Consistent with our earlier results, we find that mutual funds are, on average, less likely to support prescriptive proposals across the entire period, with this tendency becoming even more pronounced after 2021.

More importantly, we find evidence of this decline in support for prescriptive proposals among institutional shareholders with varying ideological preferences on E&S issues. Following Bolton et al. (2020) and Michaely et al. (2021), we construct an ideological spectrum for funds on E&S issues, with "pro-social" funds at one end and "financially-oriented" funds at the other. While support for prescriptive proposals has generally decreased across the large majority of funds since 2021, funds with stronger preferences for E&S issues are more likely to support prescriptive proposals, whereas funds on the financially-oriented end of the spectrum are more likely to oppose them. For example, within the set of ESG funds, ESG funds within E&S-focused families (which lean pro-social) are more likely to support prescriptive proposals compared to the average fund. In contrast, ESG funds in non-E&S families (which lean financially-oriented) show no significant difference from the average fund. Additionally, active mutual funds, which are typically more financially-oriented, are more likely to oppose prescriptive proposals. Conversely, the "Big Three" funds and other predominantly passive mutual funds, which align closer to the median voter on the E&S ideological spectrum, are indistinguishable from the average fund.

Given that prescriptive proposals are inherently more aggressive in addressing E&S issues but are also more costly to implement, our results are consistent with the hypothesis that many institutional investors do not "walk the talk" when faced with E&S issues that conflict with pecuniary maximization objectives (Goshen and Hamdani (2023); Michaely et al. (2021); Li et al. (2023b); Heath et al. (2021)). Indeed, while much emphasis has been placed on the importance of pro-social preferences in ameliorating environmental and social externalities (Hart and Zingales (2017); Hart and Zingales (2022); Broccardo et al. (2022); Barber et al. (2021); Hirst et al. (2023); Hart et al. (2024)), our findings reveal that the financial costs of prescriptive proposals often outweigh the intensity of E&S preferences for the vast majority of funds.

Our article is organized as follows. In Section 2, we provide a brief literature review and detail how our contributions to the existing literature. In Section 3, we outline the regulatory context surrounding Rule 14a-8 and describe our data sources. In Section 4, we share empirical findings on the level of support for E&S proposals in comparison to governance proposals. In Section 5, we explain how we construct the binary indicator of prescriptiveness which we harness in our study, and present empirical results on the support for prescriptive versus non-prescriptive proposals within the category of E&S proposals. In Section 6, we combine proposal-level data from Sections

4 and 5 with individual fund-level voting information and present the resulting empirical findings. Section 7 provides robustness tests concerning a key threat to our identification strategy—the presence of political backlash. Section 8 concludes. Finally, an Online Appendix (Section 10) is provided to detail additional results secondary to our primary analysis, the machine learning techniques used to develop the prescriptiveness indicator referenced in Sections 5 and 6, the data-cleaning procedures employed to obtain the findings presented in Section 6, and includes additional tables and figures that support our primary analysis.

2 Contributions to the Literature

Our article contributes to two distinct debates on E&S proposals. The first concerns the potential relationship between the prescriptive nature of shareholder proposals and shareholder support. While many commentators, including journalists (WSJ (2022)), legal practitioners (Posner (2022); Gibson-Dunn (2022); Gibson-Dunn (2023); Morgan (2024)), legal academics (Tallarita (2022); Fisch and Robertson (2023)), and even major institutional investors (Blackrock (2022)), have suggested that the "prescriptiveness" of shareholder proposals may influence voting outcomes, we know of no study which has formally investigated the existence or magnitude of this relationship.

The challenge in establishing how prescriptive proposals impact voting behavior or other corporate outcomes lies primarily in two areas. First, the textual composition of a proposal is inherently influenced by its proponents, who may strategically craft their wording to influence voting outcomes or to avoid preclusion by the SEC (Gantchev and Giannetti (2021); Tallarita (2022)). Accordingly, any quasi-exogenous variation in the level of "prescriptiveness" must arise from a shock (regulatory or otherwise) that alters the incentives for proponents whose proposals would otherwise be omitted — a context exemplified by the 2021 shift in the SEC's Rule 14a-8 policy which we exploit. Indeed, this regulatory shift could increase the prescriptiveness of proposals via two distinct mechanisms: it could encourage new proponents, who might have been excluded under previous SEC regulations, to submit more prescriptive proposals, but it could also allow existing proponents, previously constrained by SEC regulations, to better align their proposals with their actual preferences.

Second, since the textual contents of proposals are intrinsically unstructured and high-dimensional when compared to traditional quantitative measures used in causal inference (Egami et al. (2022)), devising a metric for "prescriptiveness" that remains unaffected by the researcher's subjective biases poses a significant challenge. To address these issues, we leverage advancements in corporate governance research that utilize machine learning techniques, such as embedding models and dimensionality reduction, to mitigate concerns related to the diverse contexts and themes present in proposal texts (Michaely et al. (2023); Rajan et al. (2023); Li et al. (2023a); Briscoe-Tran (2023); Andrikogiannopoulou et al. (2022)). A key contribution we make to the literature is the use of legal outcomes to label data for subsequent supervised machine learning, as opposed to the common practice of hand-labeling by researchers and their collaborators, which introduces potential biases to the training process (Gompers et al. (2003); Frankenreiter et al. (2021); Porta et al. (1998); Spamann (2010)). Indeed, our goal is *not* to develop an expert-driven, objective measure of "prescriptiveness" as suggested by Bainbridge (2016), but rather to replicate the SEC's interpretation of prescriptiveness in determining whether a proposal is excludable under Rule 14a-8(i)(7).

The second debate is about the determinants of shareholder voting support.[6] The factors affecting voting support in corporate decisions are numerous and varied, encompassing aspects like firm characteristics (Cuñat et al. (2012)), shareholder characteristics (Brav et al. (2024); Brav et al. (2022)), proponent characteristics (Gantchev and Giannetti (2021); Bebchuk et al. (2020)), proposal topics (Bolton et al. (2020); Bubb and Catan (2022); Curtis et al. (2021)), the strategic incentives of voting investors (Michaely et al. (2021); Li et al. (2023b)), proxy advisory recommendations (Iliev and Lowry (2015); Iliev and Vitanova (2022); Hu et al. (2024)), and the dynamics of management-shareholder relations (Matvos and Ostrovsky (2010)). Our key contribution to this literature underscores the significance of the *regulatory landscape* in determining voting outcomes, a factor that has not been fully explored by other authors in the broader literature.

As discussed in Section 1, we consider the 2021 Guidance as a quasi-exogenous shock that increased the "prescriptiveness" of proposals, which exhibit a higher level of commitment to E&S issues.[7] However, this higher level of commitment comes with financial implications, as prescriptive proposals are costlier for firms to implement. Prior literature has shown that voting on E&S issues often aligns with ideological dimensions. For instance, Bolton et al. (2020) demonstrate that institutional investors can be represented along a left-right spectrum. Far-left investors, described as "socially responsible", consistently vote in favor of pro-social and pro-environmental shareholder proposals, whereas far-right, "money-conscious" investors oppose proposals that could

[6] A separate strand of literature examines the economic impact of shareholder proposals that proceed to a vote. Some studies suggest that mutual fund support for E&S proposals represents informative signals about firms' potential E&S risks, highlighting the potential advantages of expanding shareholder voice on E&S issues (He et al. (2023)). However, other research presents evidence that investors respond favorably when the SEC allows for the exclusion of certain proposals, suggesting that, on average, these excluded proposals were perceived as detracting from firm value (Matsusaka et al. (2019); Matsusaka et al. (2021)). Our work is adjacent to this line of literature.

[7] We can also view this quasi-exogenous shock as an increase in the "intensity" of E&S issues to be voted on.

financially burden them.[8] Importantly, Bolton et al. (2020) find this ideological spectrum to be a primary factor separating the voting behavior of institutional investors, with governance concerns being secondary. Similarly, Michaely et al. (2021) find that fund ideology on E&S issues is the dominant driver of voting behavior on these issues, especially where the funds are likely to be pivotal voters. Authors like Dikolli et al. (2022) and Curtis et al. (2021) have also found that ESG funds vote in alignment with their stated objectives. These empirical findings align with a broader theoretical literature suggesting that investor behavior may involve balancing pro-social and pecuniary objectives (Hart and Zingales (2017); Hart and Zingales (2022); Broccardo et al. (2022); Barber et al. (2021); Hirst et al. (2023); Hart et al. (2024)). Collectively, the literature supports our hypothesis that, ceteris paribus, an increase in the prescriptiveness of proposals should induce increased voting support among pro-social investors and decreased support among financially-oriented investors, with the average fund driving the collective outcomes. Overall, our results suggest that the voting behavior of most investors is primarily driven by financially-oriented objectives, with their responses moderated by their ideological preferences on E&S issues.

Separately, we also view the shock to the "prescriptiveness" of proposals as a potential shift in the allocation of power between shareholders and managers. If implemented, prescriptive proposals enable shareholders to exert limited power over firm decision-making, effectively replacing the board's authority in certain domains. Nevertheless, it is theoretically unclear how the 2021 Guidance would impact the voting behavior of investors with preferences over governance issues (e.g., pro-management investors).[9] Indeed, the 2021 Guidance could potentially improve alignment between shareholders and managers on E&S issues but could also heighten the potential for conflicting preferences among shareholders. On one hand, empowering shareholders may reduce the risk of managers making significant decisions that deviate from shareholders' preferences (Bebchuk (2005)). Additionally, expanding shareholder voice on E&S issues may provide managers with more information about shareholders' preferences regarding non-pecuniary issues, where the risk of misalignment is higher (Tallarita (2022); He et al. (2023)).[10] Conversely, allowing shareholders with heterogeneous preferences to determine E&S issues may exacerbate the costs of collective decision-making within a firm (Hansmann (1996); Blair and Stout (1999); Tjio (2023); Lan and Lim (2024)). These problems are particularly salient for E&S issues since

[8]Formally, we assume that all investors consider both a "pro-social" component and a "pecuniary" component in their utility functions. Pro-social investors place relatively more weight on the "pro-social" component, whereas "money-conscious" (financially oriented) investors prioritize the "pecuniary" component (Matsusaka et al. (2021)).

[9]Note that these "governance" preferences are distinct from the tradeoff between pecuniary and non-pecuniary preferences in the context of E&S ideologies.

[10]Zytnick (2022) also notes that, in contrast to governance proposals, disagreement on E&S proposals likely stems from differing views on the objective function of the corporation, resulting in a genuine conflict of interest rather than information asymmetry.

shareholders are more likely to disagree on such matters than on governance or financial issues (Tallarita (2022); Zytnick (2022); Mueller (2003)), a problem known in public choice literature as "multi-dimensionality" (Mueller (2003)).

While we acknowledge that shareholders may have preferences over these "governance" issues and that voting behavior may also be driven by these preferences, we posit that governance issues are of secondary importance in our analysis. Beyond Bolton et al. (2020)'s findings that governance issues are of second-order importance across *all* proposals, our analysis focuses only on shareholder proposals, where voting outcomes are merely precatory and not binding on management (Tallarita (2022)). Consequently, we believe that shareholder activists and the investors voting on governance reforms are more likely to use separate governance proposals or alternative mechanisms, such as proxy fights, to express their governance preferences rather than through E&S proposals (Clarke and Hansmann (2022); Meirowitz et al. (2023); Brav et al. (2024)). More importantly, we explicitly investigate whether ESG funds vote differently across fund families with differing governance ideologies (i.e., pro-management or anti-management ideologies). Our results in Section 6.3 indicate no significant differences between these distinct fund families, supporting the aforementioned hypothesis.

3 Data and Institutional Setting

3.1 The Institutional Setting of Rule 14-a and the 2021 Guidance

Rule 14a-(8) mandates the incorporation of shareholder proposals that meet specific formal and substantive criteria into the proxy materials distributed by the company to its shareholders.[11] Given that the majority of shareholders typically do not attend the company's annual meeting in person and opt to vote via proxy, they would be unable to learn about or vote on proposals not included in the company's proxy materials. Rule 14a-8 addresses this issue by requiring companies to inform all shareholders about these proposals and enabling them to cast their votes on them. Consequently, the submission of shareholder proposals under Rule 14a-8 is often described as a form of "low-cost activism." (Kastiel and Nili (2020); Gantchev and Giannetti (2021); Bainbridge (2016)).

However, Rule 14a-8(i) allows companies to omit a shareholder proposal from the proxy statement if it fails to satisfy certain criteria. For instance, companies are permitted to exclude proposals

[11] 17 C.F.R. § 240.14a-8.

which deal with the company's "ordinary business operations", proposals which are "materially false or misleading", and proposals which have already been implemented by the company. Here, we focus on Rule 14a-8(i)(7), which allows the exclusion of proposals "deal[ing] with a matter relating to the company's ordinary business operations."

Management may seek to exclude a shareholder proposal by submitting a "no-action letter" request to the SEC, outlining their rationale for exclusion. This is an adversarial process similar to litigation, and it allows the proponent to counter the request for exclusion. The SEC staff then adjudicates the matter, siding either with the company or the proponent. Should the SEC allow the proposal to proceed to a vote, management virtually always recommends that shareholders vote against these proposals (Tallarita (2022)).

The SEC and its Corporation Finance Division have issued several interpretive documents to clarify which proposals regarding "significant social policy issues" fall within the "ordinary business exclusion." In particular, commencing with a sequence of Staff Bulletins in November 2017, the SEC staff has indicated that companies could exclude "social policy" proposals that were not "sufficiently significant in relation to the company", proposals that "relate[d] to the imposition or assumption of specific time-frames or methods for implementing complex policies", as well as proposals "too complex for shareholders as a group to make an informed judgment" (SEC (2017)).

However, in November 2021, the SEC rescinded these bulletins in Staff Bulletin No. 14L, reversing its position on how it would evaluate proposals concerning "significant social policy issues" under the "ordinary business exclusion". Contrary to its prior guidance, the SEC announced that "proposals seeking detail or seeking to promote timeframes or methods do not per se constitute micromanagement". Illustrating this change in policy, the SEC noted that proposals which requested that "companies adopt timeframes or targets to address climate change" would henceforth be considered non-excludable (SEC (2021)).[12]

Many observers of the 2021 guidance (i.e., Staff Bulletin No. 14L) highlighted this as a significant departure in the SEC's approach, interpreting it as a "clear move by the SEC to encourage sustainability efforts." (Era et al. (2021)). From a practical standpoint, legal practitioners also suggested that the guidance created a more difficult threshold for no-action relief, and would likely result in more E&S shareholder proposals either making it onto the agenda for a company's shareholder meeting or ending in a settlement for the company (Era et al. (2021)). In 2022, Blackrock's stewardship team (Blackrock (2022)) reported a 13% surge in E&S shareholder proposals, noting that

[12] The SEC's position on Rule 14a-8(i)(5), the economic relevance exception, was also revised in Staff Bulletin No. 14L. Henceforth, we will refer to this staff bulletin as the "2021 Guidance".

many were "more prescriptive than in prior years, enabled by changing [SEC] guidance." In contrast to proposals submitted in 2021, Blackrock (2022) also observed that a significant portion of the 2022 proposals imposed undue restrictions on management or were excessively detailed in their demands for information or deadlines. Numerous other commentators have also noted the marked rise of "prescriptive" proposals which accompanied the decrease in the number of proposals dismissed based on no-action requests (WSJ (2022); Gibson-Dunn (2022); Gibson-Dunn (2023); Posner (2022); Tallarita (2022)).

3.2 Data Sources

We procure our data from several distinct sources. The primary dataset comes from Factset,[13] from which we obtain information on all environmental, social, and governance shareholder proposals at Russell 3000 companies for the years 2018 to 2023.[14] While data on shareholder proposals is also available prior to 2018, we limit our analysis to post 2018 data so as to (1) focus on the causal impact of the 2021 Guidance which rescinded the Staff Bulletins initiated in November 2017, (2) minimize the influence of other potential confounding events on the pre-treatment proposals, such as the impact of the *Trinity Wall Street v. Wal-Mart Stores, Inc.* case in 2015,[15] and (3) ensure the analysis remains tractable when merging proposal data with voluminous individual fund-level voting data.[16] The data from Factset also provides information on several proposal characteristics, including whether a no-action letter was requested, if such a letter was granted, and the proposal's specific sub-categories. Additionally, for each proposal, there is limited data on the characteristics of the proponent, such as the type of proponent (e.g., a pension fund or an individual) and the proponent's name.[17]

As voting outcomes and proponent targets have been shown to be dependent on firm characteristics (Cuñat et al. (2012); Bebchuk et al. (2020)), we procure firm-level characteristics from the CRSP-Compustat-Merged (CCM) database and merge these characteristics to our Factset dataset at the firm-year level.[18] The CCM database offers insights into various firm-specific attributes,

[13]While most scholars like He et al. (2023) and Gantchev and Giannetti (2021) have traditionally used a similar dataset from Institutional Shareholder Services (ISS) as their primary source, we have chosen Factset as our main dataset because, unlike ISS, it includes data on the textual content of shareholder proposals.

[14]In Figures 1 and Table A2, we also utilize data on the same set of firms from 2013 to 2018. However, we exclude this data in subsequent analysis).

[15]*Trinity Wall Street v. Wal-Mart Stores, Inc.*, 792 F.3d 323 (3d Cir. 2015)

[16]For example, although Zytnick (2022) focuses solely on E&S proposals spanning from 2015 to 2017, the inclusion of individual and fund-level voting data results in a dataset comprising almost 5 million observations.

[17]Further information about these variables can be found in Table A1.

[18]Iliev and Lowry (2015) demonstrate that although funds within the same family generally vote in a similar

including a firm's total assets, leverage ratio, and its return on assets, among others.[19]

In Section 6 of our article, we attempt to investigate the relationship between individual fund-level voting behavior and the prescriptiveness of proposals. Given that the Factset database does not include data on how individual funds vote, we first merge our Factset dataset with the ISS Voting Analytics (Company Vote Results) database, which contains the proxy voting results for each company at the firm-year level. Due to the absence of a common unique identifier between the two datasets, we perform the merger using a firm identifier, the relevant meeting date, as well as the aggregate votes for, against, and abstentions. Subsequently, we integrate this combined dataset with the ISS Voting Analytics (Mutual Fund Vote Records) database using ISS unique identifiers. This database offers detailed proxy voting results for each firm, broken down to the individual fund level.

Like firm characteristics, prior research has demonstrated that voting outcomes are also influenced by characteristics specific to funds (Brav et al. (2024); Brav et al. (2022)). To incorporate fund characteristics for each observed fund in our dataset, we integrate the aforementioned dataset with the CRSP mutual fund database.[20] This merging process is challenging due to the absence of common identifiers in both datasets and the lack of quantitative measures that would facilitate merging the data at the fund-level.[21] To overcome this challenge, we scrape fund names linked to each N-PX identifier (found in the ISS dataset) from the SEC's EDGAR database.[22] We then employ fuzzy-matching techniques to match the fund names from EDGAR with those in the CRSP mutual fund database. The final merging step involves matching the datasets based on a fund identifier, relevant record dates, and a firm identifier.[23] The merged dataset encompasses details on several fund-specific characteristics, such as the percentage of a firm's ownership by a given fund, the fund's assets under management, its expense ratio, and whether it is an index fund, among others.[24]

In our primary analysis presented in Sections 4 and 5, which is centered around data at the firm-

fashion, they differ in their voting 6-7% of the time, particularly where contentious issues are involved.

[19]Further information about these variables can be found in Table A1.

[20]We also include fund characteristics from the Thomson Reuters S12 Mutual Fund database. A more detailed description of how we perform these data-cleaning procedures is provided in Section 10.5.

[21]In contrast, because proposals are observed at a more granular level compared to firms (i.e., a single firm is often associated with multiple proposals), we are able to merge proposals observed in the Factset and ISS databases using firm identifiers and data on voting results.

[22]Mutual funds and other registered management investment companies are required to disclose their proxy votes under Section 30 of the Investment Company Act of 1940 and Sections 13 and 15(d) of the Securities Exchange Act of 1934. These disclosures are known as "Form N-PX" disclosures. Each fund name in the SEC's EDGAR database is linked to a non-unique N-PX identifier.

[23]A more detailed description of how we perform these data-cleaning procedures is provided in Section 10.5.

[24]Further information about these variables can be found in Table A1.

year-proposal level, we incorporate a comprehensive set of firm-proposal control variables. Moving to Section 6, where the focus shifts to data observed at the fund-firm-year-proposal level, we accordingly expand our analysis to include a range of fund-level control variables.

4 Voting Support for E&S Proposals and Governance Proposals

After a significant increase over the past decade, voting support for E&S proposals has experienced a notable downturn in the period from 2022 to 2023. In Panel B of Figure 1, we illustrate how the average support (measured as the percentage of affirmative votes of total votes cast) for E&S proposals steadily increased between 2018 and 2021 notwithstanding the SEC policy stances during this period that imposed stricter conditions for shareholder proposals to advance to a vote (see Section 3.1). Panel B of Figure 1 also illustrates the more pronounced decline in voting support for E&S proposals after 2021 when compared to the decrease observed for governance proposals. Panels C and D of Figure 1 display similar trends when employing alternative measures of support. In Panel C, the average support is determined based on the percentage of affirmative votes relative to the total number of outstanding shares; while in Panel D, it is gauged as the percentage of affirmative votes out of the total votes for and against the proposition presented in the proposal. Taken together, these illustrations suggest that the observed decline in voting support is not attributable to voter turnout rates or the incidence of abstentions.

Figure 1 shows that, with the exception of environmental proposals in 2021, governance proposals have generally garnered more support than E&S proposals, especially in the years leading up to 2021. This observation aligns with the results of related research by He et al. (2023), who identified a significant gap in the level of support between E&S proposals and governance proposals. We report some summary statistics in Table 1 that further substantiate this point. Across the sample period, the average support for governance proposals, quantified as the percentage of affirmative votes out of the total votes cast, stands at 34.00%. This is in comparison to an average support of 28.33% for environmental proposals and 25.06% for social proposals. Table 1 reveals that a significant portion of governance proposals pertains to “Shareholder Rights/Takeover Defenses” and “Board-Related” matters, both of which secure substantial voter backing. Specifically, proposals addressing takeover defenses (typically advocating for the removal of poison pills) command 43.76% of all votes cast, whereas those related to board issues (typically advocating for board declassification) receive 33.02% of the votes.[25] Finally, Table 1 reveals that the majority of shareholder proposals (53.97%), are governance-related.

To compare voting support between E&S and governance proposals given the absence of parallel trends between these groups, we utilize the Synthetic Difference-in-Differences (SDID) methodology developed by Arkhangelsky et al. (2021). As detailed in Section 10.1, our approach relies on the plausible assumption that the 2021 SEC Guidance, which determines excludability based on whether proposals raise "significant policy issues," had a relatively stronger impact on the level of prescriptiveness in E&S proposals while exerting minimal to no impact on governance proposals (Tallarita (2022); Gibson-Dunn (2022); Gibson-Dunn (2023)). Table A2 presents our findings, showing that while governance proposals consistently received high levels of support both before and after the 2021 Guidance, firms with a higher proportion of E&S proposals experienced a notable decline in average voting support following the 2021 Guidance.[26] We delve deeper into the mechanisms underlying this decline in Section 5.

5 Prescriptive Proposals

5.1 Constructing a Measure for Proposal Prescriptiveness

While the approach in Section 4 yields preliminary insights into the effects of the regulatory change, it falls short of identifying the precise mechanism through which the change led to the noted decrease in voting support for E&S proposals. More pertinently, despite the large volume of anecdoctal evidence suggesting how the 2021 Guidance had led to more prescriptive proposals (see Sections 2 and 3.1), we lack a clear quantitative measure for identifying whether a proposal is prescriptive.

To address this challenge, we harness a mixture of supervised and unsupervised machine learning methods in Natural Language Processing (NLP) to ascertain the prescriptive nature of proposals. As an initial step, we leverage the distinction between two types of contested proposals in our dataset. As detailed in Section 3.1, the SEC staff adjudicates a contested proposal, siding with either the management or the proponent. We distinguish between proposals that the SEC decides to exclude, aligning with management's position, and those where the request for exclusion is rejected, supporting the proponent's stance. We focus exclusively on proposals contested under

[25] Note that these percentages are not reported in Table 1.

[26] A detailed explanation of the methodology used to develop these estimates is provided in Section 10.1.

the "ordinary business exclusion" of Rule 14a-8(i)(7), and we assume that, consistent with its Staff Legal Bulletins from 2017 to 2020, the SEC is inclined to exclude proposals with a higher degree of prescriptiveness. This is because prescriptive proposals, by their nature, tend to delve more into the realm of a company's routine business affairs, which are typically within the purview of the company's board or management (Bainbridge (2016)). Consistent with findings from Tallarita (2022) and Matsusaka et al. (2021), a substantial majority (61.7%) of all contested proposals in our dataset are disputed on grounds that they would interfere with a company's ordinary business operations, thereby qualifying for the Rule 14a-8(i)(7) exclusion.

Focusing on the subset of all contested proposals from 2001 to 2021 (i.e., before the 2021 Guidance), we assign all excluded proposals under Rule 14a-8(i)(7) (favoring management) with a prescriptiveness indicator value of 1, and all precluded proposals under Rule 14a-8(i)(7) (favoring the proponent) with an indicator value of 0. This approach results in the creation of a "training" set consisting of 927 proposals, and a "validation" set of 231 proposals, which is used to assess the model's out-of-sample predictions. In constructing our training and validation sets, we balance the benefits of providing the algorithm with a larger set of examples to learn from against the risk of incorrect classifications due to shifts in the SEC policy. Using our training algorithm based on Google's BERT (Bidirectional Encoder Representations from Transformers), we classified all E&S proposals that were either uncontested or withdrawn between 2018 and 2021, as well as those from 2022 to 2023.[27] This approach is consistent with the methodologies used in Michaely et al. (2023), Rajan et al. (2023), and Liu and Lapata (2019).[28] The BERT model is pre-trained on approximately 3.2 billion words from Wikipedia and 11,000 books from a variety of genres, which allows it to generate a large number of embeddings (numerical weights assigned to words) which are context specific (Liu and Lapata (2019)).[29]

While the initial supervised machine learning approach offers a preliminary means of identifying prescriptive proposals, it may not encompass the full range of such proposals. This limitation arises because the training dataset is aligned with a specific threshold set by the SEC for approving or rejecting proposals, leading to potential misclassification of proposals that greatly diverge from this threshold.[30] To mitigate this issue, we implement a "Topic Modeling" strategy in a

[27] Contested proposals from 2018 to 2021 are not classified, as they are directly assigned a value of either 0 or 1.

[28] We classify all E&S proposals from 2022 to 2023 to maintain a consistent metric of "prescriptiveness," as defined prior to the 2021 Guidance. Our supervised machine learning algorithm assigns probability values to each classified proposal. While these values are rounded to the nearest integer in our main analysis, we also utilize the raw probabilities as an indicator of the intensity of "prescriptiveness" in Section 5.2.2.

[29] A more detailed description of how we implement these machine learning algorithms is provided in Section 10.2.

[30] Intuitively, the classifier may be prone to overfitting unseen data based on the characteristics of the training data near the threshold. A formal exposition of this intuition is provided in Section 10.3. Additionally, the training

secondary step to identify prescriptive proposals (Grootendorst (2022)). This method seeks to identify groups of proposals that share common themes related to "prescriptive content," like the implementation of particular policies, thereby offering a more nuanced insight into the proposals' characteristics. Given the probable differences in content between environmental and social proposals, we independently apply our topic modeling algorithms to the sets of environmental and social proposals.

Initially, we apply an embedding model to assign context-specific weights to individual words (or combinations of words) in our dataset. Subsequently, we utilize a UMAP (Uniform Manifold Approximation and Projection) algorithm to reduce the textual data's dimensionality, aiming to retain the most critical attributes of all environmental or social proposals. Next, we employ a vectorization model to filter out common stop-words in these proposals.[31] Finally, to group similar proposals, we use the HDBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with Noise) clustering algorithm, facilitating the identification of distinct proposal clusters.[32]

The application of topic modeling algorithms to our dataset uncovers specific topic clusters that align with characteristics identified by the SEC, legal practitioners and institutional investors (Era et al. (2021); Blackrock (2022); WSJ (2022); Gibson-Dunn (2022); Gibson-Dunn (2023); Posner (2022)). For example, amongst environmental proposals, there emerges a clear cluster advocating for companies to set "time-bound" emissions targets. Another group of proposals calls for companies to "adopt a [specific] policy" (or similar expressions like "implementing," "adopting," or "committing to a policy"), such as phasing out fossil fuel exploration and development. We identify these clusters of proposals that are ostensibly "prescriptive" in nature, before assigning these proposals with a prescriptiveness indicator of 1 (Li et al. (2023a)).

5.2 Voting Support for Prescriptive Proposals

5.2.1 Preliminary Observations

In Table 2, we explore the temporal trends of prescriptive proposals by dividing them into two distinct categories.[33] One category (Panel A) includes prescriptive proposals that proceed to a vote,

dataset employed is relatively small, which heightens the likelihood of misclassifying proposals.

[31]Stop-words are common words in a language that typically carry little information relevant to the analysis (e.g., "the", "is", "and").

[32]A more detailed description of how we implement these machine learning algorithms is provided in Section 10.3.

[33]Going forward, our analysis will concentrate exclusively on E&S proposals, excluding all governance proposals from consideration.

while the other (Panel B) encompasses those that do not proceed to a vote.[34] For each category, we detail their frequencies and the percentages within each year over time. Additionally, Panel C aggregates the data from Panels A and B and presents both relative frequencies and shares of proposals across the entire sample period. As Table 2 demonstrates, the total number of proposals has generally trended upward over the sample period, despite a slight decline in 2023 compared to 2022.

Panel A of Table 2 shows a noticeable increase in the proportion of prescriptive proposals that proceed to a vote post-2021. The within-year percentage of such proposals rose from 31.61% in 2021 to 40.36% in 2022, and further to 46.71% in 2023. In contrast, Panel B illustrates a significant decline in the fraction of prescriptive proposals that are excluded by the SEC and thus do not proceed to a vote. Specifically, 63.64% of these proposals were excluded in 2021, which decreased to 56.00% in 2022 and dropped further to 49.23% in 2023.

Figure 2 provides a graphical illustration of the trends highlighted in Panels A and B of Table 2. In Panel A of Figure 2, the percentage of prescriptive proposals (out of the total number of E&S proposals) that were not excluded by the SEC is plotted, with dashed lines representing the average values for all years. The panel shows a significant rise in the share of prescriptive proposals post-2021, accompanied by a decrease in the share of non-prescriptive ones. Panel B of Figure 2 displays a similar trend for proposals that were excluded. Here, a marked reduction in the proportion of excluded proposals is observed post-2021, alongside an increase in the share of non-prescriptive proposals. Collectively, these findings suggest that the SEC's policy adjustment regarding Rule 14a-8 may have influenced the proportion of prescriptive proposals which ultimately go to a vote.[35]

To investigate whether our constructed measure of prescriptiveness is negatively associated with voting support for E&S proposals, we run panel regressions where specification (1) is modified to remove the interaction term $p_{ijktn} \times Post_t$, and p_{ijktn} denotes whether a proposal is prescriptive in line with Section 5.1. In Tables A3 and A4, we present the results from applying various versions of this specification, incorporating different fixed effects, sub-samples, dependent variables, and selection bias models.[36] Overall, our findings indicate a robust negative relationship between the prescriptiveness coefficient on p_{ijkt} and voting support, suggesting that prescriptive proposals

[34]Note that the overall proportion of prescriptive proposals among all proposals is not the primary focus of our study. Instead, the primary variable of interest is the proportion of prescriptive proposals that ultimately proceed to a vote.

[35]However, our results in Section 5.2.2 do not indicate that the rise in prescriptive proposals is a key driver of the decline in voting support for E&S proposals.

[36]We offer a comprehensive discussion of how potential selection biases are addressed in Section 10.4.

generally receive less voting support compared to their non-prescriptive counterparts.

5.2.2 Difference-in-Differences Models

To identify the causal impact of the 2021 Guidance, the effect of the regulatory shock on voting outcomes must operate *solely* through its impact on the prescriptiveness of shareholder proposals. This stipulates that the regulatory shock should not have a direct effect on voting outcomes or affect them through pathways unrelated to the prescriptiveness of proposals. Although it is straightforward to dismiss direct effects, the possibility remains that the regulatory shock could influence voting outcomes through other indirect means, such as through selection effects. We address these potential selection biases in detail in Section 10.4 but provide an intuitive illustration in Figure 3, demonstrating why selection effects on target companies are unlikely to influence our results.[37]

Figure 3 focuses on firms consistently present in our sample before and after the 2021 Guidance, referred to as "stable firms." These firms serve as the primary targets of shareholder proponents, accounting for an average of 78.34% of all proposals in our sample. This observation aligns with Tallarita (2022), who notes that the shareholder proposal market is dominated by a relatively small group of specialized actors focusing on large firms they perceive to have a significant social impact. The figure shows the yearly breakdown of E&S proposals submitted to stable firms, with 70.98% of proposals in 2019 and 81.54% in 2022 directed toward these firms, highlighting their central role across the sample period. Given the dominance of stable firms in the dataset, sample selection over firms is unlikely to pose a significant challenge to the validity of our subsequent regression estimates.

To establish the foundational results, we begin by estimating a baseline specification:

$$y_{ijktn} = \alpha + p_{ijktn}\beta + (p_{ijktn} \times Post_t)\gamma + X_{ijktn}\xi + \theta_i + \eta_j + \psi_k + \nu_t + \varepsilon_{ijktn} \tag{1}$$

[37]Furthermore, since each proposal is observed only *once* in the dataset, the "treated" unit in any empirical analysis that aims to draw causal inferences may pertain to firms, proponents, or firm-proponent pairs, as these entities are observed repeatedly over time, unlike individual proposals. Consequently, including proposal-fixed effects in the analysis is not feasible. Alternatively, following the assumption in Bolton et al. (2023), one might consider that investors would consistently vote on identical proposals in a similar manner across time periods, suggesting that investor preferences and information sets remain stable over time. In our context, we extend this logic by assuming that, absent the 2021 Guidance, proponents would continue to submit identical proposals in a similar manner across time periods. This assumption suggests that proponent preferences and information sets remain stable over time, consistent with the findings of Bolton et al. (2020). To the extent that these assumptions fall short of supporting causal inference, we refrain from asserting causality in this section.

where i indexes firms, j indexes industries, k indexes proponent-types, n indexes proposals, X is a vector of firm-proposal controls[38], while θ_i, η_j, λ_k, and ν_t represent firm, industry, proponent-type, and year fixed effects, respectively. Meanwhile, y_{ijktn} relates to a measure of voting support–in this case, the percentage of affirmative votes out of the total votes cast, while the binary indicator p_{ijktn} denotes whether a proposal is prescriptive in line with Section 5.1. Finally, $Post_t$ is a binary indicator that denotes whether the proposal occurs post-treatment (i.e., in 2022 or 2023).[39]

In column (1) of Table 3, we present our findings from employing specification 1 on all E&S proposals, where the dependent variable is the share of affirmative votes out of the total votes cast, incorporating fixed effects for firm, proponent type, and year. Contrary to the results in Table A3 where the prescriptiveness coefficient (p_{ijkt}) was negatively significant, here, the coefficient on p_{ijkt} is negative but not significantly different from zero. However, the interaction term $p_{ijkt} \times Post_t$ shows a negative coefficient significant at the 1% level, indicating a substantial decline in support for E&S proposals after the 2021 Guidance. When compared to their non-prescriptive counterparts, prescriptive E&S proposals received 8.48% less support after 2021. Notably, the coefficient on p_{ijkt} remains statistically indistinguishable from zero across all specifications, suggesting that the decline in voting support is primarily driven by changes in the prescriptiveness of proposals after 2021, rather than any variation in prescriptiveness before the 2021 Guidance.

In the specification shown in column (1), we employ firm fixed effects to control for characteristics that are constant within each firm over time. This approach effectively removes any variation between firms, which might otherwise provide valuable information for evaluating the impact of the 2021 Guidance. In column (2), we adjust the model to include industry fixed effects instead of firm fixed effects, which leads to a notable increase in the magnitude of the $p_{ijkt} \times Post_t$ coefficient, still significant at the 1% level.[40] In columns (3) and (4) of Table 3, the analysis is applied separately to environmental and social proposals, respectively. Both categories show negative and significant $p_{ijkt} \times Post_t$ coefficients at the 1% level, with a more pronounced effect for environmental proposals, which experienced a 19.47% reduction in support, compared to a 5.3% reduction for social proposals. In columns (5) and (6), we explore different variants of the dependent variable as outlined in Table A2. The interaction term's coefficient is slightly attenuated when the dependent variable relates to the percentage of affirmative votes relative to outstanding shares, but remains approximately the same as column (1) when it relates to the percentage of affirmative votes as all votes for and against the proposal.

[38]Further information about these variables can be found in Table A1.

[39]As year-fixed effects are incorporated, the term $Post_t$ becomes perfectly collinear with these fixed effects and is therefore excluded from the specification.

[40]This adjustment suggests that models relying solely on firm fixed effects might yield more conservative estimates, a point we will elaborate on in Section 10.7.

In Table A5, we revisit the specifications from columns (1), (3), and (4) of Table 3, applying corrections for potential selection bias as discussed in Section 10.4. The results show that the key coefficients (specifically, on $p_{ijkt} \times Post_t$) remain consistent with those found in Table 3, suggesting that selection bias based on observable characteristics is unlikely to explain the observed treatment effects. In Table A6, we extend the analysis presented in Table 3 by excluding the small subset of anti-ESG proposals (approximately 7.37% of all proposals in our sample) from the data. The results in Table A6 confirm that our main findings are robust to the exclusion of these proposals.[41]

As discussed in Section 2, the 2021 Guidance could have increased the prescriptiveness of proposals through two distinct mechanisms. First, it may encourage new proponents, who might have been excluded under previous SEC regulations, to submit more prescriptive proposals. Second, it could allow existing proponents, previously constrained by SEC regulations, to better align their proposals with their actual preferences.[42] We investigate the plausibility of both mechanisms sequentially. To examine whether the fall in voting support post-2021 is consistent with the hypothesis that existing proponents are changing their proposals in response to the 2021 Guidance, we modify specification (1) to include proponent fixed effects (as opposed to proponent-type fixed effects), so that all variation is limited to within-proponent variation over time. In a related specification, we also include $pshare_{kt}$, the proportion of prescriptive proposals submitted by each proponent in a given year, to assess whether the decline is driven by an increase in the proportion of prescriptive proposals submitted by existing proponents. Second, to investigate whether the fall in voting support post-2021 is consistent with the hypothesis that new proponents are submitting more prescriptive proposals, which would otherwise have been precluded by the SEC's enforcement policies pre-2021, we modify specification (1) to include an additional binary variable in the interaction term of interest, $p_{ijkt} \times Post_t \times FirstAppearance_n$. We define $FirstAppearance_n$ to take on the value 1 when a new proponent name is first observed for a given proposal, and 0 otherwise.

We report the results of this investigation in Table 4. Column (1) presents the baseline specification from column (1) of Table 3. In column (2), we replace proponent-type fixed effects with proponent fixed effects, eliminating variation between different proponents. Although the coeffi-

[41] We discuss anti-ESG proposals in greater detail in Section 7.3. While anti-ESG proposals are not excluded from our main specifications—given that our primary variable of interest, prescriptiveness, is correlated with such proposals—our results remain robust when anti-ESG proposals are excluded, as shown in Table A6, Table A15, and throughout Section 6.

[42] Broadly, these mechanisms correspond to the "extensive" and "intensive" margins. On the extensive margin, changes in post-2021 support are driven by an increase in the relative proportion of prescriptive proposals, while on the intensive margin, changes are driven by an increase in the intensity of prescriptive proposals submitted by proponents. We address the possibility that existing proponents may submit more prescriptive proposals in Table 4.

cient on the interaction term $p_{ijkt} \times Post_t$ is smaller, it remains negative and statistically significant at the 1% level, indicating that prescriptive E&S proposals received 6.59% less support post-2021 compared to non-prescriptive proposals. In column (3), we substitute firm fixed effects with industry fixed effects, which leads to a larger estimated coefficient for the interaction term. Column (4) incorporates the variable $pshare_{kt}$, and while the coefficient on $p_{ijkt} \times Post_t$ remains similar to that in column (2), the coefficient on $pshare_{kt}$ is not statistically significant.

In columns (5) and (6), we include the binary variable $FirstAppearance_n$, effectively conducting a triple difference-in-difference analysis with firm and industry fixed effects variants. However, the coefficient on the interaction term of interest, $p_{ijkt} \times Post_t \times FirstAppearance_n$, is not statistically different from 0. Collectively, these results suggest that the fall in voting support post-2021 is better aligned with the hypothesis that existing proponents are changing their proposals in response to the 2021 Guidance, even after accounting for the increase in the proportion of prescriptive proposals, as shown in Figure 2.[43] This aligns with Tallarita (2022)'s findings that the shareholder proposal market is dominated by a relatively small number of specialized actors who connect shareholders with pro-social motives with corporate stakeholders, citizens, and social and policy activists.

Our methodology in Section 5.1 codes the level of prescriptiveness as a binary variable. This approach has its advantages, as it allows for comparability between prescriptive proposals identified using both unsupervised and supervised machine learning algorithms. However, to address concerns that the observed treatment effects may be influenced by either the prescriptiveness measures derived from our unsupervised algorithms or a mechanical increase in prescriptive proposals (as shown in Figure 2),[44] we conduct additional analyses in Table A7 using proxies for prescriptiveness determined solely by our supervised machine learning algorithms described in Section 5.1.

In columns (1) and (2) of Table A7, we replicate the analysis from Table 3 using a binary variable for prescriptiveness derived from our supervised algorithm. Columns (3) through (8) extend this approach by treating prescriptiveness as a continuous variable, using the raw probability values generated by the supervised algorithms. Although the results in Table A7 are attenuated compared to those in Table 3, they consistently show a negative relationship between the interaction term of interest, $p_{ijkt} \times Post_t$, and voting support. This reinforces the robustness of our findings

[43]In other words, our results suggest that the changes in voting support are primarily driven by the intensive margin. Indeed, the average proportion of prescriptive proposals has only increased by about 7.5% following the 2021 Guidance.

[44]Note that this aligns with the "extensive margin" hypothesis, where the post-2021 decline in support is attributed to an increase in the relative proportion of prescriptive proposals.

across alternative measures of prescriptiveness.

Finally, to investigate how support for prescriptive proposals has evolved over time in light of the 2021 Guidance, we estimate the coefficients for interaction terms which combine year-specific indicators with a binary variable distinguishing prescriptive from non-prescriptive proposals.[45] These coefficients are visually depicted over time in Figure 4. Panel A of Figure 4 shows the trends for all E&S proposals, while Panels B and C illustrate the trends for environmental and social proposals, respectively. The figure reveals a noticeable decline in the estimated coefficients for all E&S proposals after 2021, with environmental proposals exhibiting a particularly sharp reduction compared to social proposals.

6 Prescriptive Proposals and Investor Characteristics

6.1 Preliminary Observations on Fund-Level Data

As discussed in Section 1, numerous studies have highlighted the significant heterogeneity in shareholder voting behaviors across various funds, especially where E&S issues are concerned (Bolton et al. (2020); Curtis et al. (2021); Bebchuk and Hirst (2019); Bebchuk and Hirst (2022); Griffin (2020); Zytnick (2022)). In light of this, our analysis seeks to explore if certain shareholder groups are influencing the decrease in support for prescriptive proposals detailed in Section 5.2.

However, integrating proposal-level data with fund-level voting information presents significant challenges. Specifically, inconsistencies and gaps in the databases, such as missing entries, necessitate the exclusion of numerous unmatched records during the data merging process. Additionally, voting records are only available for mutual funds subject to N-PX filing requirements under Section 30 of the Investment Company Act of 1940;[46] voting records for pension funds, banks, and retail investors are not subject to these disclosure obligations. Consequently, this results in the exclusion of substantial information from the merged dataset.[47]

Table 5 presents summary statistics for the variables obtained by combining firm-level and fund-

[45] Note that in estimating these coefficients, we include firm-proposal controls, along with fixed effects for firm, year, and the type of proponent. we adopt a baseline year of 2021, corresponding to the year when treatment occurred. The dependent variable relates to the percentage of affirmative votes out of the total votes cast.

[46] See also Sections 13 and 15(d) of the Securities Exchange Act of 1934.

[47] Indeed, this is the primary reason why the analysis in Section 5.2 examines data at the firm-year-proposal level, rather than at the fund-firm-year-proposal level.

level data.[48] The primary dependent variable of interest, "Binary Fund Vote," is a binary indicator that assigns a value of 1 when a specific fund votes in favor of a proposal, and 0 for all other outcomes. In line with Brav et al. (2024), another dependent variable of interest, "Ordered Fund Vote," is introduced as a categorical indicator. This variable is assigned a value of 1 for a "yes" vote, 0.5 for an "abstained" vote, and 0 for all other outcomes. Given that the variables "% of Security Owned by Fund" and "Security as % of Fund's Total Assets" are associated with a larger number of proposals when compared to other independent variables in Table 5 (owing to incomplete records for these other variables), we report regressions using subsets of these variables in some of our subsequent specifications.[49]

For an initial analysis of the relationship between fund voting support and the prescriptiveness of proposals, we estimate panel regressions of the specification:[50]

$$y_{ijktnm} = \alpha + p_{ijktnm}\beta + X_{ijktn}\xi + V_{ijktnm}\delta + \theta_i + \eta_j + \psi_k + \kappa_m + \nu_t + \varepsilon_{ijktnm} \quad (2)$$

where i indexes firms, j indexes industries, k indexes proponent-types[51], m indexes funds, n indexes proposals, X is a vector of firm-proposal controls[52], V is a vector of fund-level controls[53], while θ_i, η_j, ψ_k, κ_m, and ν_t represent firm, industry, proponent-type, fund, and year fixed effects, respectively. Meanwhile, y_{ijktnm} relates to a measure of voting support (e.g., the "Binary Fund Vote" measure described above), while p_{ijktnm} is a measure of prescriptiveness that denotes whether a given proposal is prescriptive or not, in line with Section 5.1.

In column (1) of Table 6, we present outcomes from applying specification (2) across all E&S proposals. The analysis uses the "Binary Fund Vote" as the dependent variable and incorporates fixed effects for both firm and year. Column (2) replicates the column (1) specification with the

[48] Further information about these variables can be found in Table A1.

[49] Specifically, incorporating additional variables leads to a reduced number of observations because of the removal of records with incomplete data for various variable combinations.

[50] We follow Brav et al. (2024) and Brav et al. (2022) in choosing to estimate an Ordinary Least Squares (OLS) regression instead of a probit regression with fixed effects. The OLS specification provides coefficients that are straightforward to interpret as they directly quantify the average change in the dependent variable resulting from a one-unit change in the independent variable. This is unlike in probit models, where the coefficients modify the probability of the outcome through changes in the cumulative distribution function of a standard normal distribution. Furthermore, while OLS estimates do not depend on the normality of errors for estimation purposes under the Gauss-Markov conditions, they are less sensitive to the form of the error distribution compared to probit models, which inherently assume normally distributed errors for the latent variable. Moreover, OLS models are computationally simpler than non-linear models like probit models, facilitating easier implementation.

[51] We do not include a separate index for individual proponents in this specification.

[52] Further information about these variables can be found in Table A1.

[53] Further information about these variables can be found in Table A1. Nonetheless, these variables are explicitly enumerated in Table 6.

substitution of firm fixed effects for industry fixed effects. Column (3) follows the methodology in column (1) but adds proponent-type fixed effects. Column (4) adapts the column (1) specification to include fund fixed effects. Finally, column (5) modifies the column (1) approach by incorporating both fund and proponent-type fixed effects. In column (6), we present results from specification (2) where we preserve the variables "% of Security Owned by Fund" and "Security of % of Fund's Total Assets" as the only fund-level controls, V, while incorporating firm, fund, proponent-type, and year fixed effects. In column (7), the analysis from column (6) is replicated, with the exception that all fund-level controls V are excluded. As is evident in Table 6, the coefficient for prescriptiveness, p_{ijktn}, consistently emerges as negative and statistically significant at the 5% level across a wide range of specifications.[54]

Finally, columns (9) and (10) of Table 6 utilize the "Ordered Fund Vote" as the dependent variable, replacing the "Binary Fund Vote." Column (9) follows the model outlined in column (5), while column (10) adopts the model from column (3). In both columns, the key coefficients, p_{ijktn}, exhibit negative values and are statistically significant at the 1% level. Separately, we observe a negative and statistically significant coefficient on firm ownership (% of security owned by the fund) across all of our specifications. Assuming that concentrated owners have more 'skin in the game' and therefore place a stronger emphasis on pecuniary objectives, our results suggest a tradeoff between the pecuniary and non-pecuniary effects of E&S proposals (Choi (2018)).

6.2 Voting Support after Treatment: Analysis at the Fund Level

Following Section 5.2.2, we analyze the shift in fund-level voting behavior following the 2021 Guidance. To that end, we estimate the specification:

[54]In column (8), we present results where we implement the specification used in column (7), with the key alteration being the inclusion of an "index-fund" variable as the exclusive fund-level control within V. To identify funds as "Index Funds", we begin by harnessing the CRSP mutual fund database classification of funds as an index fund or ETF. To that list, we add funds that include the terms "Index, Idx, Indx, INDEX, Ind, ETF, Russell, S&P (and its variants such as S & P, S and P, SandP, and SP), DOW (and its variants such as Dow and DJ), MSCI, Bloomberg, KBW, NASDAQ, NYSE, FTSE, Wilshire, Morningstar, 100, 400, 500, 600, 900, 1000, 1500, 2000, 3000, or 5000" in their names. In contrast to our results in columns (1) to (7), the coefficient associated with the index fund variable is negative and achieves statistical significance at the 1% level. This suggests that a significant portion of the variability in index-fund voting may be attributed to fund-level factors, such as a fund's expense ratio or its assets. This finding aligns with existing research, which notes that most index funds are linked to large institutional investors known for their very low expense ratios and substantial assets under management (Bebchuk and Hirst (2019); Fisch et al. (2019)).Note that index funds are not the central subject of our study, and this particular specification is included primarily to demonstrate that our findings are not inconsistent with the findings of Brav et al. (2024) and Zytnick (2022). These authors have documented that index funds tend to vote against E&S proposals more frequently compared to other types of funds.

$$y_{ijktnm} = \alpha + p_{ijktnm}\beta + (p_{ijktnm} \times Post_t)\gamma + X_{ijktn}\xi + V_{ijktnm}\delta + \theta_i + \eta_j + \psi_k + \kappa_m + \nu_t + \varepsilon_{ijktnm} \quad (3)$$

where specification (2) is modified so that an additional interaction term, $p_{ijktn} \times Post_t$ is included.[55]

In Table 7, we illustrate our results from implementing specification (3), incorporating fixed effects for industry, proponent-type, and year, with "Binary Fund Vote" as the dependent variable. In column (1), the interaction term $p_{ijktnm} \times Post_t$ shows a negative and statistically significant coefficient at the 1% level, revealing an 10.8% decline in support for prescriptive E&S proposals post-2021 compared to their non-prescriptive counterparts. Conversely, the coefficient for p_{ijktnm} is negative but lacks statistical significance at the 10% level, implying that the variation in prescriptiveness is predominantly associated with proposals post-2021. In column (2), we replace industry fixed effects with firm fixed effects. Here, the coefficient on the interaction term is reduced compared to column (1), indicating an 8.1% decline in support for prescriptive E&S proposals after 2021. However, it remains negative and statistically significant at the 5% level.

Columns (3) and (4) reapply the column (1) specification with varying control sets, while column (5) integrates Inverse Probability of Treatment Weights (IPTWs) into the column (1) specification. The key coefficient on $p_{ijktnm} \times Post_t$ remains negative and statistically significant at the 1% level across these adjustments. In columns (6) and (7), the analysis shifts to an alternate dependent variable, "Ordered Fund Vote," as detailed in Section 6.1. Column (6) adapts the column (1) specification for this new dependent variable, and column (7) follows suit but incorporates IPTWs. The coefficient of interest on the interaction term continues to demonstrate robustness in these varied specifications.

Overall, our results indicate a consistent and significant decline in support for prescriptive E&S proposals post-2021 across multiple specifications and dependent variables. This fund-level analysis aligns with the firm-level results presented in Section 5.2.2, reinforcing the notion that the 2021 Guidance has led to a discernible decline in voting support for such proposals.

[55] As detailed earlier in Section 10.1, $Post_t$ is a binary indicator that denotes whether the proposal occurs post-treatment (i.e., in 2022 or 2023). Furthermore, as year-fixed effects are incorporated, the term $Post_t$ becomes perfectly collinear with these fixed effects and is therefore excluded from the specification.

6.3 Heterogeneity across Funds

To explore the possibility that certain shareholder groups may be driving the observed decrease in support for prescriptive proposals (see Section 5.2), we modify specification (3) to include the additional binary variable, $FundCat_m$, where $FundCat_m$ denotes a certain class of funds in our dataset (e.g., the "Big Three" funds, or ESG-related funds).[56] Accordingly, we estimate the triple DID specification:

$$\begin{aligned} y_{ijktnm} &= \alpha + p_{ijktnm}\beta + FundCat_m\delta \\ &+ (p_{ijktnm} \times Post_t)\epsilon + (p_{ijktnm} \times FundCat_m)\zeta \\ &+ (Post_t \times FundCat_m)\eta + (p_{ijktnm} \times Post_t \times FundCat_m)\theta \\ &+ X_{ijktn}\xi + V_{ijktnm}\iota + \theta_i + \eta_j + \psi_k + \kappa_m + \nu_t + \varepsilon_{ijktnm} \end{aligned} \tag{4}$$

Our triple DID specification aims to estimate the main effect of the treatment driven by the average fund, as well as the marginal effects specific to the particular class of funds in question. Notably, a positive and significant marginal effect does not imply that a particular fund has increased its support for prescriptive E&S proposals post-2021 in absolute terms; rather, it indicates that the fund has increased its voting support relative to the average fund. In Table 8, we present the results of estimating column (2) in specification (3) for ten different subsets of fund categories, including the Big Three funds, Blackrock, active funds, funds sorted by AUM, funds sorted by ownership concentration, ESG funds, and ESG funds associated with E&S families. We find a negative and statistically significant coefficient on the interaction term of interest, $p_{ijktnm} \times Post_t$, for 8 out of the 10 categories at the 1% level.[57]

6.3.1 ESG Funds

We begin our analysis by implementing specification (4) where $FundCat_m$ serves as a binary indicator identifying ESG-related funds and their variants, incorporating fixed effects for industry, proponent-type, and year.[58] ESG funds are of particular interest because they may be associated with pro-social preferences which may dominate pecuniary interests (Bolton et al. (2020);

[56] In this specification, y_{ijktnm} relates to the binary indicator, "Binary Fund Vote".

[57] For the remaining two categories, we find a negative and statistically significant coefficient on the interaction term $p_{ijktnm} \times Post_t$ for ESG funds at the 10% level, while the same interaction term for ESG funds belonging to ES families is negative but not statistically significant.

[58] Pursuant to our analysis in Section 10.7, we do not include firm-fixed effects across all of our specifications in Section 6.3.

Michaely et al. (2021)), raising the question of how they would react to prescriptive E&S proposals. We identify ESG funds similarly to Zytnick (2022), starting with the list of ESG funds provided by Morningstar in 2022, which designates "sustainable funds" based on their incorporation of ESG criteria into investment processes or declaration of sustainability-related objectives in their prospectuses. Additionally, we include funds with names containing "Sustainable," "ESG," "Social," or "Clean Energy," along with funds from five commonly recognized ESG fund families: Calvert, Pax, Parnassus, Trillium, and Praxis. As Michaely et al. (2021) have demonstrated that E&S funds in non-ESG families may oppose E&S proposals when their vote is more likely to be pivotal, we also construct a measure of family E&S preferences based on the average support for E&S proposals at the family level in year $t-1$, following the methodology suggested by these authors.[59]

We report our findings in Table 9. In column (1), we estimate specification (4) where $FundCat_m$ denotes all ESG funds. While the coefficient on the interaction term $p_{ijktnm} \times Post_t$ remains negative and significant at the 1% level, the coefficient on the interaction term of interest, $p_{ijktnm} \times Post_t \times FundCat_m$, is positive and statistically significant at the 5% level. These results suggest that, relative to the average fund in our sample, ESG funds actually increased their support for prescriptive E&S proposals by about 5.4% after the 2021 Guidance. Additionally, the coefficient for $FundCat_m$ is positive and significant at the 1% level, indicating that E&S proposals received approximately 24.5% more voting support from ESG funds compared to non-ESG funds, even when the effects of the 2021 Guidance are not taken into account. This finding aligns with the extensive body of research demonstrating a general tendency for ESG funds to support E&S proposals more than non-ESG funds (Dikolli et al. (2022); Curtis et al. (2021); Bolton et al. (2020); Zytnick (2022)).

The results from column (1) of Table 9 suggest an ideological inclination in shareholder voting behavior on E&S issues. Socially-oriented funds may support more prescriptive E&S proposals even when other funds oppose them. Indeed, Michaely et al. (2021) suggest that ESG funds in non-E&S families are less ideological in their voting behavior, as they must balance incorporating the pro-social stakeholders' interests they advertise while maximizing shareholder value favored by their families. To test this hypothesis, we create binary variables categorizing ESG funds into "non-ES families", who face this tradeoff, and "ES families", who may prioritize pro-social goals over shareholder value maximization.

[59]For each family in each year, we use the mean proportion of votes in favor of ES proposals relative to the total number of votes cast. We then specify fund-families with a below-median level of support as "non-ES" fund families, and fund-families with an above-median level of support as "ES families" (Michaely et al. (2021)).

In column (2), we present results where $FundCat_m$ denotes ESG funds in ES families. Consistent with Michaely et al. (2021), we find that these "ideological" funds are more likely to vote for prescriptive E&S proposals, with the coefficient on the interaction term of interest ($p_{ijktnm} \times Post_t \times FundCat_m$) even higher than in column (1). In column (3), we present results for ESG funds in non-ES families. Unlike columns (1) and (2), we find no evidence that these funds are more likely to vote for prescriptive E&S proposals after the 2021 guidance. Column (4) presents results for ESG funds in five commonly recognized ESG fund families: Calvert, Pax, Parnassus, Trillium, and Praxis. These results are consistent with those in columns (1) and (2), reinforcing our earlier hypothesis concerning fund ideologies. Finally, in columns (5) and (6), we reimplement columns (1) and (2) using an alternate dependent variable, "Ordered Fund Vote," as detailed in Section 6.1. The findings in these columns demonstrate that our results are robust to these variations in the measure of voting support.

In Section 2, we argued that preferences over governance issues were of secondary importance in our analysis. In Table A11, we provide evidence to support this assertion. In column (1) of Table A11, we reimplement the baseline specification from column (1) in Table 9. We then construct a measure of fund-family governance ("G") preferences based on the average support for G proposals at the family level in the previous year, following the methodology outlined earlier for E&S fund families (Michaely et al. (2021)). In columns (2) and (3), we implement the same specification for ESG funds in G families ("anti-management") and non-G families ("pro-management"). Our results show that ESG funds vote consistently across both families, with similar coefficients across all key variables of interest (e.g., ($p_{ijktnm} \times Post_t \times FundCat_m$). In columns (4) and (5), we repeat the analysis using an alternate dependent variable, "Ordered Fund Vote," and obtain similar results. Collectively, our results indicate significant homogeneity in the governance dimension of ESG fund behavior, suggesting that governance preferences are not the primary driver of voting behavior in our dataset.

6.3.2 Big Three and Active Funds

Our findings in Section 6.3.1 suggest that ESG funds do not play a primary role in reducing support for more prescriptive E&S proposals following the 2021 Guidance. Consequently, we first turn our attention to the "Big Three" fund families (Blackrock, Vanguard, and State Street), who are the largest shareholders in many publicly listed firms where E&S proposals are advanced (Dasgupta et al. (2021)).

In column (1) of Table 10, we report the results from specification 4, where $FundCat_m$ denotes a binary indicator for whether a fund belongs to the "Big Three" fund families. The coefficient on the interaction term $p_{ijktnm} \times Post_t$ remains negative and significant at the 1% level, while the coefficient on the interaction term of interest, $p_{ijktnm} \times Post_t \times FundCat_m$, is positive but not statistically significant at the 10% level. These results suggest that, we do not have sufficient evidence to suggest that the Big Three funds behave differently from the average fund with respect to their support of prescriptive proposals. However, unlike ESG funds, the coefficient for $FundCat_m$ is negative and significant at the 1% level, indicating that E&S proposals receive about 23.8% less support from the "Big Three" funds compared to other funds. This aligns with existing literature indicating a tendency for "Big Three" funds to oppose E&S proposals (Bolton et al. (2020); Bubb and Catan (2022); Griffin (2020); Pinnington (2023); Heath et al. (2022)). Indeed, scholars like Bebchuk and Hirst (2019) and Lund (2018) suggest that "Big Three" families often follow a voting strategy aligned with management recommendations (who almost always oppose E&S proposals), primarily because a significant portion of their assets are in low-fee index funds, reducing the incentive to gather firm-specific information.

In column (2) of Table 10, we reimplement the specification from column (1), with $FundCat_m$ as a binary indicator denoting whether a fund belongs to the Blackrock fund family, given their public declarations implying a retreat from backing prescriptive proposals (Blackrock (2022)). Again, we find no evidence that Blackrock has modified their voting support relative to the average fund. While there is evidence that Blackrock has decreased its voting support for prescriptive proposals in absolute terms after the 2021 Guidance, our analysis of the heterogeneity among fund voting behavior suggests that their behavior is similar to that of the average mutual fund. This result is not surprising, as Bolton et al. (2020) suggest that Blackrock and Vanguard hold ideological positions close to the average voter on E&S issues.

Given the positive and significant coefficient on the interaction term of interest ($p_{ijktnm} \times Post_t \times FundCat_m$) for ESG funds in ES families, we hypothesize that "money-conscious" funds, which are ideologically opposed to ESG funds, may be more likely to vote against prescriptive E&S proposals relative to the average fund (Bolton et al. (2020)). Additionally, a substantial body of literature suggests that "active" mutual funds, which make deliberate voting decisions, tend to adopt significantly different voting positions compared to "passive" funds, which comprise most of the "Big Three" fund families (Iliev and Lowry (2015); Brav et al. (2024))

To further investigate this hypothesis, we generate two fund characteristics that we consider as measures of "active'" mutual funds. We construct the first measure, termed "Active (Measure 1)," by following Riley (2021) and Brav et al. (2024). This involves excluding all funds identified by

CRSP as index funds,[60] exchange-traded funds, variable annuity funds, funds whose Lipper codes identify them as following a traditional long-only U.S. equity strategy, and funds with less than 70% of their assets in common equities. We then exclude all such funds in ES families, leaving only "active" funds in non-ES families. For the second measure of "active" mutual funds, we rely on the literature suggesting that such funds earn higher alphas (Iliev and Lowry (2015)). We proxy for this by labeling funds in the highest quintile of expense ratios as "active" and then excluding all such funds in ES families. We term this measure "Active (Measure 2)".

In column (3) of Table 10, we reimplement the specification from column (1), with $FundCat_m$ as a binary indicator denoting whether a fund is labeled as "Active (Measure 1)". As in columns (1) and (2), the coefficient on the interaction term $p_{ijktnm} \times Post_t$ remains negative and significant at the 1% level. However, the coefficient on the interaction term of interest, $p_{ijktnm} \times Post_t \times FundCat_m$, is negative and statistically significant at the 1% level. These results suggest that, relative to the average fund in our sample, active funds decreased their support for prescriptive E&S proposals by about 5.8% after the 2021 Guidance–in stark contrast to the results reported in Table 9. In column (4), we implement a similar specification, using $FundCat_m$ as a binary indicator for our "Active (Measure 2)" measure. We find similar results to those in column (3), showing that active funds decreased their support for prescriptive E&S proposals by about 4.7% after the 2021 Guidance. Lastly, in columns (5) to (8), we replicate the analyses from columns (1) to (4) utilizing an alternative dependent variable, "Ordered Fund Vote", as described in Section 6.1. The results in these columns confirm that our findings are robust across different measures of voting support.

7 Political Backlash

To establish the causal impact of the 2021 Guidance, the regulatory shock's effect on voting outcomes must exclusively occur through its influence on the prescriptiveness of shareholder proposals. This means that the regulatory shock should not directly impact voting outcomes or affect them through routes unrelated to the prescriptiveness of the proposals (see Section 5.2.2). However, recent work by several scholars has suggested an alternative explanation for the decline in voting outcomes—"political backlash" (Garrett and Ivanov (2024); Zhang (2024); Tang et al. (2024); Padfield (2022)). As Curtis (2024) notes, "more than twenty states have adopted at least some type of anti-ESG measure, flows into ESG funds are [ostensibly] declining, and the

[60]This includes funds which include the terms "Index, Idx, Indx, INDEX, Ind (where indicates a space), ETF, Russell, S&P (and its variants such as S & P, S and P, SandP, and SP), DOW (and its variants such as Dow and DJ), MSCI, Bloomberg, KBW, NASDAQ, NYSE, FTSE, Wilshire, Morningstar, 100, 400, 500, 600, 900, 1000, 1500, 2000, 3000, or 5000" in their names.

performance of many ESG funds lagged the broader market in 2022." While the exact source of this backlash remains unclear, we acknowledge that political mechanisms could account for the observed decline in voting outcomes for E&S proposals, potentially violating our identification strategies employed in earlier sections.

7.1 Big Three Fund-Families

To address concerns related to political backlash, we first note that our results in Table 10 may not align with this narrative. As Bebchuk and Hirst (2022) have highlighted, the Big Three fund families ("Big Three") have a vested interest in minimizing the risk of public and political backlash, especially considering historical instances where similar concentrations of financial power have incited such responses. Bebchuk and Hirst (2022) further observe that the Big Three are likely to mitigate these risks by adopting a deferential stance towards corporate managers.

Under a counterfactual scenario where political mechanisms predominantly drive down voting support for E&S proposals, we would expect a strong negative association between support for E&S proposals and the Big Three fund families after 2021, irrespective of whether the E&S proposals are prescriptive. However, columns (1) and (5) of Table 10 show that the coefficients on the interaction terms $Post_t \times FundCat_m$ and $p_{ijktnm} \times Post_t \times FundCat_m$ are statistically insignificant. In other words, we find no evidence of the Big Three modifying their voting behavior in response to the hypothesized political backlash.

7.2 ESG Fund Flows

To further address concerns that our results might be influenced by political backlash, we follow Curtis (2024) in assessing whether ESG funds are experiencing lower fund flows compared to conventional funds after 2021. If political mechanisms were indeed driving the decline in voting support for E&S proposals, we would expect to see a corresponding decrease in flows to ESG funds relative to non-ESG funds post-2021.

We measure fund flows according to the standard definitions in the literature (Sirri and Tufano (1998); Ferreira et al. (2012)), where the fund flow for fund i in month t is calculated as:

$$Flow_{i,t} = \frac{(Assets_{i,t} - Assets_{i,t-1})(1 + Return_{i,t})}{Assets_{i,t-1}}$$

The monthly net assets and returns of funds are obtained from CRSP. Subsequently, we estimate the DID specification:

$$Flow_{it} = \alpha + (ESG_i \times Post_t)\beta + X_{it}\xi + \theta_i + \nu_t + \varepsilon_{it} \tag{5}$$

where i indexes funds, X is a vector of fund-level controls,[61] and θ_i and ν_t represent fund and month fixed effects, respectively. We define ESG_i as a binary indicator denoting whether a fund is classified as an ESG fund in accordance with Section 6.3.1, and $Post_t$ as a binary indicator which is 1 for periods after November 2021 and 0 otherwise.

We report the results of specification 5 in Table A12. As shown in the table, all coefficients for the interaction term of interest, $ESG_i \times Post_t$, are positive but not statistically significant at the 10% level. This finding contrasts with a "political backlash" hypothesis, which would predict a decrease in flows to ESG funds post-2021, indicated by a negative and statistically significant coefficient on these terms.

To reinforce our results in Table A12, we apply the triple DID specification outlined in Section 6.3 to the subset of ESG fund votes, with $FundCat_m$ as the variable of interest. In this context, $FundCat_m$ identifies ESG funds in the lowest decile, quintile, or quartile of fund flows.[62] Specifically, we examine how the 2021 Guidance influenced voting behavior on prescriptive proposals among ESG funds with the largest negative outflows. The coefficient of interest, $p_{ijktnm} \times Post_t \times FundCat_m$, measures how these funds voted on prescriptive proposals relative to the average ESG fund in our sample.

We present our findings in Table A13. While funds with significant negative outflows show lower voting support for prescriptive E&S proposals,[63] we do not find statistically significant effects for the coefficient of interest, $p_{ijktnm} \times Post_t \times FundCat_m$.[64] These findings suggest that ESG funds with the largest negative outflows may not have voted differently from the average ESG fund post-2021–further challenging the "political backlash" hypothesis, which posits that such funds would reduce their support for prescriptive E&S proposals relative to funds with smaller outflows.

[61]Further information about these variables can be found in Table A1.

[62]Since fund flows can be negative, the lowest decile, quintile, or quartile corresponds to funds with the largest negative outflows.

[63]This aligns with the idea that negative fund flows may act as a mechanism encouraging fund managers to adopt a more "money-conscious" voting approach (Li et al. (2022)).

[64]We also find no statistically significant effect for $p_{ijktnm} \times Post_t$, consistent with our earlier results in Table 9 indicating that some ESG funds support prescriptive proposals.

7.3 Anti-ESG Proposals

Finally, to address concerns that political mechanisms may be driving the observed decline in voting outcomes for E&S proposals in our main analysis, we highlight the strong association between political backlash and the increase in "anti-ESG" proposals. As noted by Welsh (2023), anti-ESG proponents often share political ideologies with politicians who have attempted to pass state laws rejecting ESG considerations in the investment process.

Anti-ESG proposals are led by proponents who urge companies to "stop doing things". These anti-ESG advocates aim to "roll back the clock to a mid-20th century world where businesses operated with little consideration of their social and environmental impacts", although "anti-ESG ideas have gained little recent traction with investors at large" (Welsh (2023)). Nevertheless, the potential impact of anti-ESG proposals on the observed decrease in support for E&S proposals cannot be overlooked, as the number of such proposals has more than doubled in the past three years, rising from 30 in 2021 to 79 in 2023.[65]

We define anti-ESG proposals according to the classification provided by Welsh (2023). Specifically, we classify all proposals made by the "National Center for Public Policy Research", the "National Legal and Policy Center", "Inspire Investing LLC", the "Bahnsen Family Trust", the "American Conservative Values ETF", and "Steve J. Milloy" as anti-ESG proposals. In Table A14, we present some summary statistics for anti-ESG proposals that proceed to a vote. Although the total number of anti-ESG proposals is relatively small—comprising only 7.37% of the total sample—there is a slightly higher proportion of prescriptive proposals that are anti-ESG proposals compared to non-prescriptive ones (9.70% vs 5.77%). Furthermore, 53.6% of all anti-ESG proposals are prescriptive. These observations prompt a closer examination of whether such anti-ESG proposals have contributed to the reduced voting support for E&S proposals after the 2021 Guidance.

To investigate whether anti-ESG proposals have impacted voting support for E&S proposals post-2021, we estimate a modification of specification (1), where the variable p_{ijktn} is replaced with a binary indicator $antiesg_{ijktn}$, which denotes whether a proposal is defined as an anti-ESG proposal. We present our findings in Table A15, using different variants of our estimated specification with varying fixed effects, IPTW weights, and measures of voting support. While the coefficient on $antiesg_{ijktn}$ is negative and statistically significant at the 1% level across all specifications—indicating a general lack of support for such proposals—the coefficient on the interaction

[65] Unlike the results reported in Table A14, these proposals include proposals which are excluded by the SEC and do not proceed to a vote.

term $antiesg_{ijktn} \times Post_t$ is negative but not statistically significant at the 10% level. This suggests that anti-ESG proposals are not driving the observed decline in voting support post-2021, contrary to the "political backlash" hypothesis, which would predict negative and statistically significant coefficients on these terms.

8 Conclusion

In this Article, we explore the significant reduction in shareholder support for E&S proposals post-2021, a trend that reverses the dramatic surge in shareholder support for E&S proposals from 2016 to 2021. Our research unveils novel evidence linking this decline to a change in the SEC's interpretation of Rule 14a-8 in 2021, which effectively allowed shareholders to submit more "prescriptive" E&S proposals. Due to the challenge of directly quantifying a proposal's prescriptiveness, we employ a combination of supervised and unsupervised machine learning techniques within Natural Language Processing (NLP) to determine the prescriptive nature of these proposals.

Our findings reveal that prescriptive proposals are less favored by voters, receiving approximately 3.75% to 5.38% less support compared to their non-prescriptive counterparts. This gap in support widened significantly following the 2021 Guidance, with a reduction in voting support ranging from about 6.60% to 8.50%. While we observe a decline in support for prescriptive proposals among various types of institutional shareholders, there is considerable heterogeneity in their willingness to back these proposals. Specifically, funds with more intense preferences for E&S issues are more likely to support prescriptive proposals, while those on the opposite end of this spectrum are more likely to oppose them. Our results are robust to multiple tests investigating whether the decline in support may be attributed to a "political backlash" hypothesis, where political mechanisms could account for the decline in voting outcomes for E&S proposals.

More broadly, our results support the argument that many institutional investors do not "walk the talk" when E&S issues conflict with pecuniary maximization objectives (Goshen and Hamdani (2023); Michaely et al. (2021); Heath et al. (2021)). While much emphasis has been placed on the importance of pro-social preferences in addressing environmental and social externalities (Hart and Zingales (2017); Hart and Zingales (2022); Broccardo et al. (2022); Barber et al. (2021); Hirst et al. (2023); Hart et al. (2024)), we reveal that for the vast majority of funds, the financial costs of prescriptive proposals often outweigh the intensity of their E&S preferences.

Finally, our findings are also consistent with existing literature that associates prescriptive proposals with indirect decreases in firm value through increased distraction costs (Matsusaka et al. (2021)) or direct decreases in the same when supported by uninformed shareholders (Gantchev and Giannetti (2021)). However, further investigation is necessary to fully understand the implications of prescriptive proposals on firm specific outcomes like valuation, profitability, or E&S-related risks (He et al. (2023)).

9 Bibliography

Admati, A. R. and Pfleiderer, P. (2009). The "wall street walk" and shareholder activism: Exit as a form of voice. *The Review of Financial Studies*, 22(7):2645–2685. 2

Andreoni, J. (1990). Impure altruism and donations to public goods: A theory of warm-glow giving. *Economic Journal*, 100(41):464–477. 2

Andrikogiannopoulou, A., Krueger, P., Mitali, S. F., and Papakonstantinou, F. (2022). Discretionary information in esg investing: A text analysis of mutual fund prospectuses. *Available at SSRN 4082263*. 7

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., and Wager, S. (2021). Synthetic difference-in-differences. *American Economic Review*, 111(12):4088–4118. 14, 58, 59, 76

Bai, J. (2009). Panel data models with interactive fixed effects. *Econometrica*, 77(4):1229–1279. 73

Bainbridge, S. M. (2016). Revitalizing sec rule 14a-8's ordinary business exclusion: Preventing shareholder micromanagement by proposal. *Fordham L. Rev.*, 85:705. 7, 9, 15, 61

Balogh, A. and Yonker, S. E. (2024). Is there a business case for racial diversity on corporate boards? *Available at SSRN*. 59

Barber, B. M., Morse, A., and Yasuda, A. (2021). Impact investing. *Journal of Financial Economics*, 139:162–185. 2, 5, 8, 34

Bebchuk, L. (2005). The case for increasing shareholder power. *Harvard Law Review*, 118:833–914. 8

Bebchuk, L. and Hirst, S. (2019). Index funds and the future of corporate governance: Theory, evidence, and policy. 119:2029. 3, 22, 24, 29

Bebchuk, L. and Hirst, S. (2022). Big three power, and why it matters. *BUL Rev.*, 102:1547. 3, 22, 31

Bebchuk, L. A., Brav, A., Jiang, W., and Keusch, T. (2020). Dancing with activists. *Journal of Financial Economics*, 137(1):1–41. 7, 11, 68, 69

Blackrock, I. S. T. (2022). 2022 climate-related shareholder proposals more prescriptive than 2021. https://www.wsj.com/articles/investors-put-forward-more-proposals-dialing-up-pressure-on-companies-11659432601. Accessed: 2024-03-01. 3, 6, 10, 11, 16, 29

Blair, M. M. and Stout, L. A. (1999). A team production theory of corporate law. *Virginia Law Review*, pages 247–328. 8

Bolton, P. and Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of financial economics*, 142(2):517–549. 2

Bolton, P. and Kacperczyk, M. (2023). Global pricing of carbon-transition risk. *The Journal of Finance*, 78(6):3677–3754. 2

Bolton, P., Li, T., Ravina, E., and Rosenthal, H. (2020). Investor ideology. *Journal of Financial Economics*, 137(2):320–352. 3, 5, 7, 8, 9, 18, 22, 26, 27, 29

Bolton, P., Ravina, E., Rosenthal, H., and Tausanovitch, C. (2023). The real effects of esg investment. In *Proceedings of the ASSA Annual Meeting 2023*. 18

Brav, A., Cain, M., and Zytnick, J. (2022). Retail shareholder participation in the proxy process: Monitoring, engagement, and voting. *Journal of Financial Economics*, 144(2):492–522. 2, 7, 12, 23

Brav, A., Jiang, W., Li, T., and Pinnington, J. (2024). Shareholder monitoring through voting: New evidence from proxy contests. *The Review of Financial Studies*, 37(2):591–638. 7, 9, 12, 23, 24, 29, 68, 70

Briscoe-Tran, H. (2023). Do employees have useful information about firms' esg practices? *Fisher College of Business Working Paper*, (2021-03):21. 7

Broccardo, E., Hart, O., and Zingales, L. (2022). Exit versus voice. *Journal of Political Economy*, 130(12):3101–3145. 2, 5, 8, 34

Bubb, R. and Catan, E. M. (2022). The party structure of mutual funds. *The Review of Financial Studies*, 35(6):2839–2878. 7, 29

Choi, A. H. (2018). Concentrated ownership and long-term shareholder value. *Harv. Bus. L. Rev.*, 8:53. 24

Clarke, C. and Hansmann, H. (2022). Between public and private enterprise: The role and structure of special-purpose governments. *Available at SSRN 4230601*. 9

Cuñat, V., Gine, M., and Guadalupe, M. (2012). The vote is cast: The effect of corporate governance on shareholder value. *The journal of finance*, 67(5):1943–1977. 7, 11

Curtis, Q. (2024). The esg backlash and the demand for esg mutual funds. Working paper. 30, 31

Curtis, Q., Fisch, J., and Robertson, A. Z. (2021). Do esg mutual funds deliver on their promises? *Mich. L. Rev.*, 120:393. 3, 7, 8, 22, 27

Dasgupta, A., Fos, V., and Sautner, Z. (2021). Institutional investors and corporate governance. *Foundations and Trends in Finance, forthcoming, European Corporate Governance Institute–Finance Working Paper*, 700:2020. 28

Dikolli, S. S., Frank, M. M., Guo, Z. M., and Lynch, L. J. (2022). Walk the talk: Esg mutual fund voting on shareholder proposals. *Review of Accounting Studies*, 27(3):864–896. 8, 27

Egami, N., Fong, C. J., Grimmer, J., Roberts, M. E., and Stewart, B. M. (2022). How to make causal inferences using texts. *Science Advances*, 8(42):eabg2652. 6

Era, A., Maia, G., and Scott, L. (2021). Sec's new approach to no-action requests for shareholder esg proposals. https://corpgov.law.harvard.edu/2021/12/04/secs-new-approach-to-no-action-requests-for-shareholder-esg-proposals/. Accessed: 2024-03-01. 10, 16, 69

Ferreira, M. A., Keswani, A., Miguel, A. F., and Ramos, S. B. (2012). The flow-performance relationship around the world. *Journal of Banking & Finance*, 36(6):1759–1780. 31

Fisch, J., Hamdani, A., and Solomon, S. D. (2019). The new titans of wall street: A theoretical framework for passive investors. *University of Pennsylvania Law Review*, pages 17–72. 24

Fisch, J. E. and Robertson, A. (2023). Shareholder proposals and the debate over sustainability disclosure. *U of Penn, Inst for Law & Econ Research Paper*, (23-29). 6

Frankenreiter, J., Hwang, C., Nili, Y., and Talley, E. (2021). Cleaning corporate governance. *U. Pa. L. Rev.*, 170:1. 7

Gantchev, N. and Giannetti, M. (2021). The costs and benefits of shareholder democracy: Gadflies and low-cost activism. *The Review of Financial Studies*, 34(12):5629–5675. 6, 7, 9, 11, 35, 71

Garrett, D. and Ivanov, I. (2024). Gas, guns, and governments: Financial costs of anti-esg policies. *Jacobs Levy Equity Management Center for Quantitative Financial Research Paper*. 30

Gibson-Dunn (2022). Client alert: Shareholder proposal developments during the 2022 proxy season. https://www.gibsondunn.com/wp-content/uploads/2022/07/shareholder-proposal-developments-during-the-2022-proxy-season.pdf. Accessed: 2024-03-01. 3, 4, 6, 11, 14, 16, 58

Gibson-Dunn (2023). Client alert: Shareholder proposal developments during the 2023 proxy season. https://www.gibsondunn.com/wp-content/uploads/2023/07/shareholder-proposal-developments-during-the-2023-proxy-season.pdf. Accessed: 2024-03-01. 3, 4, 6, 11, 14, 16, 58

Gompers, P., Ishii, J., and Metrick, A. (2003). Corporate governance and equity prices. *The quarterly journal of economics*, 118(1):107–156. 7

Goshen, Z. and Hamdani, A. (2023). Will systematic stewardship save the planet? *Available at SSRN 4605549*. 5, 34

Griffin, C. N. (2020). Environmental & social voting at index funds. *Del. J. Corp. L.*, 44:167. 3, 22, 29

Grootendorst, M. (2022). Bertopic: Neural topic modeling with a class-based tf-idf procedure. *arXiv preprint arXiv:2203.05794*. 4, 16, 65

Hansmann, H. (1996). *The ownership of enterprise*. Harvard University Press. 8

Hart, O., Thesmar, D., and Zingales, L. (2024). Private sanctions. *Economic Policy*, pages 203–268. 2, 5, 8, 34

Hart, O. and Zingales, L. (2017). Companies should maximize shareholder welfare not market value. *Journal of Law, Finance, and Accounting*, 2(2):247–275. 2, 5, 8, 34

Hart, O. and Zingales, L. (2022). The new corporate governance. *The University of Chicago Business Law Review*, 1(1):7. 5, 8, 34

He, Y. E., Kahraman, B., and Lowry, M. (2023). Es risks and shareholder voice. *The Review of Financial Studies*, 36(12):4824–4863. 2, 7, 8, 11, 13, 35

Heath, D., Macciocchi, D., Michaely, R., and Ringgenberg, M. C. (2021). Does socially responsible investing change firm behavior? *Available at SSRN 3837706*. 5, 34

Heath, D., Macciocchi, D., Michaely, R., and Ringgenberg, M. C. (2022). Do index funds monitor? *The Review of Financial Studies*, 35(1):91–131. 29

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*, pages 153–161. 68

Hirst, S., Kastiel, K., and Kricheli-Katz, T. (2023). How much do investors care about social responsibility. *Wisconsin Law Review*, 2023:977–1039. 2, 5, 8, 34

Hu, E., Malenko, N., and Zytnick, J. (2024). Custom proxy voting advice. *Available at SSRN*. 7

Ilhan, E., Krueger, P., Sautner, Z., and Starks, L. T. (2023). Climate risk disclosure and institutional investors. *The Review of Financial Studies*, 36(7):2617–2650. 2

Ilhan, E., Sautner, Z., and Vilkov, G. (2021). Carbon tail risk. *The Review of Financial Studies*, 34(3):1540–1571. 2

Iliev, P. and Lowry, M. (2015). Are mutual funds active voters? *The Review of Financial Studies*, 28(2):446–485. 7, 11, 29, 30

Iliev, P. and Vitanova, S. (2022). Investors' voting preferences. *Available at SSRN 4082127*. 7

Jiang, A. Q., Sablayrolles, A., Mensch, A., Bamford, C., Chaplot, D. S., Casas, D. d. l., Bressand, F., Lengyel, G., Lample, G., Saulnier, L., et al. (2023). Mistral 7b. *arXiv preprint arXiv:2310.06825*. 65

Joffe, M. M., Ten Have, T. R., Feldman, H. I., and Kimmel, S. E. (2004). Model selection, confounder control, and marginal structural models: review and new applications. *The American Statistician*, 58(4):272–279. 70

Joseph, V. R. (2022). Optimal ratio for data splitting. *Statistical Analysis and Data Mining: The ASA Data Science Journal*, 15(4):531–538. 61

Kastiel, K. and Nili, Y. (2020). The giant shadow of corporate gadflies. *S. Cal. L. Rev.*, 94:569. 9

Krueger, P., Sautner, Z., and Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, 33(3):1067–1111. 2

Lan, L. L. and Lim, E. (2024). Contextualising esg funds' engagement strategies in asia. *European Corporate Governance Institute-Law Working Paper*, (807). 8

Li, K., Mai, F., Wong, G., Yang, C., and Zhang, T. (2023a). Female equity analysts and corporate environmental and social performance. *Available at SSRN 4154013*. 7, 16

Li, S. Z., Maug, E., and Schwartz-Ziv, M. (2022). When shareholders disagree: Trading after shareholder meetings. *The Review of Financial Studies*, 35(4):1813–1867. 2, 32

Li, T., Naaraayanan, S. L., and Sachdeva, K. (2023b). Conflicting objectives of esg funds: Evidence from proxy voting. *Available at SSRN 3760753*. 5, 7

Liu, Y. and Lapata, M. (2019). Text summarization with pretrained encoders. *arXiv preprint arXiv:1908.08345*. 4, 15, 61

Lund, D. S. (2018). The case against passive shareholder voting. *Journal of Corporation Law*, 43(3). 29

Matsusaka, J. G., Ozbas, O., and Yi, I. (2019). Opportunistic proposals by union shareholders. *The Review of Financial Studies*, 32(8):3215–3265. 7

Matsusaka, J. G., Ozbas, O., and Yi, I. (2021). Can shareholder proposals hurt shareholders? evidence from securities and exchange commission no-action-letter decisions. *The Journal of Law and Economics*, 64(1):107–152. 7, 8, 15, 35, 71

Matvos, G. and Ostrovsky, M. (2010). Heterogeneity and peer effects in mutual fund proxy voting. *Journal of Financial Economics*, 98(1):90–112. 7, 71

Meirowitz, A., Pi, S., and Ringgenberg, M. C. (2023). Voting for socially responsible corporate policies. *Available at SSRN 4057792*. 9

Michaely, R., Ordonez-Calafi, G., and Rubio, S. (2021). Mutual funds' strategic voting on environmental and social issues. *European Corporate Governance Institute–Finance Working Paper*, (774). 5, 7, 8, 27, 28, 34

Michaely, R., Rubio, S., and Yi, I. (2023). Voting rationales. *Available at SSRN 4521854*. 7, 15, 61

Morgan, L. (2024). Reality catches up with the anti-shareholder narrative. *Harvard Law School Forum on Corporate Governance*. Accessed: 2024-07-22. 3, 6

Moskalev, A. (2019). Funds of a feather: Influencing corporate elections by voting together. *Job Market Paper*. 70

Mueller, D. C. (2003). *Public choice III*. Cambridge University Press. 9

Padfield, S. J. (2022). An introduction to anti-esg legislation. *Transactions: Tenn. J. Bus. L.*, 24:291. 30

Pinnington, J. (2023). Are passive investors biased voters? *Available at SSRN 4396879*. 29

Porta, R. L., Lopez-de Silanes, F., Shleifer, A., and Vishny, R. W. (1998). Law and finance. *Journal of political economy*, 106(6):1113–1155. 7

Posner, C. (2022). More prescriptive proposals, less support for 2022 proxy season. https://corpgov.law.harvard.edu/2022/08/22/more-prescriptive-proposals-less-support-for-2022-proxy-season/. Accessed: 2024-03-01. 3, 6, 11, 16

Rajan, R., Ramella, P., and Zingales, L. (2023). What purpose do corporations purport? evidence from letters to shareholders. Technical report, National Bureau of Economic Research. 7, 15, 61

Rambachan, A. and Roth, J. (2023). A more credible approach to parallel trends. *Review of Economic Studies*, 90(5):2555–2591. 58

Riley, T. B. (2021). Portfolios of actively managed mutual funds. *Financial Review*, 56(2):205–230. 29

Rosenbaum, P. R. (1987). Model-based direct adjustment. *Journal of the American statistical Association*, 82(398):387–394. 69

SEC (2017). Shareholder proposals: Staff legal bulletin no. 14i (cf); no. 14j (cf), no. 14k (cf). https://www.sec.gov/corpfin/staff-legal-bulletin-14i-shareholder-proposals?; https://www.sec.gov/corpfin/staff-legal-bulletin-14j-shareholder-proposals.htm?; https://www.sec.gov/corpfin/staff-legal-bulletin-14k-shareholder-proposals? Accessed: 2024-03-01. 10

SEC (2021). Shareholder proposals: Staff legal bulletin no. 14l (cf). https://www.sec.gov/corpfin/staff-legal-bulletin-14l-shareholder-proposals? Accessed: 2024-03-01. 3, 10

Sirri, E. R. and Tufano, P. (1998). Costly search and mutual fund flows. *The journal of finance*, 53(5):1589–1622. 31

Spamann, H. (2010). The "antidirector rights index" revisited. *The Review of Financial Studies*, 23(2):467–486. 7

Tallarita, R. (2022). Stockholder politics. *Hastings LJ*, 73:1697. 2, 4, 6, 8, 9, 10, 11, 14, 15, 18, 21, 58, 73

Tang, O., Shi, X., and Jiu, L. (2024). Value creation or political trick? an event study on anti-esg regulations. *Finance Research Letters*, 65:105530. 30

Tjio, H. (2023). Sustainable directors' duties and reasonable shareholders. *European Business Organization Law Review*, pages 1–25. 8

Welsh, H. (2023). Anti-esg shareholder proposals in 2023. https://corpgov.law.harvard.edu/2023/06/01/anti-esg-shareholder-proposals-in-2023/. Accessed: 2024-06-29. 33

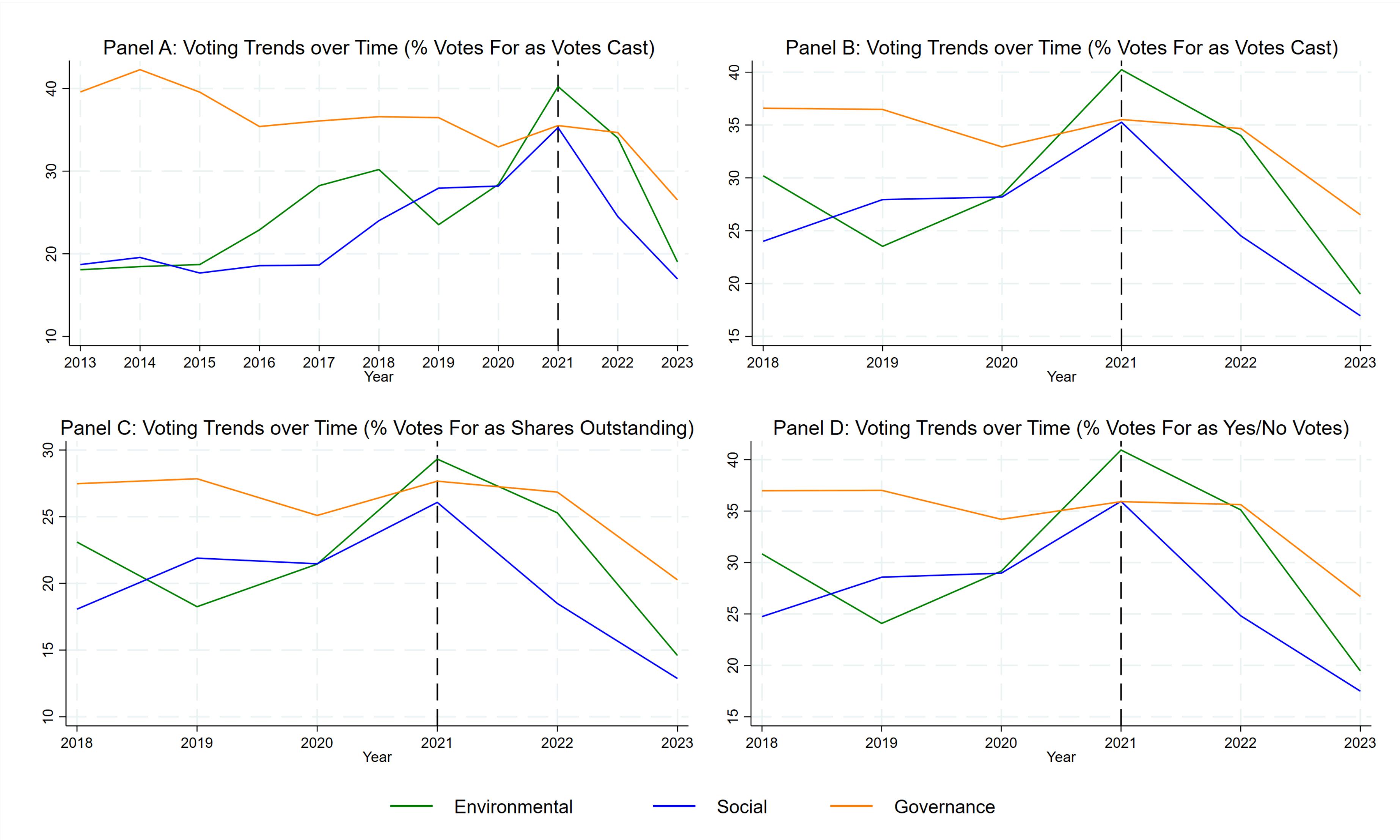
WSJ, J. W.-A. (2022). Investors put forward more proposals, dialing up pressure on companies. https://www.wsj.com/articles/

investors-put-forward-more-proposals-dialing-up-pressure-on-companies-11659432601. Accessed: 2024-03-01. 3, 6, 11, 16

Zhang, J. D. (2024). How anti-esg pressure affects investment: Evidence from retirement savings. 30

Zytnick, J. (2022). Do mutual funds represent individual investors? *NYU Law and Economics Research Paper*, (21-04). 3, 8, 9, 11, 22, 24, 27, 68, 72

Figure 1: Average Voting Support over Time (E&S Proposals)



Note: This figure displays the trends over time in voting support for shareholder proposals on environmental (depicted in green) and social (in blue) issues. Panel A charts the support for these proposals from 2013 to 2023, quantified by the proportion of affirmative votes out of the total votes cast. Panel B mirrors Panel A but focuses on the period from 2018 to 2023. Panel C offers a comparative view for the years 2018 to 2023, but measures voting support differently, using the percentage of affirmative votes out of all outstanding shares. Lastly, Panel D, akin to Panels B and C, illustrates voting support for the same timeframe but determines it as the percentage of affirmative votes out of the total of affirmative and negative votes.

Table 1: Summary Statistics: Firm-Proposal Level Data

	Proxy Category			
	Environmental (N=463)	**Governance (N=2,182)**	**Social (N=1,398)**	**Total (N=4,043)**
Votes For As % Votes Cast	28.33 (21.26)	34.00 (21.48)	25.06 (17.41)	30.54 (20.64)
Votes For As % Shares Out	21.33 (16.00)	26.03 (16.89)	18.99 (13.41)	23.28 (16.08)
Votes For As % Yes & No	29.04 (21.92)	34.64 (21.97)	25.65 (17.77)	31.17 (21.10)
Log Mkvalt	10.91 (1.71)	10.34 (1.98)	11.36 (1.71)	10.76 (1.92)
Tobin's Q	2.11 (1.66)	2.50 (2.33)	2.95 (2.26)	2.61 (2.25)
RoA	0.12 (0.08)	0.12 (0.11)	0.14 (0.10)	0.13 (0.10)
Leverage Ratio	-2.75 (107.94)	1.63 (26.11)	0.32 (15.76)	0.68 (42.25)
Firm Size	11.06 (1.85)	10.38 (2.01)	11.11 (1.70)	10.71 (1.93)
HHI	0.26 (0.25)	0.29 (0.25)	0.32 (0.27)	0.30 (0.26)
Inst Own	0.66 (0.21)	0.71 (0.19)	0.66 (0.19)	0.69 (0.20)
Inst HHI	0.04 (0.03)	0.04 (0.03)	0.04 (0.02)	0.04 (0.03)
Proxy Subcategory				
Board Related	0 (0.0%)	508 (23.3%)	0 (0.0%)	508 (12.6%)
Capital Stock	0 (0.0%)	2 (0.1%)	0 (0.0%)	2 (0.0%)
Environmental Issues	463 (100.0%)	0 (0.0%)	0 (0.0%)	463 (11.5%)
Executive Compensation Related	0 (0.0%)	288 (13.2%)	0 (0.0%)	288 (7.1%)
Fund Related	0 (0.0%)	1 (0.0%)	0 (0.0%)	1 (0.0%)
Miscellaneous	0 (0.0%)	37 (1.7%)	0 (0.0%)	37 (0.9%)
Miscellaneous Corporate Governance	0 (0.0%)	196 (9.0%)	0 (0.0%)	196 (4.8%)
Proxy Fight Specific	0 (0.0%)	34 (1.6%)	0 (0.0%)	34 (0.8%)
Shareholder Rights/Takeover Defense	0 (0.0%)	1,083 (49.6%)	0 (0.0%)	1,083 (26.8%)
Social Issues Related	0 (0.0%)	0 (0.0%)	1,398 (100.0%)	1,398 (34.6%)
Value Maximization	0 (0.0%)	33 (1.5%)	0 (0.0%)	33 (0.8%)
Proponent Type Description				
Misc	52 (11.2%)	148 (6.8%)	114 (8.2%)	314 (7.8%)
Corporation	0 (0.0%)	2 (0.1%)	0 (0.0%)	2 (0.0%)
Hedge Fund Company	6 (1.3%)	29 (1.3%)	5 (0.4%)	40 (1.0%)
Individual	97 (21.0%)	1,472 (67.5%)	298 (21.3%)	1,867 (46.2%)
Investment Adviser	63 (13.6%)	36 (1.6%)	101 (7.2%)	200 (4.9%)
Labor Union	9 (1.9%)	103 (4.7%)	104 (7.4%)	216 (5.3%)
Mutual Fund Manager	3 (0.6%)	1 (0.0%)	11 (0.8%)	15 (0.4%)
Other Institutions	11 (2.4%)	32 (1.5%)	85 (6.1%)	128 (3.2%)
Other Stake Holders	141 (30.5%)	193 (8.8%)	364 (26.0%)	698 (17.3%)
Public Pension Fund	32 (6.9%)	130 (6.0%)	153 (10.9%)	315 (7.8%)
Religious Groups	49 (10.6%)	36 (1.6%)	163 (11.7%)	248 (6.1%)
Has No Action Letter Sought				
No	272 (58.7%)	1,524 (69.8%)	913 (65.3%)	2,709 (67.0%)
Yes	191 (41.3%)	658 (30.2%)	485 (34.7%)	1,334 (33.0%)

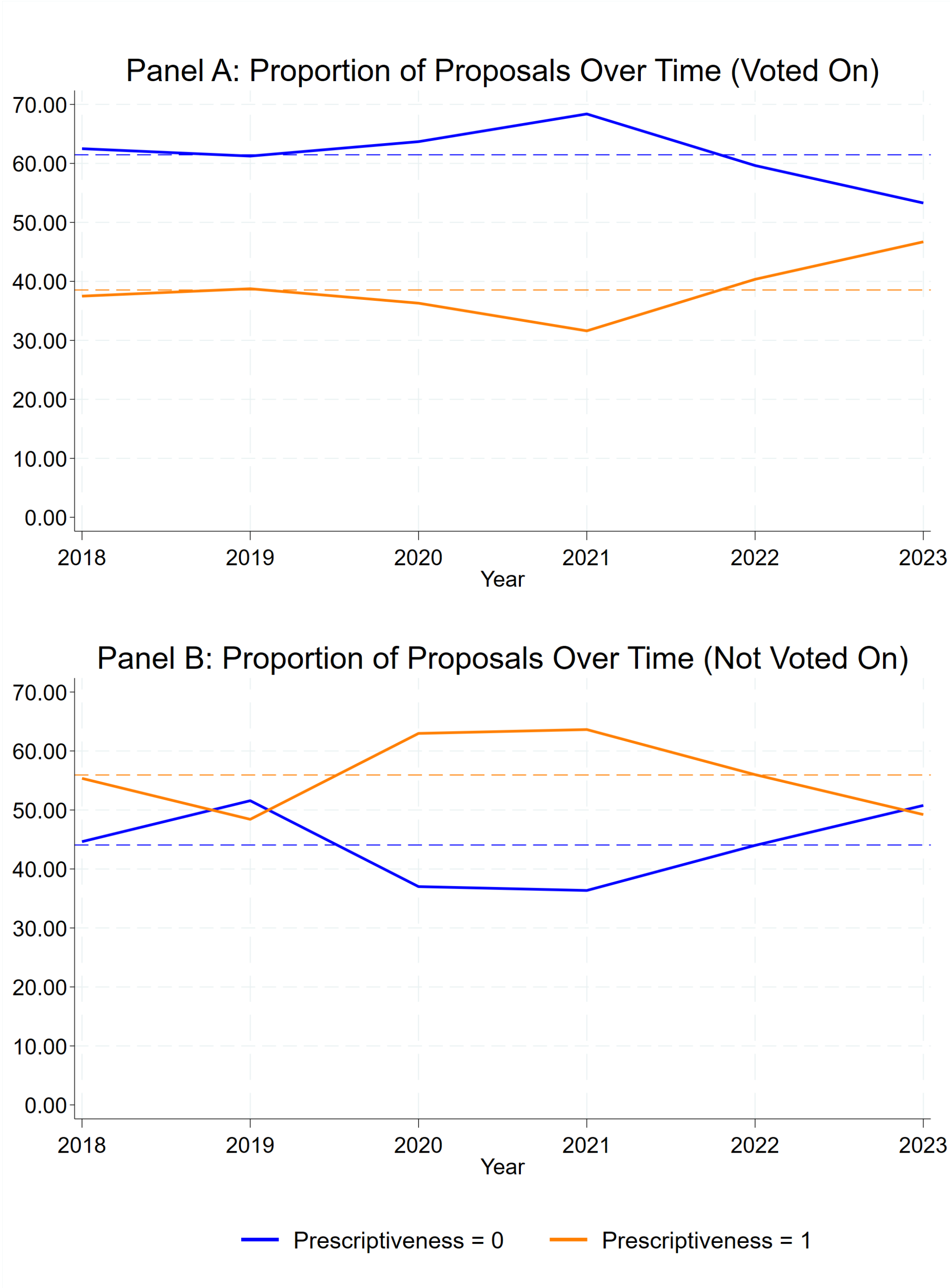
Note: This table provides summary statistics for our dataset at the firm-proposal-year level, omitting information related to the "prescriptiveness" metric and fund-level data. Mean values for continuous variables are presented without the use of parentheses, whereas their standard deviations are enclosed in parentheses. In the case of factor or binary variables, the frequencies of these variables are provided without parentheses, while the percentages of factor variables are indicated within parentheses.

Table 2: Summary Statistics: Frequencies and Percentages of Prescriptive Proposals

	Year						
	2018	2019	2020	2021	2022	2023	Total
Panel A: Prescriptiveness (Voted On)							
Prescriptiveness = 0							
Frequency	95	98	107	106	167	162	735
Percent (Within-Year)	62.50	61.25	63.69	68.39	59.64	53.29	60.30
Prescriptiveness = 1							
Frequency	57	62	61	49	113	142	484
Percent (Within-Year)	37.50	38.75	36.31	31.61	40.36	46.71	39.70
Panel B: Prescriptiveness (Not Voted On)							
Prescriptiveness = 0							
Frequency	50	49	47	52	44	33	275
Percent (Within-Year)	44.64	51.58	37.01	36.36	44.00	50.77	42.83
Prescriptiveness = 1							
Frequency	62	46	80	91	56	32	367
Percent (Within-Year)	55.36	48.42	62.99	63.64	56.00	49.23	57.17
Panel C: Total (Voted and Not Voted On)							
Prescriptiveness = 0							
Frequency	145	147	154	158	211	195	1,010
Percent (Within-Year)	0.55	0.58	0.52	0.53	0.56	0.53	0.54
Prescriptiveness = 1							
Frequency	119	108	141	140	169	174	851
Percent (Within-Year)	0.45	0.42	0.48	0.47	0.44	0.47	0.46
All Proposals (Prescriptiveness = 0 or 1)							
Frequency	264	255	295	298	380	369	1,861
Percent (Across-Years)	14.19	13.70	15.85	16.01	20.42	19.83	100.00

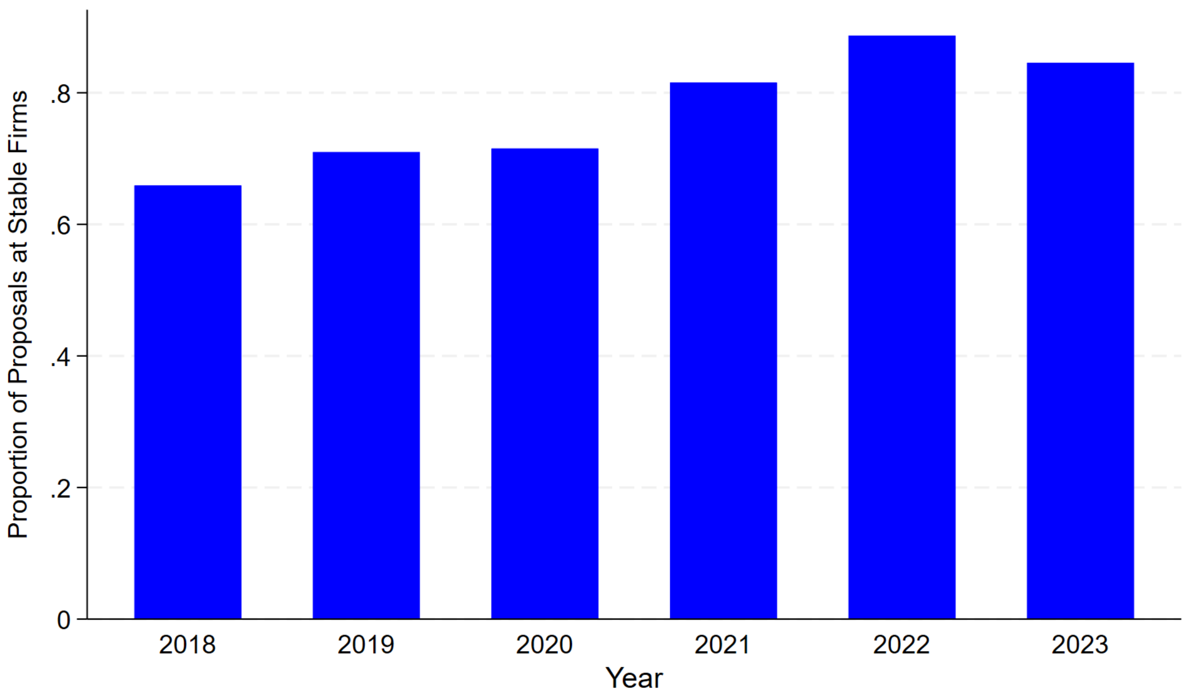
Note: This Table illustrates the frequencies and within-year percentages of prescriptive proposals over time. In Panels A and B, proposals are categorized based on whether they advance to a vote. Panel C then combines these categories, while also providing frequencies and across-year percentages for all proposals (regardless of whether they are prescriptive or not). Prescriptive proposals are indicated by the header "Prescriptiveness = 1", while non-prescriptive proposals are indicated by the header "Prescriptiveness = 0".

Figure 2: Proportion of Prescriptive Proposals over Time



Note: This figure highlights the evolving trends over time in the percentages of prescriptive shareholder proposals. Panel A charts the proportion of shareholder proposals which proceed to a vote, where the orange line represents prescriptive proposals and the blue line denotes non-prescriptive ones. Panel B, on the other hand, illustrates the percentage of shareholder proposals that do not advance to a vote, encompassing proposals that are withdrawn, settled, or excluded. Like Panel A, the orange line represents prescriptive proposals, while the blue line denotes non-prescriptive proposals.

Figure 3: Proportion of E&S Proposals submitted to Stable Firms



Note: This figure provides an annual breakdown of the proportion of E&S proposals submitted to "Stable Firms", which we define as firms present in our sample both before and after the 2021 Guidance. On average, 78.34% of all proposals in our sample were submitted to stable firms. Specifically, 65.91% of proposals in 2018, 70.98% in 2019, 71.53% in 2020, 81.54% in 2021, 88.68% in 2022, and 84.55% in 2023 were directed toward these firms.

Table 3: Changes in Prescriptiveness Post Treatment

	Votes For As % Votes Cast				Votes For As % Shares Out	Votes For As % Yes & No
	(1)	(2)	(3)	(4)	(5)	(6)
	E & S	E & S	Env	Social	E & S	E & S
Prescriptiveness × Post	-8.476***	-11.000***	-19.466***	-5.299**	-6.605***	-8.497***
	(0.000)	(0.000)	(0.001)	(0.023)	(0.000)	(0.000)
Prescriptiveness	-0.777	-0.784	0.371	-1.985	-0.289	-0.947
	(0.626)	(0.606)	(0.943)	(0.235)	(0.808)	(0.559)
Observations	1082	1180	205	831	1082	1080
Firm FE	Yes	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Proponent-Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Proposal Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.414	0.321	0.543	0.447	0.435	0.416
F Statistic	4.256	8.036	12.144	2.288	4.549	4.256

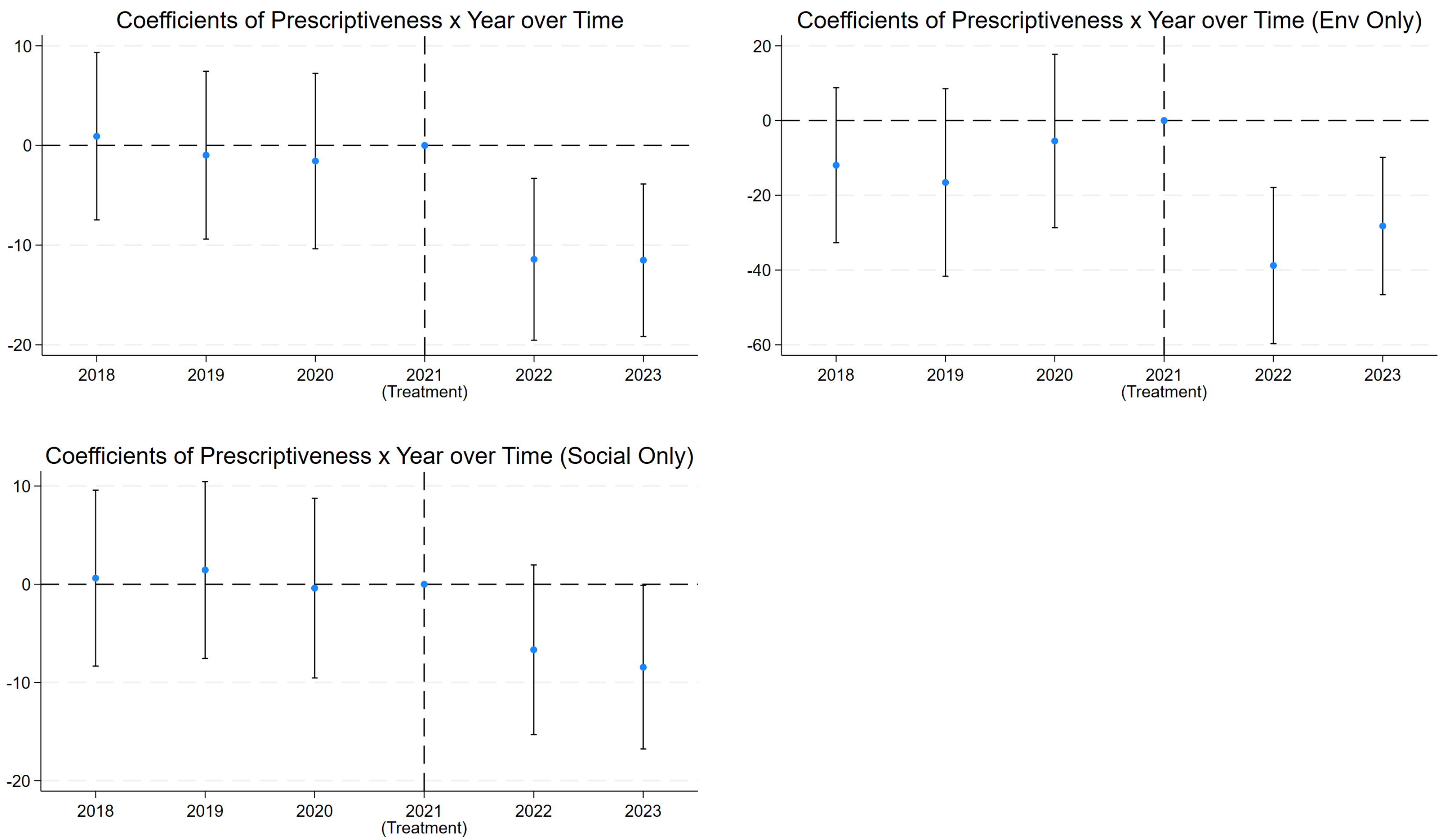
Note: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$. P-values are reported in parentheses. In specifications (1) through (4), the dependent variable relates to the percentage of affirmative votes out of the total votes cast. For specification (5), it relates to the percentage of affirmative votes out of all outstanding shares. In specification (6), it relates to the percentage of affirmative votes out of the total of affirmative and negative votes. Additionally, specifications (1), (2), (5), and (6) apply to all E&S proposals. Specification (3) specifically addresses environmental proposals, and specification (4) focuses on social proposals. we suppress reporting of the constant term and firm-proposal controls. Standard errors are clustered at the meeting-level.

Table 4: Changes in Prescriptiveness Post Treatment: New vs Existing Proponents

	Baseline	Proponent FE			New Proponents	
	(1)	(2)	(3)	(4)	(5)	(6)
Prescriptiveness × Post	-8.476***	-6.587***	-8.635***	-6.501***	-7.315***	-11.561***
	(0.000)	(0.008)	(0.000)	(0.008)	(0.008)	(0.000)
Prescriptiveness	-0.777	1.634	0.689	1.411	-1.966	-0.898
	(0.626)	(0.367)	(0.689)	(0.455)	(0.363)	(0.682)
Share of Prescriptive Proposals				0.733		
				(0.780)		
First Apperance					1.713	4.299**
					(0.362)	(0.035)
Prescriptiveness × First Appearance					2.853	0.223
					(0.299)	(0.936)
Post × First Apperance					0.418	-5.385*
					(0.877)	(0.051)
Prescriptiveness × Post × First Apperance					-2.398	3.049
					(0.593)	(0.478)
Observations	1082	923	1011	923	1082	1180
Firm FE	Yes	Yes	No	Yes	Yes	No
Industry FE	No	No	Yes	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Proponent-Type FE	Yes	No	No	No	Yes	Yes
Proponent FE	No	Yes	Yes	Yes	No	No
Firm-Proposal Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.414	0.527	0.457	0.527	0.415	0.323
F Statistic	4.256	2.861	4.425	2.666	3.608	6.443

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. The dependent variable in all specifications relates to the proportion of affirmative votes out of the total votes cast. In specifications (2) and (3), we replace proponent-type fixed effects with proponent fixed effects. In specifications (4) and (5), we include an additional variable in a triple DID specification, "First Appearance", which denotes when a proposal is first submitted by a new proponent not observed in prior years. We suppress reporting of the constant term and firm-proposal controls. Standard errors are clustered at the meeting-level.

Figure 4: Voting Support for Prescriptive Proposals over Time



Note: This figure displays the coefficients of interaction terms which combine year-specific indicators with a binary variable distinguishing prescriptive from non-prescriptive proposals. In estimating these coefficients, we include firm-proposal controls along with fixed effects for firm, year, and the type of proponent. we adopt a baseline year of 2021, corresponding to the year when treatment occurred. The dependent variable relates to the percentage of affirmative votes out of the total votes cast. Confidence intervals are drawn at the 95% level. Panel A of the figure illustrates the coefficients for E&S proposals, Panel B showcases those for environmental proposals, and Panel C presents the coefficients for social proposals.

Table 5: Summary Statistics: Fund-Firm-Proposal Level Data

	Proxy Category		
	Environmental Issues (N=185,294)	**Social Issues Related (N=714,926)**	**Total (N=900,220)**
Binary Fund Vote	0.4466 (0.4971)	0.3990 (0.4897)	0.4088 (0.4916)
Ordered Fund Vote	0.4197 (0.4797)	0.3748 (0.4714)	0.3841 (0.4735)
% of Security owned by Fund	0.0004 (0.0022)	0.0004 (0.0020)	0.0004 (0.0020)
Security as % of Fund's Total Assets	0.0114 (0.0191)	0.0139 (0.0212)	0.0134 (0.0208)
Total Fund Assets	5.7939 (2.2630)	5.7133 (2.2481)	5.7299 (2.2514)
Mgmt Fees	0.3189 (0.5520)	0.3221 (0.5882)	0.3215 (0.5809)
Expense Ratio	0.0065 (0.0048)	0.0068 (0.0048)	0.0067 (0.0048)
Turnover Ratio	0.6050 (0.8947)	0.6128 (0.8729)	0.6112 (0.8774)
Index Fund	0.4586 (0.4983)	0.4236 (0.4941)	0.4308 (0.4952)

Note: This table provides summary statistics for our dataset at the fund-firm-proposal-year level, omitting information related to the "prescriptiveness" metric and firm-proposal-level data. Mean values for continuous variables are presented without the use of parentheses, whereas their standard deviations are enclosed in parentheses. In the case of factor or binary variables, the frequencies of these variables are provided without parentheses, while the percentages of factor variables are indicated within parentheses.

Table 6: Panel Regressions of Individual Fund Votes on Prescriptiveness

	Binary Fund Vote								Ordered Fund Vote	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Prescriptiveness	-0.092***	-0.094***	-0.085***	-0.092***	-0.085***	-0.085***	-0.084***	-0.084***	-0.081***	-0.082***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% of Security owned by Fund	-4.557***	-4.668***	-4.572***	-2.949***	-2.986***	-3.158***			-2.977***	-4.567***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			(0.000)	(0.000)
Security as % of Fund's Total Assets	-0.950***	-0.857***	-0.949***	-0.117	-0.112	-0.080			-0.131*	-0.950***
	(0.000)	(0.000)	(0.000)	(0.112)	(0.122)	(0.237)			(0.057)	(0.000)
Total Fund Assets	-0.027***	-0.027***	-0.027***	0.000	0.001				0.005***	-0.027***
	(0.000)	(0.000)	(0.000)	(0.906)	(0.758)				(0.008)	(0.000)
Mgmt Fees	0.008***	0.008***	0.008***	0.008	0.009				0.008	0.008***
	(0.002)	(0.002)	(0.003)	(0.119)	(0.107)				(0.123)	(0.001)
Expense Ratio	7.679***	7.602***	7.680***	-0.529	-0.464				-0.277	7.903***
	(0.000)	(0.000)	(0.000)	(0.645)	(0.683)				(0.798)	(0.000)
Turnover Ratio	-0.001	-0.000	-0.001	0.004	0.004				0.003	-0.001
	(0.392)	(0.829)	(0.389)	(0.165)	(0.175)				(0.288)	(0.611)
Index Fund	0.045***	0.046***	0.045***	-0.017	-0.016			-0.018***	-0.014	0.041***
	(0.000)	(0.000)	(0.000)	(0.115)	(0.136)			(0.000)	(0.197)	(0.000)
Observations	582861	582861	582861	582509	582509	802593	875372	848795	582509	582861
Firm FE	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	No	No	No	No	No	No
Fund FE	No	No	No	Yes	Yes	Yes	Yes	No	Yes	No
Proponent-Type FE	No	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Proposal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.152	0.113	0.160	0.363	0.371	0.384	0.385	0.127	0.375	0.163
F Statistic	143.256	141.521	144.250	4.200	4.151	4.818	3.147	7.188	5.025	139.536

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. In specifications (1) through (8), the dependent variable relates to the variable "Binary Fund Vote", which takes on a value of 1 when a specific fund votes in favor of a proposal, and 0 for all other outcomes. In specifications (9) and (10), the dependent variable relates to the variable "Ordered Fund Vote", which is assigned a value of 1 for a "yes" vote, 0.5 for an "abstained" vote, and 0 for all other outcomes. We suppress reporting of the constant term and firm-proposal controls. Standard errors are clustered at the meeting-level.

Table 7: Changes in Prescriptiveness Post Treatment: Fund-Level

	Binary Fund Vote					Ordered Fund Vote	
	(1) Uncorrected	(2) Uncorrected	(3) Uncorrected	(4) Uncorrected	(5) IPTW	(6) Uncorrected	(7) IPTW
Prescriptiveness × Post	-0.108***	-0.081**	-0.109***	-0.111***	-0.110***	-0.111***	-0.109***
	(0.002)	(0.025)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Prescriptiveness	-0.033	-0.041	-0.031	-0.030	-0.032	-0.027	-0.031
	(0.249)	(0.180)	(0.272)	(0.277)	(0.269)	(0.333)	(0.254)
% of Security owned by Fund	-4.690***	-4.560***	-17.243***		-4.547***	-4.664***	-4.479***
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Security as % of Fund's Total Assets	-0.847***	-0.947***	-0.494***		-0.812***	-0.851***	-0.811***
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Total Fund Assets	-0.027***	-0.027***			-0.027***	-0.027***	-0.026***
	(0.000)	(0.000)			(0.000)	(0.000)	(0.000)
Mgmt Fees	0.008***	0.008***			0.008***	0.008***	0.008***
	(0.002)	(0.003)			(0.002)	(0.001)	(0.000)
Expense Ratio	7.601***	7.670***			7.249***	7.839***	7.463***
	(0.000)	(0.000)			(0.000)	(0.000)	(0.000)
Turnover Ratio	-0.000	-0.001			-0.001	0.000	-0.000
	(0.857)	(0.383)			(0.638)	(0.901)	(0.844)
Index Fund	0.046***	0.045***			0.044***	0.042***	0.040***
	(0.000)	(0.000)			(0.000)	(0.000)	(0.000)
Constant	0.795***	1.374**	0.723***	0.722***	0.824***	0.811***	0.836***
	(0.000)	(0.033)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	582861	582861	803030	898820	582861	582861	582861
Firm FE	No	Yes	No	No	No	No	No
Industry FE	Yes	No	Yes	Yes	Yes	Yes	Yes
Proponent-Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Proposal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.125	0.161	0.096	0.090	0.129	0.127	0.120
F Statistic	134.010	134.979	111.062	5.597	122.601	132.670	119.653

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. In specifications (1) through (5), the dependent variable relates to the variable "Binary Fund Vote", which takes on a value of 1 when a specific fund votes in favor of a proposal, and 0 for all other outcomes. In specifications 6 and (7), the dependent variable relates to the variable "Ordered Fund Vote", which is assigned a value of 1 for a "yes" vote, 0.5 for an "abstained" vote, and 0 for all other outcomes. Additionally, in specifications (5) and (7), we implement the Inverse Probability of Treatment Weighting (IPTW) model introduced in Section 10.4. We suppress reporting of the constant term and firm-proposal controls. Standard errors are clustered at the meeting-level.

Table 8: Changes in Prescriptiveness Post Treatment: Fund-Level (Subsets)

	(1) Big Three	(2) Blackrock	(3) Active	(4) 5th Quintile AUM	(5) 1st Quintile AUM	(6) 5th Quintile Concentration	(7) 1st Quintile Concentration	(8) ESG Fund	(9) ESG Fund (Non-ES Family)	(10) ESG Fund (ES Family)
Prescriptiveness × Post	-0.073**	-0.106***	-0.153***	-0.078***	-0.129***	-0.105***	-0.091**	-0.068*	-0.078**	-0.058
	(0.012)	(0.003)	(0.001)	(0.007)	(0.002)	(0.000)	(0.049)	(0.078)	(0.045)	(0.184)
Prescriptiveness	-0.020	-0.006	-0.042	-0.018	-0.039	-0.003	-0.064	-0.052	-0.040	-0.064*
	(0.356)	(0.818)	(0.282)	(0.455)	(0.246)	(0.872)	(0.104)	(0.103)	(0.232)	(0.069)
Constant	0.904***	0.653***	0.637***	0.721***	0.693***	0.844***	0.752***	0.601***	0.324	0.454*
	(0.000)	(0.002)	(0.003)	(0.000)	(0.001)	(0.000)	(0.002)	(0.002)	(0.148)	(0.051)
Observations	94292	44224	44455	133572	127960	141372	118520	37290	12517	24763
Firm FE	No	No	No	No	No	No	No	No	No	No
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Proponent-Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Proposal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.183	0.314	0.129	0.132	0.114	0.146	0.112	0.163	0.118	0.260
F Statistic	19.554	4.648	19.258	71.929	15.919	67.248	15.006	43.367	9.620	31.072

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. The dependent variable in all specifications relates to the proportion of affirmative votes out of the total votes cast. In specification (1), we estimate the model for Big Three funds; in specification (2), for Blackrock funds; in specification (3), for Active funds (defined in Section 6.3.2); in specification (4), for the top quintile of funds sorted by Assets under Management (AUM); in specification (5), for the bottom quintile of funds sorted by AUM; in specification (6), for the top quintile of funds sorted by their concentration of holdings; in specification (7), for the bottom quintile of funds sorted by their concentration of holdings; in specification (8), for ESG funds; in specification (9), for ESG funds in non-ES families (defined in Section 6.3.1); and in specification (10), for ESG funds in ES families (defined in Section 6.3.1). We drop all anti-ESG proposals which we identify in Section 7.3. We suppress reporting of the constant term and firm-proposal controls. Standard errors are clustered at the meeting-level.

Table 9: Changes in Prescriptiveness Post Treatment: Heterogeneity amongst ESG Funds

	Binary Fund Vote				Ordered Fund Vote	
	(1)	(2)	(3)	(4)	(5)	(6)
Prescriptiveness × Post × ESG Fund	0.054**				0.056**	
	(0.021)				(0.016)	
Prescriptiveness × Post × ESG Fund (ES Family)		0.066**				0.066**
		(0.032)				(0.032)
Prescriptiveness × Post × ESG Fund (Non-ES Family)			0.017			
			(0.472)			
Prescriptiveness × Post × ESG Fund (Large-ES Family)				0.091**		
				(0.011)		
Prescriptiveness × Post	-0.100***	-0.100***	-0.096***	-0.097***	-0.104***	-0.103***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.002)	(0.002)
ESG Fund	0.245***				0.242***	
	(0.000)				(0.000)	
ESG Fund (ES Family)		0.402***				0.396***
		(0.000)				(0.000)
ESG Fund (Non-ES Family)			-0.121***			
			(0.000)			
ESG Fund (Large-ES Family)				0.529***		
				(0.000)		
Prescriptiveness	-0.025	-0.025	-0.026	-0.026	-0.019	-0.019
	(0.363)	(0.354)	(0.344)	(0.342)	(0.474)	(0.462)
Observations	528153	528153	528153	528153	528153	528153
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Proponent-Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Proposal Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.121	0.130	0.115	0.122	0.124	0.133
F Statistic	162.434	196.758	118.711	319.507	155.840	185.752

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. The dependent variable in specifications (1) to (4) relates to the variable "Binary Fund Vote", which takes on a value of 1 when a specific fund votes in favor of a proposal, and 0 for all other outcomes. In specifications (5) and (6), the dependent variable relates to the variable "Ordered Fund Vote", which is assigned a value of 1 for a "yes" vote, 0.5 for an "abstained" vote, and 0 for all other outcomes. We drop all anti-ESG proposals which we identify in Section 7.3. We suppress reporting of the constant term, firm-proposal controls, fund controls, as well as all interaction terms in specification (4) (e.g., $Post_t \times FundCat_m$) which are unreported in this Table. Standard errors are clustered at the meeting-level.

Table 10: Prescriptiveness Post Treatment: Heterogeneity amongst Big Three and Active Funds

	Binary Fund Vote				Ordered Fund Vote			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prescriptiveness × Post × Big Three	0.052				0.051			
	(0.107)				(0.111)			
Prescriptiveness × Post × Blackrock		0.016				0.017		
		(0.679)				(0.668)		
Prescriptiveness × Post × Active (Measure 1)			-0.058***				-0.057***	
			(0.005)				(0.007)	
Prescriptiveness × Post × Active (Measure 2)				-0.046***				-0.046***
				(0.007)				(0.006)
Prescriptiveness × Post	-0.104***	-0.098***	-0.092***	-0.088***	-0.107***	-0.101***	-0.096***	-0.091***
	(0.005)	(0.006)	(0.006)	(0.008)	(0.003)	(0.004)	(0.004)	(0.005)
Big Three	-0.263***				-0.268***			
	(0.000)				(0.000)			
Blackrock		-0.297***				-0.282***		
		(0.000)				(0.000)		
Active (Measure 1)			-0.055***				-0.054***	
			(0.000)				(0.000)	
Active (Measure 2)				-0.047***				-0.052***
				(0.000)				(0.000)
Prescriptiveness	-0.027	-0.027	-0.026	-0.026	-0.022	-0.021	-0.020	-0.019
	(0.355)	(0.340)	(0.336)	(0.328)	(0.445)	(0.444)	(0.446)	(0.442)
Post × Big Three	0.024				0.021			
	(0.225)				(0.285)			
Observations	528153	528153	528153	528153	528153	528153	528153	528153
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Proponent-Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Proposal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.140	0.132	0.115	0.115	0.144	0.133	0.117	0.117
F Statistic	112.885	116.944	116.907	117.140	112.033	114.169	115.126	116.114

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. The dependent variable in specifications (1) to (4) relates to the variable "Binary Fund Vote", which takes on a value of 1 when a specific fund votes in favor of a proposal, and 0 for all other outcomes. In specifications (5) through (8), the dependent variable relates to the variable "Ordered Fund Vote", which is assigned a value of 1 for a "yes" vote, 0.5 for an "abstained" vote, and 0 for all other outcomes. We drop all anti-ESG proposals which we identify in Section 7.3. We suppress reporting of the constant term, firm-proposal controls, fund controls, as well as all interaction terms in specification (4) (e.g., $Post_t \times FundCat_m$) which are unreported in this Table. Standard errors are clustered at the meeting-level.

10 Online Appendix

10.1 Estimating Changes in E&S Support Using Synthetic Difference-in-Differences

As mentioned in Section 1, determining the impact of the SEC's 2021 Guidance on E&S proposal support is challenging due to the ostensible absence of a suitable "control" group for establishing a counterfactual scenario without the treatment.[66] Given the consistently high levels of support for governance proposals over time (see Figure 1), using governance proposals as a control group would violate the "parallel trends" assumption required for a Difference-in-Differences (DID) analysis. Indeed, the identifying assumption behind a DID analysis requires that the differences between control and treatment groups remain constant over time in the absence of the treatment. If the control and treatment groups were to have different pre-existing trends, treatment effects which are estimated from such models could be biased, as changes in the outcome variable that are due to pre-existing trends might be incorrectly attributed to the treatment (Rambachan and Roth (2023)).

As an initial strategy to address these concerns, we employ the Synthetic Difference-in-Differences (SDID) methodology introduced by Arkhangelsky et al. (2021). This approach is consistent with the plausible assumption that the 2021 Guidance, which determines the excludability of proposals based on whether they raise "significant policy issues," would primarily impact the level of prescriptiveness of E&S proposals while having minimal or no effect on governance proposals (Tallarita (2022); Gibson-Dunn (2022); Gibson-Dunn (2023)).[67] As Arkhangelsky et al. (2021) point out, the SDID methodology is particularly effective in addressing this issue because it allows for treated and control units to trend on entirely different levels before a regulatory shock. Specifically, the presence of unit-fixed effects in SDID allows for the matching of treated and control units based on pre-treatment trends rather than requiring similarity in both pre-treatment trends and levels. Since SDID necessitates the use of a balanced panel, we aggregate the data at the firm-year level, designating a firm as treated if more than 50% of the proposals it faces in a given year relate to E&S proposals relative to governance proposals.[68] All other firms are labeled

[66]Note that the caveats outlined in Section 5.2.2 (regarding the fact that each proposal is observed only once in the dataset) also apply to this setting. To the extent that these assumptions fall short of supporting causal inference, we refrain from asserting causality in this section.

[67]To the extent that these assumptions fall short of supporting causal inference, we refrain from asserting causality in this section.

[68]To ensure the resulting panel dataset is balanced, we backfill and forward-fill all missing values with the most recent available data. Following the approach of Arkhangelsky et al. (2021), we also assume that once a unit is treated,

as untreated. We then proceed to estimate the following parameters:

$$\left(\hat{\tau}^{\mathrm{SDID}}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \underset{\tau,\mu,\alpha,\beta}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(y_{it}^{res} - \mu - \theta_i - \nu_t - W_{it}\tau \right)^2 \hat{\omega}_i^{\mathrm{SDID}} \hat{\lambda}_t^{\mathrm{SDID}} \right\} \tag{6}$$

where μ is a constant, i indexes firms, and t indexes years. θ_i and ν_t represent firm and year fixed effects, respectively. The variable y_{it}^{res} represents the residuals obtained after regressing a measure of voting support y_{it} (e.g., the percentage of votes in favor relative to total votes cast) on a vector of firm-proposal controls, X_{it} (aggregated at the firm-year level), where $y_{it}^{res} = y_{it} - X_{it}\hat{\beta}$. W_{it} is a categorical variable indicating whether a firm is treated, determined by whether it faces more than 50% of E&S (or, alternatively, environmental or social proposals) relative to governance proposals in a given year. Finally, we harness the weights $\hat{\omega}_i^{\mathrm{SDID}}$ and $\hat{\lambda}_t^{\mathrm{SDID}}$ as defined by Arkhangelsky et al. (2021) to match treated and control units based on pre-treatment trends.

In column (1) of Table A2, we present the results for specification (6), where the dependent variable relates to the percentage of votes in favor relative to the total votes cast, controlling for firm-proposal controls, as well as firm and time fixed effects. Our analysis focuses on the estimated parameter $\hat{\tau}^{\mathrm{SDID}}$, which represents the average treatment effect on the treated (ATT). Despite the consistently high levels of support for governance proposals both before and after the 2021 Guidance, our estimates indicate a 4.11% decrease in support for treated firms (those facing a higher proportion of E&S proposals) following the shock, compared to untreated firms. In column (2), we observe a similar decline in support, around 4.72%, when treated firms are defined as those exposed to a higher proportion of environmental proposals.[69] Column (3) presents a parallel analysis for firms facing a relatively higher proportion of social proposals, showing that these firms received approximately 3.77% more support than governance proposals prior to 2021.

In column (4), we estimate an alternative specification that designates firms facing a higher proportion of environmental proposals than social proposals as the treatment group and those facing a higher proportion of social proposals than environmental proposals as the control group. This approach is based on the assumption that commitments to environmental reform are more costly for firms than social reforms (Balogh and Yonker (2024)). Alternatively, this specification could be motivated by the assumption that the 2021 Guidance had a more significant impact on environmental proposals, as it explicitly stated that proposals "adopting timeframes or targets to address climate change" would no longer be excluded. Although environmental and social pro-

it remains exposed to the treatment indefinitely.

[69]Note that we exclude all social proposals from this analysis before aggregating the data to the firm-year level. Similarly, we exclude all environmental proposals for a similar analysis in column (3).

posals have followed similar trends over time, we observe a 4.97% decrease in support for firms classified as treated compared to those in the control group. Finally, columns (5) and (6) report the results of specification 6 where different variants of the dependent variable are used: column (5) considers the percentage of affirmative votes relative to outstanding shares, and column (6) looks at the percentage of affirmative votes as all votes for and against the proposal. The findings in these last two columns closely mirror those in column (1).

To visually illustrate how support for E&S proposals has changed over time following the creation of a synthetic control that matches the parallel trends of treated units (while accounting for a comprehensive set of firm-proposal controls), we present a time series of the weighted voting support for E&S and governance proposals at the firm-year level in Figure 7.[70] As shown in the figure, the weights used in the SDID methodology allow treated and control units to follow different levels prior to the 2021 Guidance. Panel A demonstrates that firms with a higher proportion of governance proposals consistently received significantly more voting support than firms with a higher proportion of E&S proposals, both before and after the regulatory shock in 2021. Panels B and C provide similar illustrations, where treated firms are defined as those facing a greater proportion of environmental or social proposals, respectively. Figure 7 also highlights the negative ATTs reported in Table A2. Specifically, after 2021, firms exposed to a relatively larger number of E&S proposals (Panel A) experienced a much sharper decline in voting support compared to control firms exposed to more governance proposals. Similar trends are evident in Panels B and C.

10.2 BERT: Supervised Machine Learning

Supervised machine learning methods inherently rely on a "labeled" or "training" dataset to guide the classification of new data. As explained in Section 5.1, we utilize a specific subset of contested proposals from our dataset, specifically those involving Rule 14a-8(i)(7) prior to the 2022, as a foundational basis for labeling the proposals in our dataset. When resolving a disputed proposal, the SEC either supports the company's management by agreeing to exclude the proposal, or backs the proposal's advocate by denying the exclusion request. The key assumption made here is that the SEC, guided by the "ordinary business exception" in Rule 14a-8(i)(7), tends to exclude proposals that exhibit a greater level of prescriptiveness. This assumption, as detailed in Section 5.1, is motivated by the observation that prescriptive proposals often venture into the details of a company's day-to-day business operations, which usually fall under the domain of the company's

[70]We harness a measure of voting support where the dependent variable is the percentage of votes in favor relative to the total votes cast.

board or management (Bainbridge (2016)).

Focusing on the subset of all contested proposals from 2001 to 2021, we assign all excluded proposals under Rule 14a-8(i)(7) (favoring management) with a prescriptiveness indicator value of 1, and all precluded proposals under Rule 14a-8(i)(7) (favoring the proponent) with an indicator value of 0. This results in the creation of a "training and validation" set consisting of 1,158 proposals. In constructing our "training and validation" set, we weigh the advantage of providing the algorithm with a larger pool of examples to learn from against the risk of incorrect classifications due to shifts in SEC policy.

As is common in the literature, we randomly split our 1,158 proposals into a training set (80%) and a validation set (20%) (see Joseph (2022)). The validation set includes proposals drawn randomly across different years, allowing us to test the model on data it has not encountered during training. This random split ensures robust out-of-sample validation, helping to confirm that the algorithm generalizes well to new, unseen data.

Harnessing our training algorithm, we then classify all E&S proposals that were either uncontested or withdrawn (including settlements) between 2018 and 2021, as well as those from 2022 to 2023, employing Google's BERT (Bidirectional Encoder Representations from Transformers) algorithm. This approach is consistent with the methodologies used in Michaely et al. (2023), Rajan et al. (2023), and Liu and Lapata (2019). The BERT model is pre-trained on approximately 3.2 billion words from Wikipedia and 11,000 books from a variety of genres, which allows it to generate a large number of embeddings (numerical weights assigned to words) which are context specific (Liu and Lapata (2019)).

The BERT algorithm employs multiple steps to achieve classification, each of which will be outlined below:

1. **Tokenization:** Each text sample (i.e., an individual proposal) in our labeled training set is first broken down into smaller components called tokens (words or subwords). These tokens serve as the basic representation of the input text. Each token is then converted into an embedding vector, which assigns numerical weights to various aspects of the token, including its type, position in the text, and any associated segments.

2. **Classification Layers and Fine-Tuning:** The BERT model we use is already pre-trained on large text corpora (about 3.2 billion words from Wikipedia and 11,000 books across various genres), giving it a strong foundation for understanding language. However, to adapt it to our specific classification task, we add a new classification layer initialized with random weights.

During fine-tuning, both the pre-trained layers of BERT and this newly added classification layer are updated based on the labeled training data. The goal of this process is to minimize classification loss (in this case, binary cross-entropy), ensuring that the model can accurately classify proposals as either prescriptive or not.

3. **Validation:** To ensure that the model generalizes well and avoids over-fitting to the training data, we reserve 20% of the labeled proposals as a validation set. This set is used exclusively to test the model's performance during the fine-tuning process. By evaluating the model's accuracy on this unseen validation data, we can detect any signs of over-fitting and adjust the model as needed. Standard metrics like accuracy, precision, recall, and F1-score are used to assess how well the model performs on the validation set.

4. **Prediction on Unlabeled Data:** Once the model has been fine-tuned and validated, we apply it to entirely new, unlabeled data. This includes all uncontested and withdrawn proposals in our dataset from 2018 to 2021, as well as all proposals from 2022 to 2023. The model processes these new proposals through the BERT architecture and classification layer, generating a prediction score (typically a probability) indicating the likelihood of whether the SEC would have excluded the proposal prior to 2021 under the "ordinary business exception". As is standard in the literature, we assign a value of 1 for probabilities ≥ 0.5 and a value of 0 for probabilities < 0.5.

In training our classification model, we employ early stopping and model checkpointing as key strategies (in the fine-tuning and validation process) to prevent overfitting and to optimize performance. Early stopping halts the training when there is no improvement in validation loss after a predefined number of epochs, a hyperparameter that helps control the training duration. Model checkpointing saves the model configuration with the lowest validation loss, ensuring the best model is retained. Figure 5 provides a graphical illustration of this process, where the training duration is halted when there is no further (significant) decrease in the validation loss.

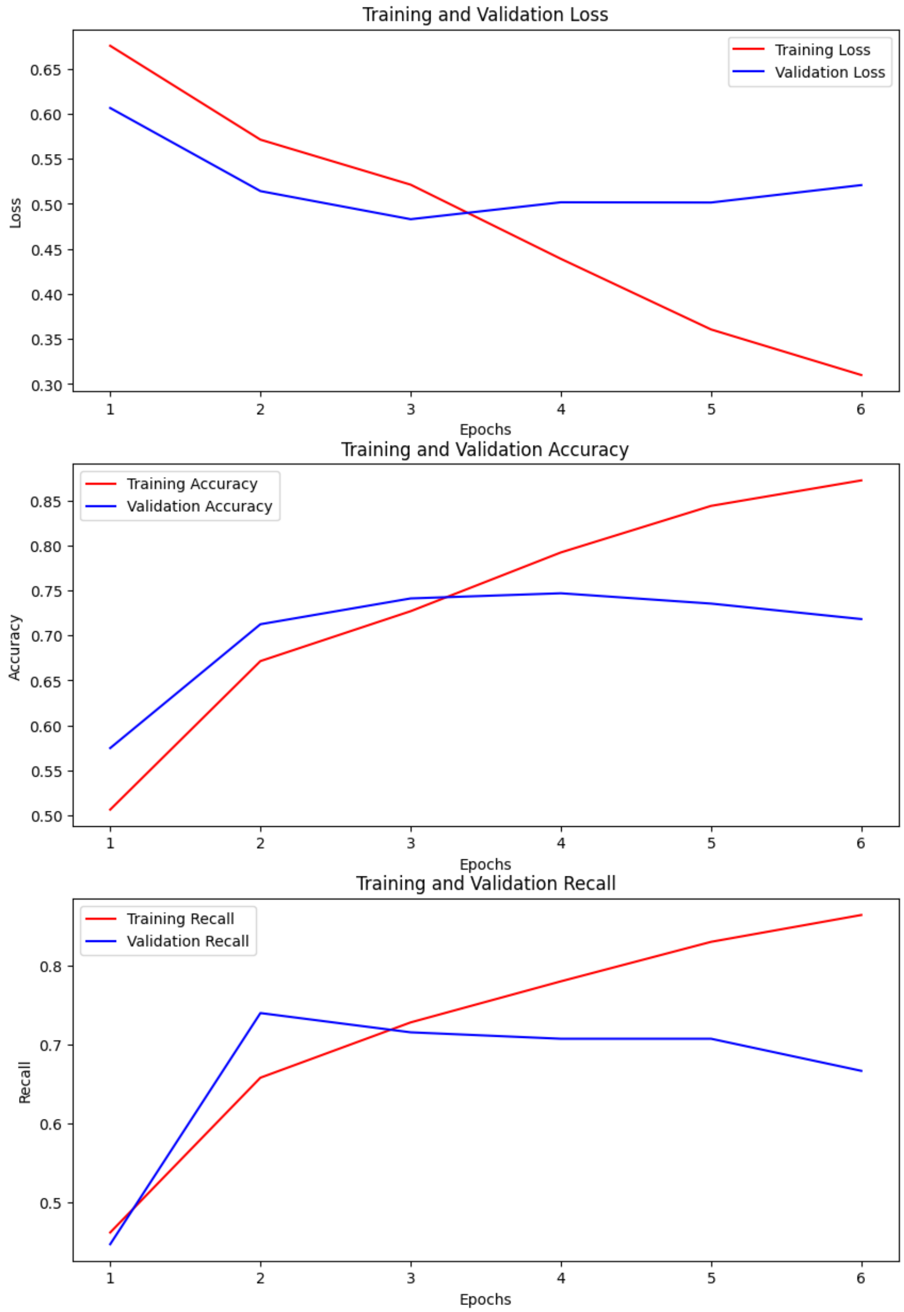


Figure 5: Illustration of early stopping and model checkpointing in the training process.

Upon completion of the fine-tuning process, the model attained an accuracy rate of roughly 71.26%, signifying that the bulk of its predictions concerning unseen data were accurate. Its recall rate of 68.63% reflects a strong ability to identify positive cases, which is crucial for applications where missing positives can be particularly detrimental.[71]

[71] The model has an accuracy of 0.71264, a recall of 0.6863, and a loss of 0.5625 after 6 epochs.

10.3 Unsupervised Machine Learning: Topic Modeling

While the initial supervised machine learning approach offers a preliminary means of identifying prescriptive proposals, it may not encompass the full range of such proposals. This limitation arises because the training dataset is aligned with a specific threshold set by the SEC for approving or rejecting proposals, leading to potential misclassification of proposals that greatly diverge from this threshold.[72] Additionally, the characteristics of firms, proponents, or investors linked to contested proposals might substantially differ from those related to uncontested or withdrawn proposals, further exacerbating the risk of misclassification.[73]

To formalize this potential for misclassification, consider a classifier $f : X \to Y$, where X relates to the textual data (an input feature) and Y is a set of target labels. The classifier is trained on a labeled dataset $D_{train} = \{x_i, y_i\}_{i=1}^{n}$ where each $x_i \in X$ is a textual observation and $y_i \in Y$ is its corresponding label, with n the number of laeled examples. The training data is centered around a certain threshold h, which represents a specific boundary (determined by the SEC in excluding proposals) in the data distribution.

Consider a datapoint x_j from the dataset D_{test} to which the classifier is applied. If x_j is far from the threshold h around which D_{train} is centered, then the likelihood of f misclassifying x_j increases. Here, the classifier has the potential to overfit the data to the characteristics of the training data near h. Consider the probability of incorrect classification $P_{error}(x_j)$ as a function of the distance $d(x_j, h)$ from the threshold h:

$$P_{error}(x_j) = g(d(x_j, h))$$

where $g : \mathbb{R} \to [0, 1]$ is a function that maps the distance to an error probability, and $d(x_j, h)$ is a distance metric measuring how far x_j is from the threshold h. As $d(x_j, h)$ increases, $g(d(x_j, h))$ is expected to increase as well, indicating a higher probability of x_j being misclassified by f.

[72] Additionally, the training dataset employed is relatively small, which heightens the likelihood of misclassifying proposals.

[73] Unsupervised machine learning transformers, such as Mistral 7B, are particularly well-suited for tasks that involve uncovering latent structures or relationships in data without the need for labeled examples. These models utilize self-supervised learning objectives to generate high-dimensional embeddings that effectively capture the contextual nuances of text. This makes them ideal for exploratory tasks like clustering or dimensionality reduction, where the aim is to identify patterns/groupings that are not predefined. In contrast, supervised transformers like BERT are optimized for leveraging labeled data in task-specific fine-tuning, enabling precise and interpretable predictions. However, their reliance on labeled data can limit their applicability in settings where such data is scarce or unavailable. We selected Mistral 7B for our analysis as it was one of the leading models on HuggingFace's leaderboards at the time of writing.

To mitigate the risk of misclassification, we implement a "Topic Modeling" strategy in a secondary step to identify prescriptive proposals (Grootendorst (2022)). This method seeks to identify groups of proposals that share common themes related to "prescriptive content", like the implementation of particular policies, thereby offering a more nuanced insight into the proposals' characteristics. Given the probable differences in content between environmental and social proposals, we apply our topic modeling algorithms to each set of environmental and social proposals independently. Like the techniques employed in Section 10.2, our algorithm utilizes a series of steps to discern distinct topics, which are detailed as follows:

1. **Embedding**: In this step, we employ an embedding model from Mistral (Mistral 7B) which assigns numerical weights to the words, phrases, and sentence structures in our proposals (Jiang et al. (2023)). Mistral 7B's strength lies in its pre-training on an extensive range of internet-scale data, encompassing 7 billion parameters. This vast foundation enables Mistral 7B to assign context-specific weights to textual elements, enhancing the model's ability to represent the underlying semantic relationships within the data.

2. **Dimensionality Reduction**: Subsequently, we utilize a UMAP (Uniform Manifold Approximation and Projection) algorithm to reduce the textual data's dimensionality, aiming to retain the most critical attributes of environmental or social proposals. UMAP applies mathematical principles from topology to condense complex, high-dimensional data, such as Mistral 7B embeddings. UMAP is based on the concept that data points can be represented as a connected graph in high-dimensional space, and seeks to preserve these connections when projecting the data into a lower-dimensional space. The algorithm uses Riemannian geometry to adjust local metrics, ensuring that dense regions do not dominate the layout. This allows UMAP to maintain the inherent topological features of the dataset.

3. **Vectorization**: During this stage, we implement a filtering process to remove common stop-words — words that are frequent in the language but typically carry little information relevant to the analysis (e.g., "the", "is", "and"). Eliminating these words focuses the analysis on more meaningful, content-specific words, thereby enhancing the effectiveness of text-based models.

4. **Clustering**: we use the HDBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with Noise) clustering algorithm to facilitate the identification of distinct proposal clusters. HDBSCAN starts by modifying the dataset through a mutual reachability distance that incorporates density into the distance measure between data points, thereby accentuating dense regions. A minimum spanning tree is then constructed to highlight these dense areas, from which a hierarchy of clusters is derived. This hierarchy is condensed based on cluster

stability across different density levels, with the final step being the pruning of this condensed tree to extract significant clusters. This approach allows HDBSCAN to detect meaningful clusters while disregarding less significant ones as noise.

The application of topic modeling algorithms to our dataset uncovers specific topic clusters that align with characteristics identified by the SEC, legal practitioners and institutional investors. In Figure 6, we provide a two-dimensional representation of environmental proposals.[74] Amongst these proposals, there emerges a clear cluster advocating for companies to set "time-bound" or "company-wide" emissions targets (Topic 8: "GHG Emissions Management Goals Adoption policy in Corporations").[75] Another group of proposals calls for companies to "adopt a [specific] policy" (or similar expressions like "implementing," "adopting," or "committing to a policy"), such as phasing out fossil fuel exploration and development (Topic 23: "Finance Commitment to Net Zero Emissions by 2050" and Topic 28: "Fossil Fuel Phase-Out Policies by Major Banks").[76] we identify these clusters of proposals that are ostensibly "prescriptive" in nature, before assigning these proposals with a prescriptiveness indicator of 1.

[74]Note that we repeat the same process for all social proposals.

[75]For instance, one of these resolutions provides that "Resolved: Shareholders request Illinois Tool Works, Inc. (ITW) adopt time-bound, quantitative, company-wide, science-based targets for reducing greenhouse gas (GHG) emissions, consistent with the goals of the Paris Climate Agreement, and report annually, at reasonable cost and omitting proprietary information, on its plans and progress towards achieving these targets."

[76]For instance, one of these resolutions provides that "Resolved: Shareholders request that the Board of Directors adopt a policy for a time-bound phase-out of BAC's lending and underwriting to projects and companies engaging in new fossil fuel exploration and development."

Figure 6: Two-Dimensional Representation of Environmental Proposals.

Note: In this figure, topic labels have been condensed to three keywords for conciseness. Nevertheless, we utilize a representation model from OpenAI to relabel topics based on their key words. For example, Topic 1 is linked with the label “Corporate Sustainability Reporting on ESG Metrics.”

10.4 Selection Bias Models

There are two types of selection bias that could potentially distort the observed treatment effects. The first relates to sample selection bias, characterized by endogenous or non-random selection into the sample. For example, the SEC's 2021 Guidance might lead company management to refrain from contesting proposals. Specifically, Bebchuk et al. (2020) have noted that larger firms face more severe reputational risks if a contested proposal is decided in favor of the proponent. Should these managers alter their actions in response to the SEC's 2021 Guidance, this could lead to variations in voting support that are not directly tied to changes in the prescriptiveness of E&S proposals.

To mitigate the possibility of sample selection bias, we employ a Heckman selection model (Heckman (1979)), which accounts for the potential selection bias arising from proposals that were either excluded by the SEC or withdrawn by the proponent (Zytnick (2022); Brav et al. (2024)).[77] To implement the Heckman selection model, we first estimate the probit specification:

$$\Pr(S_n = 1) = \Phi(Z_{in}\gamma)$$

where S_n is a binary variable indicating whether a proposal is excluded/withdrawn ($S_n = 0$) or whether it has proceeded to a vote ($S_n = 1$), Z_{in} is a vector of observed firm-proposal controls,[78] Φ represents the cumulative distribution function of the standard normal distribution, and γ is a vector of parameters to be estimated. Given the estimated parameters $\hat{\gamma}$, we compute the Inverse Mills Ratio (IMR) λ_n for each proposal:

$$\lambda_n = \frac{\phi(Z_{in}\hat{\gamma})}{\Phi(Z_{in}\hat{\gamma})}$$

where $\phi(\cdot)$ denotes the probability density function of the standard normal distribution.[79]

In a second stage, we estimate the outcome equation as per specification (1), adjusting for selec-

[77] Note that shareholder proposals must be contested by firm management prior to being excluded by the SEC. Bebchuk et al. (2020) detail a large number of firm and proponent characteristics that may influence whether a proposal is contested. These factors include the activist's stake, insider ownership, the target firm's share class structure, the firm's performance, historical success rates in past engagements, and the board's structure, among others.

[78] Since proposals are observed at a more granular level when compared to firms, proposals within the same firm will have similar firm-level controls. Further information about these variables can be found in Table A1.

[79] Note that the dot product of Z_{in} and $\hat{\gamma}$ is a scalar, so λ_n may be computed as a ratio of scalars.

tion bias from the first step by including the IMR in the specification:

$$y_{ijktn} = \alpha + p_{ijktn}\beta + (p_{ijktn} \times Post_t)\gamma + X_{ijktn}\xi + \theta_i + \eta_j + \psi_k + \nu_t + \lambda_n\delta + \varepsilon_{ijktn}$$

where ε_{ijktn} is assumed to be independent from the error term in the first-stage probit specification.

The second form of selection bias concerns the possibility of being selected for treatment, which, in this context, relates to the prescriptiveness of a specific proposal. For instance, the 2021 Guidance might encourage proponents to direct more prescriptive proposals towards larger firms, under the belief that E&S proposals at such entities post-2021 have a better chance of proceeding to a vote (Era et al. (2021); Bebchuk et al. (2020)). In such a scenario, if the size of the firm influences voting support, neglecting to adjust for this bias could lead to biased estimates of the treatment effects.

To ameliorate these concerns, we calculate propensity scores for both prescriptive (the treatment group) and non-prescriptive proposals (the control group). These scores represent the likelihood of a proposal being assigned to the treatment group, based on an array of observable characteristics. By incorporating these propensity scores into the analysis, we aim to ensure that the treatment and control groups are essentially equivalent, with no systematic differences between them aside from their levels of "prescriptiveness". In a first stage, we estimate a probit regression to predict the likelihood of treatment:

$$\Pr(T_n = 1) = \Phi\left(Z_{in}\gamma\right)$$

where T_n is a binary variable indicating whether a proposal is prescriptive ($T_n = 1$) or whether it is non-prescriptive ($T_n = 1$), Z_{in} is a vector of observed firm-proposal controls,[80] Φ represents the cumulative distribution function of the standard normal distribution, and γ is a vector of parameters to be estimated. After deriving the propensity scores $\tau(Z_{in}) = \Phi(Z_{in}\hat{\gamma})$ by estimating the coefficients $\hat{\gamma}$ in the aforementioned specification, we follow Rosenbaum (1987) in computing an inverse probability of treatment weight (IPTW), where the IPTW w_n is defined as:

$$w_n = \frac{T_n}{\tau(Z_{in})} + \frac{1 - T_n}{1 - \tau(Z_{in})}$$

[80]Since proposals are observed at a more granular level when compared to firms, proposals within the same firm will have similar firm-level controls. Further information about these variables can be found in Table A1.

As the IPTW is equal to the inverse of the observation's probability of receiving the treatment, weighting a regression model with IPTWs allows for a specification that consistently estimates the true treatment effect (Joffe et al. (2004)).

10.5 Data Cleaning Procedures: Fund-Level Matching

As noted in Section 3.2, matching funds between the ISS dataset and the CRSP mutual fund database is non-trivial due to the lack of common identifiers in both datasets. To tackle this challenge, we begin by extracting the "Series Name" (i.e., fund name), the "Series ID," and the CIK (Central Index Key) linked to each N-PX identifier (obtained from the ISS dataset) from the SEC's EDGAR database. This process enables us to associate a CIK identifier, an N-PX file identifier, and a Series Name identifier from EDGAR with each voting record observed in the ISS dataset.

Unfortunately, these identifiers do not uniquely identify the voting records observed in the ISS dataset, as multiple funds are linked with each N-PX identifier documented in the ISS dataset. To address this issue, we perform fuzzy-matching between funds *within* an N-PX filing (identified by its "Series Name") and funds in the ISS dataset (identified by its "Fund Name") pursuant to a procedure indicated by Moskalev (2019), who matches funds with similar Levenshtein distances. For matches with Levenshtein distances of 3 or smaller (where 0 corresponds to a perfect match) we assume that we assume that funds in both datasets represent the same fund. Additionally, for any unmatched funds with a minimum distance of 4 or greater, we perform a hand matching process (aided by sorting the within-N-PX filing funds based on their similarity to the fund in question). If no suitable match is identified, we drop the fund from our dataset.

Following the matching of ISS records with EDGAR data, we utilize the "CRSP CIK MAP" sourced from WRDS (Wharton Research Data Services). This dataset connects pairs of CIK identifiers and "Series ID" identifiers from EDGAR to CRSP fund numbers within the CRSP mutual fund database. This enables the matching of funds in ISS to their corresponding CRSP fund numbers. Finally, we merge fund characteristics, which may be associated with CRSP portfolio numbers, into this dataset using either CRSP fund or portfolio numbers along with the nearest record date provided in the ISS dataset. When dealing with portfolio numbers, we rely on CRSP's mapping between fund numbers and portfolio numbers to facilitate this matching process.

While the CRSP mutual fund database offers ownership data for certain funds in our dataset, it does not provide comprehensive coverage for all included funds. To ameliorate these gaps in coverage, we follow Brav et al. (2024) by incorporating data from the TR (Thomson Reuters) S12 mutual fund database. Notably, while the TR S12 database provides data at a quarterly frequency, the CRSP mutual fund database operates at a monthly frequency. Consequently, we include only March, June, September, and December holdings from the CRSP mutual fund database to create a comprehensive set of mutual fund holdings at the quarterly frequency.

To match the CRSP mutual fund database to the TR S12 database, we use the MFLINKS tables from WRDS to link each fund in the CRSP to the Thomson Reuters S12 data, using the provided link between a CRSP portfolio number and an S12 fund number. For funds in our dataset linked to an S12 fund number, we utilize ownership data from the TR S12 database. Conversely, for funds in our dataset lacking links to an S12 fund number, we rely on ownership data from the CRSP mutual fund database.

10.6 Alternative Indicators for Prescriptiveness

While we have outlined the need for a more complex approach to develop a measure of prescriptiveness for proposals in our dataset, it is reasonable to consider whether a simpler proxy could effectively capture a proposal's "prescriptiveness." For example, one might consider a binary indicator for whether a proposal was contested under Rule 14a-8(i)(7)'s "ordinary business exception." However, this simpler approach has significant drawbacks. As discussed in Section 5.1, proposals with greater prescriptiveness are less likely to reach a vote due to a higher likelihood of being excluded by the SEC. Therefore, limiting the analysis to only contested proposals could substantially under-represent highly prescriptive proposals. Furthermore, a large majority (63.68%) of the proposals in our dataset are uncontested. This is possibly because managers often have strong incentives to avoid contesting shareholder proposals, perhaps due to career concerns (Gantchev and Giannetti (2021); Matvos and Ostrovsky (2010)), the direct (e.g., legal expenses) and indirect (e.g., the impact on firm value from the uncertainty brought about by no-action letters) costs of contesting proposals (Matsusaka et al. (2021)), or the risks involved in challenging the recommendations of proxy advisory firms (Gantchev and Giannetti (2021)). These incentives to avoid contesting proposals might be further influenced by the SEC's 2021 Guidance, with firm managers potentially reluctant to oppose an outcome that would likely favor the proponent.

In Table A8, we present preliminary evidence supporting these claims by replacing the binary prescriptiveness indicator (p_{ijkt}) with a binary variable indicating whether a proposal was contested under Rule 14a-8(i)(7). While the coefficients on the interaction terms of interest are negative, they generally lack statistical significance across different specifications, including adjustments for industry fixed effects and the selection models outlined in Section 10.4. These results suggest that the potential negative association between the proposed proxy variable and the 2021 Guidance may not be robust.

10.7 Variance Decomposition

To justify the choice of fixed effects in our main analysis, we consider the hierarchical nature of our fund-level dataset (which includes various layers such as firms, industries, proponents, funds, and years) and follow Zytnick (2022) by decomposing the sources of variation in voting. To this end, we estimate the following specification:

$$y_{ijktnmc} = \alpha + \theta_i + \eta_j + \psi_k + \kappa_m + \delta_c + \nu_t + \varepsilon_{ijktnmc} \tag{7}$$

where α is a constant, i indexes firms, j indexes industries, k indexes proponent-types, m indexes funds, c indexes proponents, t indexes years, and n indexes proposals.[81] Meanwhile, $y_{ijktnmc}$ relates to the binary indicator, "Binary Fund Vote", while θ_i, η_j, ψ_k, κ_m, δ_c and ν_t represent firm, industry, proponent-type, fund, proponent, and year fixed effects, respectively.

Table A9 presents the outcomes from applying specification (7). In column (1) of Panel A, a baseline model incorporating only year fixed effects is estimated, yielding an expectedly low R^2 value of 0.022. Column (2) introduces proponent-type fixed effects alongside year fixed effects. Column (3) revisits the baseline model but includes industry fixed effects, whereas column (4) incorporates firm fixed effects. Column (5) adds proponent fixed effects, and column (6) includes fund fixed effects in the analysis. The findings illustrate that the between-fund variation in our dataset is substantial (as evidenced by an R^2 value of 0.286 in column (6)), suggesting that fund-related differences account for a significant portion of the variability in voting behavior when compared to other factors. In terms of the hierarchy of voting variation contributors, fund characteristics emerge as the most significant, followed by proponents, firms, industries, proponent-types, and years, in decreasing order of impact. In Panels B and C of Table A9, the same analysis is conducted for environmental and social proposals respectively, yielding results that closely mirror those from Panel A.

Employing fixed effects for a given set of entities (e.g., firms) involves a balancing act–while they account for unobserved, time-invariant attributes of the entities under study, they also remove variation between these entities. This may potentially weaken the statistical power of the analy-

[81] Note that the notation utilized here deviates slightly from what was elucidated in specification (2).

sis (Bai (2009)). Specifically, incorporating firm fixed effects eliminates the variation across firms, which could explain a considerable amount of the variation in voting behavior. In the analyses that follow, we consistently apply year and proponent-type fixed effects where applicable. However, to preserve some between-entity variation, we opt for industry fixed effects instead of firm fixed effects in various iterations of our findings.

Table A10 demonstrates the aforementioned tradeoffs by applying specification (3) to both environmental and social proposals independently.[82] Since environmental proposals represent a smaller share of the dataset than social proposals, preserving some degree of variation between entities is of increased importance. This necessity is underscored by the tendency of environmental proposals to target specific firms, notably within sectors like the fossil fuel industry (Tallarita (2022)).[83] In columns (1) and (3) of Table A10, the larger standard errors associated with the prescriptiveness coefficient, p_{ijktnm}, is evident when firm fixed effects are included. On the other hand, columns (2) and (4) show consistent and statistically significant negative coefficients at the 5% level when industry fixed effects replace firm fixed effects. For social proposals, as shown in columns (5) to (8), these methodological considerations do not appear to have a substantial impact.

10.8 Additional Tables and Figures

In this section, we provide additional tables and figures that supplement the main analysis presented in the paper. These tables offer alternative specifications and robustness checks that support our findings.

[82]The dependent variable here relates to the binary indicator, "Binary Fund Vote".

[83]Both factors suggest that the introduction of firm fixed effects would consume relatively more of the available degrees of freedom, relative to social proposals.

Table A1: List of Variables

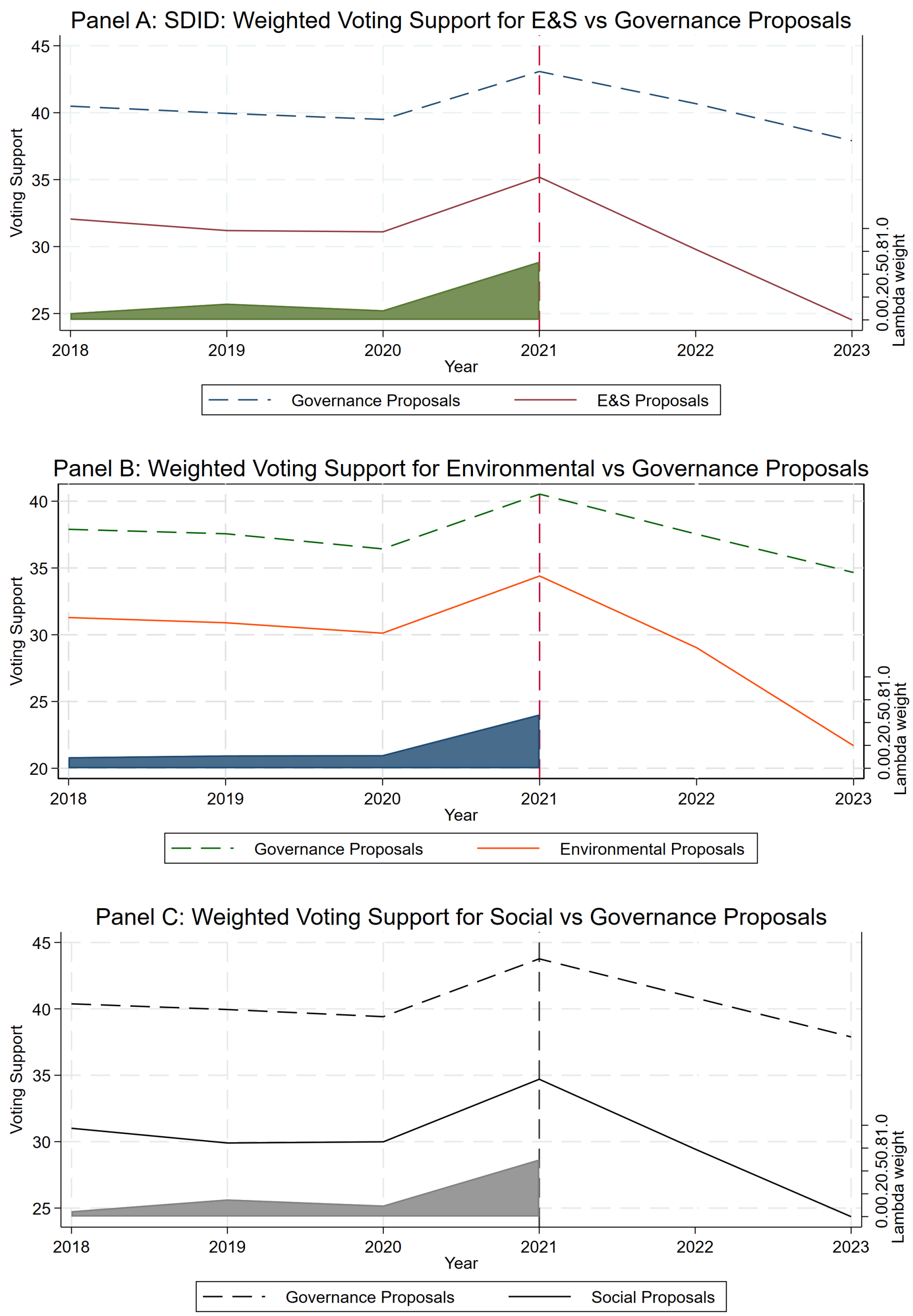
Variable	Definition
Firm-Proposal Controls	
Log Mkvalt	Logarithm of the firm's market capitalization
Firm Size	Logarithm of the firm's total assets
Return on Assets (RoA)	Net income scaled by total assets
Leverage Ratio	Total debt scaled by total assets
Tobin's Q	Market capitalization of equity plus total debt, divided by total assets
HHI	Sum of squared market shares for each firm within the firm's 4-digit SIC industry code
Inst Own	% of firm equity owned institutional investors (i.e., 13F investors)
Inst HHI	Sum of squared ownership shares for each investor within the firm
Has No Action Letter Sought	Binary variable denoting whether the proposal is subject to a No Action Letter request
Fund Controls	
% of Security owned by Fund	Percentage of a firm's outstanding shares owned by the fund
Security as % of Fund's Total Assets	Percentage of the fund's total assets represented by a firm's holdings
Total Fund Assets	Total assets under management by the fund
Mgmt Fees	Management fees charged by the fund, including fee waivers/reimbursements
Expense Ratio	Ratio of total investment that shareholders pay for the fund's operating expenses, which include 12b-1 fees
Turnover Ratio	Ratio of the fund's aggregated sales/purchases of securities over a year, divided by the fund's average annual total net assets
Index Fund	Binary variable coded as 1 if the fund is passively managed

Table A2: SDID Estimates: E&S vs Governance Proposals

	Votes For As % Votes Cast				Votes For As % Shares Out	Votes For As % Yes & No
	(1)	(2)	(3)	(4)	(5)	(6)
	E&S	Environmental	Social	Environmental (With S as Control)	E&S	E&S
Average Treatment Effect on the Treated (ATT)	-4.106***	-4.716***	-3.764***	-4.972***	-3.060***	-3.962***
	(0.000)	(0.006)	(0.009)	(0.005)	(0.000)	(0.000)
Observations	3084	3234	3162	1752	3084	3066
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Proposal Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. All data is aggregated at the firm-year level, with firms classified as treated if they face more than 50% of E&S (or, alternatively, Environmental or Social proposals) proposals relative to governance proposals, with the exception of column (4) where social proposals are used as a control instead. In specifications (1) through (4), the dependent variable of interest relates to the percentage of affirmative votes out of the total votes cast. For specification (5), it relates to the percentage of affirmative votes out of all outstanding shares. In specification (6), it relates to the percentage of affirmative votes out of the total of affirmative and negative votes. We compute the standard errors using placebo simulations, which involve randomly reassigning the treatment status across units to generate a distribution of placebo estimates; these simulations are repeated 50 times to account for sampling variability.

Figure 7: Weighted Voting Support for E&S vs Governance Proposals



Note: This figure presents the time series of weighted voting support, defined as the percentage of votes in favor relative to the total votes cast, for E&S and governance proposals at the firm-year level. Firms are classified as treated if they face more than 50% of E&S proposals (or, alternatively, Environmental or Social proposals) relative to governance proposals and are depicted by the solid lines, while control firms are represented by the dashed lines. Following specification (6), we harness the weights $\hat{\omega}_i^{\text{SDID}}$ and $\hat{\lambda}_t^{\text{SDID}}$ as defined by Arkhangelsky et al. (2021) to match treated and control units based on pre-treatment trends. The distribution of the weights $\hat{\lambda}_t^{\text{SDID}}$ over time is represented by the shaded areas in each panel, with the intensity of the weights indicated by the legend on the right side of the panels.

Table A3: Panel Regressions of Voting Support on Prescriptiveness

	Votes For As % Votes Cast				Votes For As % Shares Out	Votes For As % Yes & No
	(1) E & S	(2) E & S	(3) Environmental	(4) Social	(5) E & S	(6) E & S
Prescriptiveness	-5.219***	-6.340***	-11.158***	-4.741***	-3.750***	-5.382***
	(0.000)	(0.000)	(0.006)	(0.000)	(0.000)	(0.000)
Observations	1082	1180	205	831	1082	1080
Firm FE	Yes	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Proponent-Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Proposal Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.403	0.302	0.515	0.442	0.423	0.405
F Statistic	3.087	5.466	11.979	2.099	3.334	3.155

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. In specifications (1) through (4), the dependent variable relates to the percentage of affirmative votes out of the total votes cast. For specification (5), it relates to the percentage of affirmative votes out of all outstanding shares. In specification (6), it relates to the percentage of affirmative votes out of the total of affirmative and negative votes. Additionally, specifications (1), (2), (5), and (6) apply to all E&S proposals. Specification (3) specifically addresses environmental proposals, and specification (4) focuses on social proposals. we suppress reporting of the constant term and firm-proposal controls. Standard errors are clustered at the meeting-level.

Table A4: Panel Regressions of Voting Support on Prescriptiveness:
Heckman Selection and IPTW Variants

	Heckman Selection Models			IPTW Models		
	(1) E & S	(2) Environmental	(3) Social	(4) E & S	(5) Environmental	(6) Social
Prescriptiveness	-5.218***	-11.417***	-4.750***	-5.188***	-10.777***	-4.711***
	(0.000)	(0.006)	(0.000)	(0.000)	(0.007)	(0.000)
Inverse Mills Ratio	-84.427	-1139.885	97.707			
	(0.826)	(0.741)	(0.791)			
Observations	1856	461	1395	1082	205	831
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Proponent-Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Proposal Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.402	0.513	0.442	0.405	0.508	0.449
F Statistic				2.975	11.992	2.077
Chi-Square	25.097	19.140	20.728			

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. The dependent variable in all specifications relates to the proportion of affirmative votes out of the total votes cast. In specifications (1) through (3), we implement the Heckman Selection model introduced in Section 10.4, while in specifications (4) through (6), we implement the Inverse Probability of Treatment Weighting (IPTW) model introduced in the same Section. we suppress reporting of the constant term and firm-proposal controls. Standard errors are clustered at the meeting-level.

Table A5: Changes in Prescriptiveness Post Treatment:
Heckman Selection and IPTW Variants

	Heckman Selection Models			IPTW Models		
	(1) E & S	(2) Env	(3) Social	(4) E & S	(5) Env	(6) Social
Prescriptiveness × Post	-8.483***	-19.311***	-5.297**	-8.507***	-19.050***	-5.133**
	(0.000)	(0.009)	(0.030)	(0.000)	(0.001)	(0.026)
Prescriptiveness	-0.773	0.064	-1.995	-0.738	0.616	-2.046
	(0.654)	(0.992)	(0.279)	(0.639)	(0.903)	(0.217)
Inverse Mills Ratio	-92.632	-947.227	95.704			
	(0.798)	(0.776)	(0.813)			
Observations	1856	461	1395	1271	205	831
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Proponent-Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Proposal Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.414	0.541	0.446	0.417	0.539	0.453
F Statistic				4.149	12.251	2.278
Chi-Square	42.864	25.764	24.317			

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. The dependent variable in all specifications relates to the proportion of affirmative votes out of the total votes cast. In specifications (1) through (3), we implement the Heckman Selection model introduced in Section 10.4, while in specifications (4) through (6), we implement the Inverse Probability of Treatment Weighting (IPTW) model introduced in the same Section. we suppress reporting of the constant term and firm-proposal controls. Standard errors are clustered at the meeting-level.

Table A6: Changes in Prescriptiveness Post Treatment
(without Anti-ESG Proposals)

	Votes For As % Votes Cast				Votes For As % Shares Out	Votes For As % Yes & No
	(1) E & S	(2) E & S	(3) Env	(4) Social	(5) E & S	(6) E & S
Prescriptiveness × Post	-7.412***	-10.503***	-22.734***	-4.240*	-5.871***	-7.381***
	(0.001)	(0.000)	(0.000)	(0.095)	(0.001)	(0.002)
Prescriptiveness	-0.754	-0.550	2.770	-1.518	-0.266	-0.930
	(0.634)	(0.719)	(0.529)	(0.370)	(0.824)	(0.563)
Observations	983	1082	195	750	983	981
Firm FE	Yes	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Proponent-Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Proposal Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.419	0.301	0.560	0.428	0.428	0.420
F Statistic	2.997	6.541	11.696	1.408	3.312	2.987

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. In specifications (1) through (4), the dependent variable relates to the percentage of affirmative votes out of the total votes cast. For specification (5), it relates to the percentage of affirmative votes out of all outstanding shares. In specification (6), it relates to the percentage of affirmative votes out of the total of affirmative and negative votes. Additionally, specifications (1), (2), (5), and (6) apply to all E&S proposals. Specification (3) specifically addresses environmental proposals, and specification (4) focuses on social proposals. We drop all anti-ESG proposals which we identify in Section 7.3. We suppress reporting of the constant term and firm-proposal controls. Standard errors are clustered at the meeting-level.

Table A7: Panel Regressions of Voting Support on Prescriptiveness:
Supervised Machine-Learning Measure

	Votes For As % Votes Cast						Votes For As % Shares Out	Votes For As % Yes & No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prescriptiveness (Binary)	0.094	0.933						
	(0.956)	(0.598)						
Prescriptiveness (Binary) × Post	-5.345**	-6.140**						
	(0.042)	(0.015)						
Prescriptiveness (Original)			0.978	0.851				
			(0.658)	(0.708)				
Prescriptiveness (Original) × Post			-6.778*	-5.872				
			(0.076)	(0.104)				
Prescriptiveness (Log-Transformed)					1.720	0.845	1.358	1.816
					(0.538)	(0.751)	(0.521)	(0.524)
Prescriptiveness (Log-Transformed) × Post					-8.701**	-7.115*	-6.497**	-8.830**
					(0.040)	(0.068)	(0.037)	(0.041)
Observations	1082	1180	1082	1180	1082	1180	1082	1080
Firm FE	Yes	No	Yes	No	Yes	No	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Proponent-Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Proposal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.392	0.283	0.389	0.280	0.390	0.281	0.411	0.391
F Statistic	1.660	2.700	1.398	2.270	1.492	2.452	1.741	1.531

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. In specifications (1) through (6), the dependent variable relates to the percentage of affirmative votes out of the total votes cast. For specification (7), it relates to the percentage of affirmative votes out of all outstanding shares. In specification (8), it relates to the percentage of affirmative votes out of the total of affirmative and negative votes. Columns (1) and (2) use binary values, derived by rounding probability values from our supervised machine learning algorithm described in Section 5.1 as proxies for prescriptiveness. Columns (3) and (4) use raw probability values as proxies, while columns (5) and (6) transform these values by applying a logarithmic function and then normalizing them to a range between 0 and 1 (to reduce the heteroskedasticity in our residuals). Finally, columns (7) and (8) present similar specifications from columns (5) and (6) using alternative definitions of the dependent variable. We suppress reporting of the constant term and firm-proposal controls. Standard errors are clustered at the meeting-level.

Table A8: Ordinary Business Exception Proxy for Prescriptiveness

	Uncorrected		Heckman Selection Models		IPTW Models	
	(1)	(2)	(3)	(4)	(5)	(6)
14-a(8)(i)(7) × Post	-4.363	-5.167*	-4.364	-5.167*	-0.167	2.164
	(0.153)	(0.066)	(0.111)	(0.051)	(0.955)	(0.465)
Post			-1.360	-2.193		
			(0.533)	(0.186)		
14-a(8)(i)(7)	0.010	-0.323	0.010	-0.323	0.453	-2.248
	(0.997)	(0.878)	(0.996)	(0.871)	(0.854)	(0.324)
Observations	1082	1180	1856	1856	1082	1180
Firm FE	Yes	No	Yes	No	Yes	No
Industry FE	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Proponent-Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Proposal Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.389	0.281			0.502	0.418
F Statistic	1.482	3.018			0.426	0.940
Chi-Square			0.1367	0.3395		

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. The dependent variable in all specifications relates to the proportion of affirmative votes out of the total votes cast. In specifications (3) and (4), we implement the Heckman Selection model introduced in Section 10.4, while in specifications (5) and (6), we implement the Inverse Probability of Treatment Weighting (IPTW) model introduced in the same Section. We suppress reporting of the constant term and firm-proposal controls. Standard errors are clustered at the meeting-level.

Table A9: Decomposition of Variation in Voting for E&S Proposals

Panel A: E & S Proposals

	(1) Year FE Only	(2) Year and Proponent-Type FE	(3) Year and Industry FE	(4) Year and Firm FE	(5) Year and Proponent FE	(6) Year and Fund FE
Observations	877227	877227	877227	877227	877227	876760
R-Sq	0.022	0.037	0.071	0.112	0.140	0.286
Firm FE	No	No	No	Yes	No	No
Industry FE	No	No	Yes	No	No	No
Fund FE	No	No	No	No	No	Yes
Proponent FE	No	No	No	No	Yes	No
Proponent-Type FE	No	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Environmental Proposals

	(1) Year FE Only	(2) Year and Proponent-Type FE	(3) Year and Industry FE	(4) Year and Firm FE	(5) Year and Proponent FE	(6) Year and Fund FE
Observations	173584	173584	173584	173584	173584	172789
R-Sq	0.044	0.062	0.161	0.209	0.211	0.305
Firm FE	No	No	No	Yes	No	No
Industry FE	No	No	Yes	No	No	No
Fund FE	No	No	No	No	No	Yes
Proponent FE	No	No	No	No	Yes	No
Proponent-Type FE	No	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Social Proposals

	(1) Year FE Only	(2) Year and Proponent-Type FE	(3) Year and Industry FE	(4) Year and Firm FE	(5) Year and Proponent FE	(6) Year and Fund FE
Observations	703643	703643	703643	703643	703643	703150
R-Sq	0.021	0.038	0.067	0.106	0.135	0.297
Firm FE	No	No	No	Yes	No	No
Industry FE	No	No	Yes	No	No	No
Fund FE	No	No	No	No	No	Yes
Proponent FE	No	No	No	No	Yes	No
Proponent-Type FE	No	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the R^2 statistics associated with regressing the dependent variable "Binary Fund Vote" on a variety of fixed effects and a constant. we suppress reporting of the constant term. Panel A outlines these R^2 statistics for E&S proposals, Panel B for environmental proposals specifically, and Panel C for social proposals.

Table A10: Panel Regressions of Individual Fund Votes on Prescriptiveness: Environmental/Social Distinction

	Environmental				Social			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prescriptiveness	-0.086**	-0.112***	-0.116**	-0.123***	-0.065***	-0.065***	-0.063***	-0.066***
	(0.045)	(0.008)	(0.015)	(0.004)	(0.005)	(0.002)	(0.005)	(0.001)
Observations	106252	106252	106252	106252	421901	421901	421901	421901
Firm FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Fund FE	No	No	No	No	No	No	No	No
Proponent-Type FE	No	No	Yes	Yes	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Proposal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.238	0.189	0.246	0.201	0.140	0.107	0.144	0.111
F Statistic	39.011	41.996	42.915	42.250	125.279	128.946	124.783	126.747

Note: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$. P-values are reported in parentheses. The dependent variable in all specifications relates to the variable "Binary Fund Vote", which takes on a value of 1 when a specific fund votes in favor of a proposal, and 0 for all other outcomes. Specifications (1) to (4) focus on environmental proposals, whereas specifications (5) to (8) target social proposals. we suppress reporting of the constant term, firm-proposal controls and fund controls. Standard errors are clustered at the meeting-level.

Table A11: Changes in Prescriptiveness Post Treatment: Heterogeneity amongst ESG Funds (Governance-Families)

	Binary Fund Vote			Ordered Fund Vote	
	(1)	(2)	(3)	(4)	(5)
Prescriptiveness × Post × ESG Fund	0.054**				
	(0.021)				
Prescriptiveness × Post × ESG Fund (G Family)		0.049**		0.052**	
		(0.045)		(0.029)	
Prescriptiveness × Post × ESG Fund (Non-G Family)			0.053**		0.053**
			(0.041)		(0.038)
Prescriptiveness × Post	-0.100***	-0.098***	-0.098***	-0.101***	-0.101***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)
ESG Fund	0.245***				
	(0.000)				
ESG Fund (G Family)		0.226***		0.224***	
		(0.000)		(0.000)	
ESG Fund (Non-G Family)			0.228***		0.224***
			(0.000)		(0.000)
Prescriptiveness	-0.025	-0.026	-0.025	-0.020	-0.019
	(0.363)	(0.344)	(0.358)	(0.451)	(0.468)
Observations	528153	528153	528153	528153	528153
Industry FE	Yes	Yes	Yes	Yes	Yes
Proponent-Type FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm-Proposal Controls	Yes	Yes	Yes	Yes	Yes
Fund Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.121	0.117	0.117	0.120	0.119
F Statistic	162.434	160.620	137.576	155.279	133.675

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. The dependent variable in specifications (1) to (3) relates to the variable "Binary Fund Vote", which takes on a value of 1 when a specific fund votes in favor of a proposal, and 0 for all other outcomes. In specifications (4) and (5), the dependent variable relates to the variable "Ordered Fund Vote", which is assigned a value of 1 for a "yes" vote, 0.5 for an "abstained" vote, and 0 for all other outcomes. We drop all anti-ESG proposals which we identify in Section 7.3. We suppress reporting of the constant term, firm-proposal controls, fund controls, as well as all interaction terms in specification (4) (e.g., $Post_t \times FundCat_m$) which are unreported in this Table. Standard errors are clustered at the meeting-level.

Table A12: Changes in ESG Fund Flows Post Treatment

	(1)	(2)	(3)	(4)	(5)
ESG Fund × Post	0.149	0.125			
	(0.725)	(0.794)			
ESG Fund (ES Family) × Post			0.216		
			(0.690)		
ESG Fund (Non-ES Family) × Post				0.036	
				(0.956)	
ESG Fund (Large-ES Family) × Post					0.488
					(0.661)
ESG Fund	-0.118	0.138			
	(0.616)	(0.890)			
ESG Fund (ES Family)			-0.141		
			(0.629)		
ESG Fund (Non-ES Family)				-0.069	
				(0.858)	
ESG Fund (Large-ES Family)					-0.180
					(0.758)
Observations	523510	523456	523510	523510	523510
Fund FE	No	Yes	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes
Fund Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.000	-0.004	0.000	0.000	0.000
F Statistic	0.376	0.159	0.376	0.348	0.368

Note: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$. P-values are reported in parentheses. The dependent variable in all specifications relates to the monthly fund flows of a given fund as defined in Section 7.2. ESG fund variables are defined in Section 6.3.1. We suppress reporting of the constant term and fund-proposal controls. Standard errors are clustered at the meeting-level.

Table A13: Changes in Prescriptiveness Post Treatment:
Heterogeneity in Fund Flows amongst ESG Funds

	Binary Fund Vote			Ordered Fund Vote
	(1)	(2)	(3)	(4)
Prescriptiveness × Post × Btm Decile (Fund Flow)	-0.030			-0.038
	(0.586)			(0.492)
Prescriptiveness × Post × Btm Quintile (Fund Flow)		-0.013		
		(0.737)		
Prescriptiveness × Post × Btm Quartile (Fund Flow)			-0.022	
			(0.550)	
Prescriptiveness × Post	-0.049	-0.049	-0.048	-0.053
	(0.185)	(0.187)	(0.206)	(0.145)
Btm Decile (Fund Flow)	-0.134***			-0.140***
	(0.000)			(0.000)
Btm Quintile (Fund Flow)		-0.060***		
		(0.001)		
Btm Quartile (Fund Flow)			-0.066***	
			(0.000)	
Prescriptiveness	-0.035	-0.037	-0.038	-0.030
	(0.246)	(0.224)	(0.210)	(0.320)
Observations	33463	33463	33463	33463
Industry FE	Yes	Yes	Yes	Yes
Proponent-Type FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm-Proposal Controls	Yes	Yes	Yes	Yes
Fund Controls	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.133	0.132	0.132	0.132
F Statistic	38.243	35.752	36.834	41.761

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. The dependent variable in specifications (1) to (3) relates to the variable "Binary Fund Vote", which takes on a value of 1 when a specific fund votes in favor of a proposal, and 0 for all other outcomes. In specification (4), the dependent variable relates to the variable "Ordered Fund Vote", which is assigned a value of 1 for a "yes" vote, 0.5 for an "abstained" vote, and 0 for all other outcomes. Observations not linked to ESG-fund votes, as well as all anti-ESG proposals identified in Section 7.3, are excluded. We suppress reporting of the constant term, firm-proposal controls, fund controls, as well as all interaction terms in specification (4) (e.g., $Post_t \times FundCat_m$) which are unreported in this Table. Standard errors are clustered at the meeting-level.

Table A14: Summary Statistics: Anti-ESG Proposals

	Year						
	2018	2019	2020	2021	2022	2023	Total
Panel A: Prescriptive Proposals							
Non-Anti-ESG							
Frequency	57	62	61	49	113	142	484
Percent (Within-Year)	98.28	87.32	98.39	100.00	86.92	85.54	90.30
Anti-ESG							
Frequency	1	9	1	0	17	24	52
Percent (Within-Year)	1.72	12.68	1.61	0.00	13.08	14.46	9.70
Panel B: Non-Prescriptive Proposals							
Non-Anti-ESG							
Frequency	95	98	107	106	167	162	735
Percent (Within-Year)	97.94	100.00	97.27	95.50	92.27	88.52	94.23
Anti-ESG							
Frequency	2	0	3	5	14	21	45
Percent (Within-Year)	2.06	0.00	2.73	4.50	7.73	11.48	5.77
Panel C: Total							
Non-Anti-ESG							
Frequency	152	160	168	155	280	304	1,219
Percent (Within-Year)	98.06	94.67	97.67	96.88	90.03	87.11	92.63
Anti-ESG							
Frequency	3	9	4	5	31	45	97
Percent (Within-Year)	1.94	5.33	2.33	3.13	9.97	12.89	7.37

Note: This Table illustrates the frequencies and within-year percentages of anti-ESG proposals which proceed to a vote. Panels A and B classify these proposals by whether they are prescriptive or non-prescriptive, respectively. Panel C then combines the data from Panels A and B.

Table A15: Changes in Anti-ESG Proposals Post Treatment

	Votes For As % Votes Cast				Votes For As % Shares Out	Votes For As % Yes & No
	(1) Uncorrected	(2) Uncorrected	(3) IPTW	(4) IPTW	(5) Uncorrected	(6) Uncorrected
Anti ESG	-14.505***	-16.541***	-13.442***	-15.896***	-10.002***	-14.822***
	(0.002)	(0.000)	(0.003)	(0.000)	(0.002)	(0.002)
Anti ESG × Post	-3.865	-1.762	-4.833	-2.049	-3.076	-3.973
	(0.418)	(0.645)	(0.301)	(0.580)	(0.359)	(0.414)
Observations	1082	1180	1082	1180	1082	1080
Firm FE	Yes	No	Yes	No	Yes	Yes
Industry FE	No	Yes	No	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Proponent-Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm and Proposal Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.446	0.337	0.448	0.344	0.460	0.447
F Statistic	11.411	15.770	11.714	15.451	12.155	11.448

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. In specifications (1) through (4), the dependent variable relates to the percentage of affirmative votes out of the total votes cast. For specification (5), it relates to the percentage of affirmative votes out of all outstanding shares. In specification (6), it relates to the percentage of affirmative votes out of the total of affirmative and negative votes. In specifications (3) and (4), we implement the Inverse Probability of Treatment Weighting (IPTW) model introduced in the Section 10.4. We suppress reporting of the constant term and firm-proposal controls. Standard errors are clustered at the meeting-level.