Beyond Bias: AI as a Proxy Advisor

Finance Working Paper N° 1131/2026
September 2026

Choonsik Lee
College of Business, University of Rhode Island
Matthew E. Souther
Darla Moore School of Business, University of South Carolina

ECGI Working Paper Series in Finance

Beyond Bias: AI as a Proxy Advisor

Working Paper N° 1131/2026
September 2026

Choonsik Lee
Matthew E. Souther

Beyond Bias: AI as a Proxy Advisor*

September 18th, 2026

Choonsik Lee
College of Business
University of Rhode Island
Kingston, RI 02881
choonsiklee@uri.edu

Matthew E. Souther
Department of Finance
Darla Moore School of Business
University of South Carolina
Columbia, SC 29208
matthew.souther@moore.sc.edu

Abstract

We evaluate the use of AI as an unbiased proxy advisor for shareholder proposals. When provided with ISS guidelines, our model matches ISS recommendations in 75% of proposals and better predicts shareholder support than ISS recommendations alone. Extensive tests confirm this alignment is a result of AI's rule application rather than lookahead bias. AI-ISS disagreements are more likely when firms disclose a governance consultant, consistent with firm efforts and capacity to influence recommendations. AI recommendations on ES proposals also predict subsequent ES incidents. These findings illuminate the proxy advisor industry's conflicts of interest and demonstrate AI's potential to improve transparency.

Keywords: AI; Llama; Proxy Advisor; Proxy Recommendations; Shareholder Proposals
JEL Classification: D80, G14, G28, G30, G38

* The authors thank Lauren Cohen, Fabrizio Ferri, Caroline Flammer, Simi Kedia, Nadya Malenko, Pedro Monteiro, Jiyeon Seo, Chi Wan, Adam Yore, H. Zafer Yuksel, and session participants at the University of Rhode Island, the University of South Carolina, Chung-Ang University, the 2025 RCF-ECGI Conference, the 2026 University of Delaware Weinberg Center/ECGI Corporate Governance Symposium, the 2026 KAIST Finance Alumni Conference, and the 2026 SKKU International Conference on AI Convergence in Business, Economics, Finance, and Society for valuable comments and suggestions. Also, the authors thank Meta for providing access to the Llama model used in this research. The authors are grateful to John Ampong and Maniraj Muthyala for their assistance with data work. All remaining errors are the fault of the authors.

1. Introduction

Proxy advisors play a central role in corporate voting by issuing recommendations that can meaningfully shape shareholder support (Ertimur, Ferri, and Oesch, 2013; Iliev and Lowry, 2015; Malenko and Shen, 2016). This practice has faced heightened scrutiny in recent years, particularly given potential conflicts of interest arising when proxy advisors also provide consulting services to corporate issuers (Li, 2016). In such settings, a proxy advisor may simultaneously advise a firm and evaluate that firm's ballot items. However, assessing whether and how these potential conflicts of interest affect the objectivity of recommendations remains difficult because client relationships are often opaque and data on client identities are limited.

Proxy advisors broadly dismiss these concerns by pointing to their annually released voting guidelines, which they claim provide an objective framework for recommendations. They further assert that their consulting services are wholly independent from their recommendation functions.[1] Nonetheless, these assurances do little to alleviate suspicion from many practitioners and regulators, and firms remain incentivized to shape proxy advisor recommendations through external influence.

To address these concerns empirically, we introduce a novel approach: using artificial intelligence (AI) to serve as an unbiased proxy advisor. We task an AI model with issuing binary ("For" or "Against") recommendations on shareholder proposals by following the rubric provided by publicly available voting guidelines from ISS, the largest and most influential proxy advisor, alongside textual information from proxy filings. The AI model then processes increasingly subjective and conditional ISS guidelines to arrive at this binary recommendation. Because the AI

[1] In a 2020 comment letter to the SEC, ISS refers to a "firewall…between the core institutional business and the [consulting] business." See https://www.sec.gov/comments/s7-22-19/s72219-6732023-207470.pdf.

has no financial relationship with firms and follows stated guidelines deterministically, its recommendations provide a unique benchmark for evaluating potential bias in traditional proxy advisory decisions.

The AI in our study makes recommendations that align closely with ISS across most cases. These AI recommendations broadly appear to be capturing shareholder preferences; controlling for the effect of the ISS recommendation, a positive recommendation from the AI is associated with a significantly higher level of shareholder support, and higher support from the specific subset of presumably informed actively voting mutual funds. We then examine whether outcomes differ in settings where firms disclose retaining third-party governance consultants; these consultants would represent management's interest in opposing these shareholder proposals.[2] We find that disagreements between AI and ISS are more likely in these settings. This pattern is consistent with (but does not establish) an association between consultant involvement and the recommendation environment, and it may also reflect other contemporaneous firm efforts that correlate with consultant retention. While our analysis cannot definitively identify the source of influence involving these consultants, it supports the concerns that proxy advisor recommendations can be influenced through external mechanisms. Our findings therefore speak directly to ongoing regulatory debates about the transparency and independence of proxy advisory firms.

Our study focuses exclusively on shareholder proposals for several reasons. Most importantly, the proposal generally includes both supporting statements from shareholders and opposing statements from managers. The AI is thus able to evaluate both sides' arguments and how they fit into ISS's stated policies. Second, ISS policies are generally clearly stated on these

[2] Management is nearly universally opposed to shareholder proposals. In our sample, management explicitly opposes 98.1% of proposals. In the remaining 1.9% of proposals, management refrains from issuing a recommendation. Thus, an ISS recommendation of "Against" would broadly align with management's preferences.

proposals, and the statements contain the relevant information that ISS policies explicitly consider. Thus, the proposal can be evaluated solely based on the statements, without incorporating additional datapoints that would be necessary for other proposal types. Third, shareholder proposals are nearly universally opposed by managers, so we can clearly evaluate whether hiring an external consultant reduces the likelihood of an opposed statement getting passed. And finally, unlike contested director elections or say-on-pay votes, shareholder proposals rarely receive significant media attention, so the ISS recommendations remain locked behind paywalls rather than in AI training data. Thus, it is highly unlikely that the AI recommendations are affected by lookahead bias from a model trained on publicly available data.[3]

Our study begins with an analysis of annual voting guidelines released by ISS for shareholder proposals. In these guidelines, ISS specified the conditions in which they will recommend a vote "For" or "Against" each type of proposal. ISS's language surrounding these guidelines falls into one of several categories: 1) *Vote For (Against) Without Exceptions*, in which ISS states that they will recommend a vote in favor of (against) the proposal without listing any additional conditions, 2) *Vote For With Exceptions*[4], in which ISS states that they will recommend in favor of a proposal unless specified conditions are met, 3) *Generally Vote For (Against)*, in which ISS states that they will typically issue a supporting (opposing) recommendation but will consider various stated factors, and 4) *Case-by-case*, in which ISS will state the factors that they will consider in deciding how to issue a recommendation. We find that, over the course of our 2009-2021 sample, ISS guidelines have become increasingly reliant on more subjective *Case-by-Case* and *Generally Vote For (Against)* decisions. In 2021, nearly 45% of guidelines on

[3] Subsequent tests also support this claim empirically.
[4] During our sample period, ISS has no proposals in which they issue a *Vote Against with Exceptions* policy guideline.

shareholder proposals are classified as *Case-by-Case*, compared to less than 15% in earlier years of the sample.

We next examine the AI's voting recommendations, how they align with those of ISS, and whether alignment improves when the AI is provided with additional information. We test the AI in two progressive scenarios: first, analyzing only the text of the proposal from the shareholder sponsor ("P"), its supporting statement ("S"), and the opposition statement from management ("O"); second, analyzing these items with the addition of the publicly available ISS voting guideline ("G"). We find that, although AI has strong alignment with only PSO (71.7%), alignment significantly improves when the ISS guideline is provided, culminating in 75% consistency when all information is incorporated in our "PSOG" model. We conclude that AI can reasonably act as a proxy advisor in shareholder proposals when provided with a reasonably detailed set of criteria to consider. Examining alignment by year and guideline category, we find that alignment is highest for the most prescriptive guidelines and lowest for Case-by-Case guidelines, consistent with more discretionary voting policies producing less predictable recommendations. Notably, even in the "Vote for Without Exception" category, alignment falls short of 100% in several earlier years of the sample, driven by ISS issuing recommendations that seemingly contradict its stated policies.

To what extent do these AI-driven recommendations actually reflect the specific content of the proposal and its applied guideline, as opposed to merely reproducing priors learned from the training data (i.e., "lookahead bias")? Although lookahead bias is unlikely to affect our results given our prompt design and the media's infrequent coverage of shareholder proposals, we provide a set of direct tests to address any remaining concerns. First, we create a set of falsified guidelines to see the impact they have on the AI recommendation. If AI is relying on training data instead of processing the provided guideline, we would expect the output recommendations to have similar alignment with ISS with the falsified guideline. However, we find that alignment substantially worsens with a falsified guideline, suggesting that AI is indeed reading and processing the guideline. Second, we examine a subset of proposals for which ISS has no stated guideline. If lookahead bias drives the AI alignment, we would expect alignment to also be high in the sample. However, we find alignment falls substantially when no guideline is provided. Third, we analyze the AI's confidence level in its generated recommendation by utilizing a relative confidence score. We find that, despite the AI's high degree of alignment with ISS recommendations, model confidence declines when we apply more complex and/or vague guidelines that demand discretionary judgment, again suggesting that the AI is processing the guideline text and not relying on training data. Finally, we run a separate test providing redacted proposal text to the AI, with all company identifying information removed. The AI continues to generate recommendations that are virtually unchanged from the main tests. Across all four tests, the consistent takeaway is that the AI model actively applies reasonable judgement when evaluating individual proposals, rather than merely retrieving memorized ISS recommendations.

A proxy advisor is tasked with representing shareholder interests. Our next tests evaluate the AI proxy advisor's performance in this regard by testing how closely its recommendations align with shareholder support. Our empirical design controls for the effect of recommendations from both ISS and management, shown in prior work to be a significant determinant of shareholder support (Ertimur, Ferri, and Oesch, 2013; Malenko and Shen, 2016; Iliev and Lowry, 2015), along with a variety of other firm and proposal characteristics. In this multivariate setting, we find that a positive recommendation from the AI proxy advisor is associated with significantly higher levels of shareholder support, suggesting that the AI recommendations are more effective in capturing shareholder preferences than a positive ISS recommendation alone. We then test whether this higher support is also present among a sample of actively voting mutual funds, which we define as funds that deviate from ISS recommendations on more than 5% of votes, subject to a minimum of 200 proposals during the previous year. The AI recommendation continues to be predictive of voting support from these presumably informed voters.

Given the influence of proxy advisor recommendations, firms have incentive to influence recommendations by engaging external governance consultants. Notably, both major proxy advisors, ISS and Glass Lewis, provide consulting services to corporations, but they do not disclose client identities, which limits researchers' ability to directly study these relationships. We therefore rely on firms' voluntary disclosures of hiring a governance consultant, recognizing that these disclosures typically omit the consultant's identity and may also capture other simultaneously deployed tactics to influence and engage proxy advisors.

Our empirical design analyzing the impact of these governance consultants focuses on the likelihood of a specific outcome: an ISS recommendation opposing the proposal (and therefore aligned with managerial preferences), when the AI proxy advisor issues a recommendation "For" the proposal when prompted to follow ISS policies. We find that this outcome is significantly more likely when a governance consultant is present. With the above caveats in mind, we interpret this pattern cautiously as evidence consistent with intensified firm engagement being associated with ISS recommendations that are more favorable to management than the guidelines-based benchmark would predict.

Our final set of tests aims to examine whether our AI advisor is able to identify proposals that are informative about subsequent risk. Specifically, we examine whether a supportive recommendation from the AI proxy advisor predicts the number of ES incidents in the following year. In a multivariate setting, we find a clear pattern for ES proposals: when the AI advisor recommends voting "For," firms experience a higher number of ES incidents in the subsequent year, even after controlling for the ISS recommendation, which does not provide any significant predictive power. Overall, these results suggest that the AI benchmark captures meaningful information about underlying ES risk that later materializes in related incidents, reinforcing the interpretation that AI-ISS divergences are systematically related to firm characteristics and risk rather than random disagreement.

Our study contributes to an expanding literature on the role and influence of proxy advisors. Prior research documents the substantial impact of proxy advisor recommendations on shareholder voting outcomes (Bethel and Gillan, 2002; Cai, Garner, and Walkling, 2009; Alexander, Chen, Seppi, and Spatt, 2010; Ertimur, Ferri, and Oesch, 2013; Malenko and Shen, 2015). This influence is amplified among institutional investors that systematically follow proxy advisor guidelines (Iliev and Lowry, 2015). Other recent work explores how proxy advisor policies evolve via customization (Hu, Malenko, and Zytnick, 2025) and how firms strategically respond to these policies through revised policies (Larcker, McCall, and Ormazabal, 2015). Several studies document the benefits of proxy advisors, which come largely in the form of processing information and dispersing it to institutional shareholders (Choi, Fisch, and Kahan, 2010; McCahery, Sautner, and Starks, 2016).

Li (2016) provides evidence suggesting that ISS's dual role as both proxy advisor and governance consultant may introduce bias into its recommendations. To circumvent the lack of disclosure on consulting relationships, Li exploits variation in market competition, examining how ISS recommendations change when Glass Lewis, at the time unaffiliated with any consulting services, begins covering a firm (notably, Glass Lewis has since begun offering consulting services). He finds that ISS becomes more critical of management once Glass Lewis enters as an independent competitor, consistent with the hypothesis that ISS softens its recommendations in the absence of external scrutiny. While this study offers compelling indirect evidence of potential conflicts, it remains limited by its reliance on market structure as a proxy for firm-level consulting activity. By contrast, our study introduces an AI-based benchmark that is explicitly constrained to follow public policy guidelines, enabling direct observation of potential bias at the firm level. This approach allows us to isolate individual cases in which ISS recommendations deviate from an unbiased standard in a manner consistent with managerial influence.

Our analysis of evolving ISS voting guidelines relates to emerging work by Couvert (2025). In this study, Couvert analyzes proxy voting guidelines released by 29 mutual fund families and finds these guidelines are heterogeneous and impact the funds' voting behavior. Further, portfolio firms adapt to the preferred governance policies of their fund shareholders. To our knowledge, our study is the first to focus on voting guidelines from ISS.

Our study also contributes to the growing literature on the application of AI models in accounting and finance. Recent work has shown that large language models can be powerful tools for extracting and analyzing information from various firm-level texts. In the context of earnings call Q&A, Bai, Boyson, Cao, Liu, and Wan (2025) develop a measure of information content based on the discrepancy between executive and AI-generated answers, showing language models may reveal hidden managerial insights. Similarly, Li, Mai, Shen, Yang, and Zhang (2025) use AI models to parse analyst reports and extract language associated with corporate culture. Our study highlights the use of AI in analyzing shareholder proposals, a distinct form of corporate texts, by integrating inputs from multiple parties to generate unbiased assessments.

Related research by Cao, Jiang, Wang, and Yang (2024) highlights the complementary strengths of human and AI analysts. While AI excels at processing large volumes of data, humans are better suited for tasks requiring institutional knowledge. Consistent with this view, our study does not aim to replace proxy advisors like ISS but proposes that AI can serve as a valuable complement.

We note that our study comes alongside a movement by institutional investors to incorporate AI into proxy voting practices. In January of 2026, public reporting indicated that JPMorgan's asset management unit intended to replace its external proxy advisors with an internally developed AI platform, which has sense become known as ProxyIQ.[5] Shortly after this announcement, SEC Director Brian Daly gave a speech framing AI-assisted proxy voting as a way to fulfill the investment manager's fiduciary standards. Souther (2026) provides a more detailed description of these events and the potential legal conflicts of AI use by fiduciary advisors. To our knowledge, our study is the first to empirically analyze AI-generated proxy recommendations.

2. Data, AI model, and methodology

2.1. Voting Data and Textual Content of Shareholder Proposals

Our empirical analysis is primarily based on the ISS Shareholder Proposals dataset, which includes detailed information on shareholder-sponsored proposals at U.S. public companies from 2006. We restrict our sample to proposals presented at regular annual meetings, excluding those originating from proxy contests or special meetings due to their distinct procedural and strategic contexts. Similarly, we exclude proposals that receive management support, given that such

[5] See *JPMorgan Cuts All Ties With Proxy Advisers in Industry First*, Wall St. J. (Jan. 7, 2026), https://www.wsj.com/finance/banking/jpmorgan-cuts-all-ties-with-proxy-advisers-in-industry-first-78c43d5f; JP Morgan Investment Management Form ADV, 2026, *See* J.P. Morgan Inv. Mgmt. Inc., *Form ADV Part 2A Firm Brochure* 109-10 (June 30, 2026), https://am.jpmorgan.com/content/dam/jpm-am-aem/americas/us/en/supplemental/disclosure-booklet/JPMIM-Form-ADV-Part-2A.pdf.

endorsements are typically strategic and strongly predictive of high shareholder approval. Furthermore, we only include proposals with disclosed final voting outcomes, thereby excluding withdrawn, pending, or otherwise incomplete proposals. While the ISS Shareholder Proposals dataset is more limited compared to the broader ISS Voting Analytics, it provides important attributes such as sponsor identity and proposal type. For instance, proposals sponsored by certain institutional investors, such as pension funds, tend to receive greater shareholder support and are more likely to succeed (Del Guercio and Hawkins, 1999; Gillan and Starks, 2000; Blank, Hadley, and Lee, 2025).

We then merge this baseline dataset with several other data sources. Additional proposal-level characteristics, including ISS voting recommendations through 2021, are obtained from earlier versions of the ISS Voting Analytics. Because the Shareholder Proposal dataset does not contain the actual proposal texts, we identify the corresponding CIK of each target firm using COMPUSTAT and extract the full text of the proposals from associated proxy statements available through the SEC EDGAR. We also incorporate firm-level control variables from CRSP and COMPUSTAT to support multivariate analyses. Appendix A provides definitions of all variables used in the analysis.

Each proposal's textual content is structured into three parts: (1) the proposal itself, (2) the supporting statement by the sponsor, and (3) the board of directors' opposition statement. For proposals deviating from this standardized format, we manually reorganize the content to ensure uniformity across the dataset. We also remove legal and operative elements, such as "Resolved" and "Whereas" as well as section titles, restructuring the content to fit a consistent format in our prompt. Proposals missing any of the three textual components are excluded from the sample. In preparing the text data for use in natural language prompts, we carefully remove footnotes, hyperlinks, and other non-substantive references to maintain clarity without altering the context. We also drop tables and figures, as they do not contribute to the semantic content needed for model interpretation. Additionally, we exclude procedural content unrelated to the rationales in the board's opposition statements, such as legal disclaimers on broker voting or vote thresholds.

From the textual content, we construct variables for the volume of arguments from each party: the natural log of the number of tokens[6] in a) the proposal and supporting statement by the sponsor, b) the opposition statement by the board, and c) the ISS guidelines.

2.2. ISS Guidelines

We also incorporate ISS Voting Guidelines, which ISS publicly releases and updates annually. We collect these guidelines beginning with the version applicable to the 2009 proxy season, covering meetings from February 1, 2009. Earlier versions, including those from 2006 through 2008, are either unavailable or lack sufficient detail and are therefore excluded.

ISS Guidelines have an extensive list of proposal categories and state how ISS arrives at its voting recommendation for each. We then classify the ISS policy into the following categories based on the language in the stated guideline: "Vote For Without Exceptions," "Vote for with Exceptions," "Generally Vote For," "Vote Case-by-Case," "Generally Vote Against," or "Vote Against Without Exceptions." In the "Without Exception" categories, ISS states a clear policy with no exceptions listed. In the "With Exception" categories, ISS similarly lists a clear policy, but this policy is typically followed by the word "unless" or "except," with a list of several conditions that

[6] A token is a small unit of text, such as a word, part of a word, or punctuation mark, that a language model reads and processes to understand and generate language.

would lead ISS to issue a recommendation in the opposite direction. The “Case-by-Case” guidelines introduce the most uncertainty and the most expansive set of criteria to be considered. The “Generally Vote For (Against)” categories also have an expansive set of criteria but with an established tendency to favor a certain position. We use these latter two category types as measures of ISS recommendation uncertainty in our tests. We report examples of all guideline types in Appendix B.

We then match each proposal to its relevant guideline. In total, after merging all relevant datasets, our final sample comprises 5,184 shareholder proposals from February 1, 2009, through the end of 2021, for which ISS recommendations are available.[7] Out of 5,184 proposals, 4,565 proposals have matched ISS guidelines.

Although our focus is on ISS guidelines, we also perform some additional analysis and robustness checks using Glass Lewis (GL) guidelines. GL has a narrower set of guidelines, and we were unable to locate their guidelines for earlier years of our sample. As a result, the sample is smaller, with 2,164 proposals matched to GL guidelines. We thank Shu (2024) for providing the GL recommendations.

2.3. Summary Statistics

Panel A of Table 1 presents summary statistics for the full sample. The average support rate for shareholder proposals is 31.2%, with considerable variation. ISS recommends voting "For" in approximately 74.1% of the proposals, suggesting that ISS recommendations are significantly

[7] ISS recommendations were historically available in Voting Analytics but have been removed from the database, both retroactively and on an ongoing basis. As a result, we rely on legacy data for ISS recommendations.

more positive. Management offers no formal recommendation in just 1.9% of the cases, indicating that the majority of proposals face clear stances from both parties. The log number of tokens averages 6.24 for the proposal and supporting statement, and 6.61 for the opposition statement. The target firms in the sample show meaningful variations for the control variables. We include variables for agency concerns (firm size, cash holdings, and dividend yield), profitability (market-to-book, ROA, and past stock performance), and shareholder base (institutional ownership). We also include indicator variables for sponsor identities. Pension funds, SRI funds, and other funds are the most frequent, while unions, religious groups, and special interest groups appear less commonly. Panel B shows summary statistics for the sample where ISS guidelines are matched to proposals. Compared to shareholder and management statements, the ISS guidelines tend to be more concise, as reflected in the lower log number of tokens. In 26.4% of cases, ISS guidelines include case-by-case evaluation criteria, and in 76.8%, ISS uses either case-by-case or a "Generally" vote for/against guideline.

2.4. AI model, configuration, and prompts

To analyze the textual content of shareholder proposals, we utilize Meta's Llama-3.3-70B-Instruct model.[8] Designed for superior instruction following and contextual reasoning with 70 billion parameters, it is particularly effective in interpreting the nuanced language and normative framing found in shareholder proposals. The model has been trained on a comprehensive and diverse dataset that includes business, legal, and governance-related materials, making it highly

[8] The model is available at https://huggingface.co/meta-llama/Llama-3.3-70B-Instruct. Released on December 6, 2024, and trained on approximately 15 trillion tokens from publicly available sources, it was among the most capable open-weight language models available at the start of this project.

applicable to our domain of inquiry. One of its key technical strengths is a substantial input token limit of 128,000 tokens, which allows for the inclusion of full-length proposal texts and extensive contextual details within a single inference run, minimizing the need for truncation or segmentation.

We use *bfloat16* precision for model inference, which enables efficient utilization of memory and computing resources while preserving numerical accuracy.[9] Unlike other formats that rely on quantization to reduce computational load, our implementation avoids any compromises in linguistic precision. This choice ensures that the model operates with full parameter expressiveness, which is especially important when evaluating subtle distinctions in language within complex shareholder proposals with two contrasting perspectives, one from the shareholder sponsor and another from management.

We choose Meta's Llama because it is an open-weight model that can be downloaded and run in a local computing environment, enabling us to deploy the model on a standalone computing setup, which provides full control over inference parameters, system resources, and operational constraints. This standalone configuration allows us to tailor every aspect of the model's performance to our specific use case. For example, we disable sampling with *do_sample* to ensure virtually deterministic outputs.[10] This level of consistency is crucial for reliably generating binary voting recommendations ("For" or "Against") in a zero-shot setting. These choices enable

[9] The Llama-3.3-70B-Instruct model supports *bfloat16* as its highest precision format. *bfloat16* is a 16-bit number format that reduces memory usage and speeds up model inference without relying on quantization. Unlike quantized formats, which may lose accuracy due to limited range or reduced precision, *bfloat16* maintains a wide dynamic range, making it more reliable for large models.

[10] The *do_sample* parameter, when set to false, disables random sampling and ensures the model always selects the highest-probability token at each step. In this case, parameters that control sampling in language models, such as *temperature*, *top_p*, and *top_k*, have no effect, because no sampling is performed.

complete reproducibility of results. Each time the same prompt is submitted under identical conditions, the model produces the exact same recommendation.[11]

A zero-shot setting generates answers without being shown any examples of how similar tasks were solved in the prompt itself. We adopt this approach to maintain simplicity and reproducibility: the model directly interprets the instruction and produces a classification without potential biases introduced by curated examples. In contrast, few-shot prompting would require us to provide selected training examples, raising concerns about representativeness, subjective curation, and reproducibility. We also do not use further fine-tuning with a specialized training data, as our objective is to assess the model's baseline capacity for general instruction-following rather than to optimize its alignment with a particular set of proxy advisory recommendations.

To enhance the reliability and comparability of model outputs, we standardize the prompt structure using markdown formatting. This structured formatting helps delineate sections such as the proposal text, supporting and opposing statements, and corresponding guidelines (when included). Markdown's visual hierarchy contributes to improved attention alignment within the model's processing.

We begin each prompt with the sentence: "*You are an analyst at a proxy advisory firm that provides voting recommendations.*" This framing is intended to let the model adopt the analytical mindset, evaluative standards, and institutional perspective associated with proxy advisory firms. By doing so, we ensure that the model's interpretations and recommendations align with the

---

[11] All results in this paper were obtained using the *transformers* library (Hugging Face) version 4.57.1 and Meta's Llama-3.3-70B-Instruct model (commit 6f6073b423013f6a7d4d9f39144961bfbfbc386b), with PyTorch 2.9.0 + CUDA 13.0 in Python 3.14.0.

domain knowledge of proxy advisory services, thereby increasing the relevance of the AI-generated outputs to real-world institutional decision-making processes.

We note potential concerns with lookahead bias in AI models prompted with tasks similar to our setting. Lookahead bias, where a model is asked to predict a future event and "cheats" by having already seen it, is a common problem with models prompted with a *forecasting* task (for example, "predict stock returns based on these firm characteristics"). Thus, we intentionally avoid any type of forecasting task in our prompt and instead provide the AI with an explicit *rule-following* task: "Your task is to evaluate the following 'Shareholder Proposal' by objectively assessing the 'Supporting Statement' provided by the sponsor of the proposal and the 'Opposition Statement' provided by the company. Apply the relevant 'Voting Recommendation Guidelines' as the primary analytical framework." From the AI's perspective, the "correct answer" to the prompt is defined by the guideline and the proposal, not by any subsequent event. It is akin to asking the AI to grade an old essay following a grading rubric.[12]

The next part of the prompt aims to further minimize lookahead bias concerns by following standard practice of imposing a temporal constraint within each prompt: "*Base your evaluation exclusively on information available prior to {Date of Proxy Statement}.*" In a later section for empirical tests (Section 3.3), we also conduct explicit stress tests by evaluating model behavior under falsified guidelines, measuring output confidence across guideline variations, and redacting

[12] While we acknowledge this concern, direct memorization of Institutional Shareholder Services (ISS) voting recommendations remains inherently improbable. According to Meta, the Llama model was trained on publicly available sources (see https://huggingface.co/meta-llama/Llama-3.3-70B-Instruct), whereas ISS research reports are proprietary, subscription-gated products that are not likely indexed in open repositories. Outside of occasional high-profile proxy battles, executive compensation issues reported in mainstream financial news, and occasional coverage in blogs and newsletters, the vast majority of ISS recommendations, particularly those concerning shareholder proposals, are likely absent from public training corpora.

all organization names and their aliases from each prompt. The results show that our prompt and its evaluations remain robust against potential lookahead contamination.

Each input is constructed using one of two prompt types. The first includes the proposal, supporting statement, and opposition statement; the second supplements this with the matched voting guidelines.[13] In both formats, the input is framed by a fixed instruction header (###) to anchor the model's interpretation. To further enforce output conciseness and reduce extraneous reasoning, each prompt concludes with the instruction: "*Provide a deterministic voting recommendation as either "For" or "Against", without any explanations.*" This phrasing makes the model to deliver only the binary decision, without justifying its choice. All final prompt templates used in this analysis are available in Appendix C.

3. Results

In this section, we present our empirical results analyzing the performance of our AI proxy advisor in making recommendations on shareholder proposals.

3.1. ISS Voting Recommendations

Panel A of Table 2 reports the annual breakdown of ISS voting recommendations. ISS generally issues "For" recommendations in shareholder proposals- thus supporting the shareholder and opposing manager preferences- approximately 70-80% of the time in each year of our sample.

[13] ISS guidelines serve as the primary baseline for the matched voting guidelines, with GL guidelines used in supplementary tests. To prevent source identification, all references to ISS and GL are redacted from the matched guideline texts.

Though the number of proposals fluctuates from year to year, the support rate stays relatively consistent.

In Panel B, we analyze ISS voting guidelines. For each year, we report the number of unique guidelines applied to shareholder proposals in our dataset. A single unique guideline may be applied to multiple similar proposals within the year. In the following columns, we report the number of unique guidelines within each recommendation category: "Vote For Without Exceptions," "Vote For With Exceptions," "Generally Vote For," Case-by-Case," "Generally Vote Against," "Vote Against With Exceptions," and "Vote Against Without Exceptions." The final three columns report the percent of total guidelines that fall into one of the three "For" ("Against") Categories, and the percent of guidelines classified as "Case-by-Case."

Over the course of our sample, we observe a broad trend towards more "Case-by-Case" and "Generally" guidelines. After a major shift in guidelines after the 2009 proxy season (influenced by controversies around the 2008-2009 Financial Crisis), ISS relied on case-by-case decisions in only 15.22% of applied guidelines. Between 2010 and 2021, we observe a major shift towards more case-by-case decisions; the shift is especially evident in 2013, where proposals with "Case-by-Case" and "Generally Vote For" classifications increased by a factor of 3x from the prior year. In the final years of our sample, approximately 45% of proposals have a case-by-case guideline.

It is important to highlight the tradeoffs with case-by-case guidelines. Though they allow the proxy advisor more flexibility to tailor recommendations based on the characteristics of the company under review (thus moving away from the oft-cited "one-size-fits-all" approach to recommendations), they also allow a great deal of subjectivity to enter the decision framework. As an example, in our prompt example from Appendix B.2, the ISS guideline on retention requirement proposals, which ISS states are a "Case-by-case" issue, states the following:

> *The following factors will be taken into account:*
>
> *- Whether the company has any holding period, retention ratio, or officer ownership requirements in place. These should consist of: a) rigorous stock ownership guidelines; b) a holding period requirement coupled with a significant long-term ownership requirement; or c) a meaningful retention ratio;*
>
> *- Actual officer stock ownership and the degree to which it meets or exceeds the proponent's suggested holding period/retention ratio or the company's own stock ownership or retention requirements;*
>
> *- Post-termination holding requirement policies or any policies aimed at mitigating risk taking by senior executives;*
>
> *- Problematic pay practices, current and past, which may promote a short-term versus a long-term focus.*

While these criteria may lead to a detailed analysis of a firm's compensation plan, they also rely on a significant amount of subjective judgement from the proxy advisor. Thus, the broader trend observed in Panel B of Table 2 highlights the increasing role of these subjective judgement calls in proxy advisor recommendations.

Panel C of Table 2 complements Panel B by reporting the distribution of proposals across guideline categories. While Panel B captures shifts in the set of guidelines ISS maintains, Panel C reports how those shifts translate into the composition of proposals. The contrast over the sample period is again striking: in 2010 and 2011, over 90% of proposals were governed by clear "Vote For" guidelines. Beginning in 2013, proposals under "Generally Vote For" and "Case-by-Case" rise sharply and combined account for over 60% of proposals.

In Panel D, we examine how ISS's recommendations vary based on the guideline categories. We note several unexpected patterns in these recommendations. Although most external observers would likely expect the *Vote For Without Exception* category to have highly predictable recommendation patterns, we find that ISS does not always support these proposals, especially in earlier years of our sample. Similarly, most observers would expect the *Case-by-Case* guideline to essentially be a coin flip, but annual support for those proposals ranges from 64% to 94%. ISS is generally opposed to proposals without a published guideline. We note the challenges these unexpected recommendation outcomes present when asking our rules-based AI advisor to replicate ISS recommendations.

3.2. Alignment Between Traditional Proxy Advisors and AI

Table 3 introduces our AI proxy advisor and reports the level of agreement between the AI-generated recommendations and those issued by ISS. We begin by asking AI to make a recommendation based only on the shareholder proposal (P), the proposer's supporting statement (S), and the managerial opposition statement (O), excluding the voting guidelines. We refer to analysis based on these statements as PSO. As reported in Panel A, the AI proxy advisor aligns with ISS recommendations in 71.72% of proposals. Of the 5,184 proposals in our dataset, 3,438 (66.32%) were issued supporting recommendations by both ISS and AI, while 280 (5.40%) were issued opposing recommendations by both advisors.

In Panel B, we illustrate the AI proxy advisor's ability to incorporate voting guidelines. In addition to the proposal (P), supporting statement (S), and opposition statement (O) used in Panel A, we now also provide the AI with ISS's stated guideline (G) on the given proposal, as reported in ISS's annually published proxy voting guidelines for the year of the proposal.[14] We refer to models based on these statements, including the guideline, as PSOG. The alignment between ISS and AI increases to 75.03% with the provided guideline.[15]

Although our primary focus is on ISS guidelines, we provide some additional tests using guidelines from the second largest proxy advisor, Glass Lewis. For these tests, we follow the same process in matching each proposal to a guideline. Glass Lewis guidelines are notably more complex and broader than ISS guidelines[16], which presents greater challenges for AI replication. Glass Lewis also has fewer publicly stated guidelines that apply to a narrower set of proposals, and we are missing Glass Lewis guidelines for many earlier years of the sample. Despite these challenges, Panel C of Table 3 reports that AI issues recommendations reasonably consistent with Glass Lewis, with 64.37% alignment in the sample.

We run several different variations on the prompt to ensure that our results are reasonably consistent and not overly dependent on the language of our primary prompt. In Panel A of Appendix D1, we provide additional instructions to the AI model to strictly follow the guideline.[17] Although the more prescriptive instructions more explicitly constrain the model to the intended analytical framework, they also introduce competing directives, restricting the model to provided

[14] We note that 619 proposals did not have an explicitly stated ISS guideline and are therefore excluded from these statistics.

[15] We evaluate alternative models with larger parameter counts and more recent release relative to Llama-3.3-70B-Instruct. However, they do not exhibit greater alignment with ISS voting recommendations. This indicates that incremental gains in parameter count and newer model vintages do not necessarily yield superior performance in specialized, domain-intensive tasks such as proxy advisory services.

[16] The log of the number of tokens for Glass Lewis guidelines is 5.61, compared to 4.61 for ISS.

[17] The role prompt for this robustness check is as follows, with the underlined part indicating the modification: "You are an analyst at a proxy advisory firm that provides voting recommendations. Your task is to evaluate the following 'Shareholder Proposal' by objectively assessing the 'Supporting Statement' provided by the sponsor of the proposal and the 'Opposition Statement' provided by the company. Apply the relevant 'Voting Recommendation Guidelines' as the sole analytical framework, and you are strictly forbidden from using external knowledge. Base your evaluation exclusively on information available prior to {Proxy Filing Date}. Provide a deterministic voting recommendation as either "For" or "Against", without any explanations."

guidelines while forbidding external knowledge, that move the decision environment away from how actual proxy analysts operate. These more prescriptive instructions increase alignment only slightly to 76.34%, suggesting that our baseline prompt already captures the intended domain logic. This result underscores two key insights regarding the use of AI models for proxy recommendations. First, it suggests that even when explicitly instructed to prioritize provided guidelines, the model continues to rely on significant latent domain knowledge to navigate the nuances of individual proposals. Second, the absence of a more substantial increase in alignment suggests that the written guidelines themselves may not perfectly mirror ISS's historical recommendations, highlighting potential ambiguities or contradictions within the institutional framework. We provide further analysis of these alignment patterns in the subsequent analysis (Table 4).

In Panel B of Appendix D1, we conduct a robustness check by varying the persona in the prompting. Specifically, we replace the "proxy advisory firm" role in our role prompt with that of a "fund manager."[18] This modification addresses potential concerns regarding data contamination coming from the possibility that the "proxy advisor" label acts as a heuristic that triggers the retrieval of memorized ISS historical voting records from the AI's training corpus. By shifting to a "fund manager" persona, we test whether the model's performance is contingent on specific institutional role-play or reflects a generalized application of domain knowledge. We find that

[18] The role prompt for this check is as follows, with the underlined part indicating the modification to the persona: "<u>You are an institutional fund manager, voting on shareholder proposals as a fiduciary of your clients.</u> Your task is to evaluate the following 'Shareholder Proposal' by objectively assessing the 'Supporting Statement' provided by the sponsor of the proposal and the 'Opposition Statement' provided by the company. Apply the relevant 'Voting Recommendation Guidelines' as the primary analytical framework. Base your evaluation exclusively on information available prior to {Proxy Filing Date}. Provide a deterministic voting recommendation as either "For" or "Against", without any explanations."

alignment decreases only slightly to 72.18%, suggesting the results are not driven by the specific persona assigned in the prompt.

In Table 4, we report the alignment by year and guideline category. We note that alignment is stable across the entire sample period, suggesting that the AI's ability to interpret proxy materials does not vary systematically with changes in proposal composition or guideline language over time. Across guideline categories, alignment is highest in the "Without Exceptions" categories and lowest in the "Case-by-Case" category, which is consistent with more subjective and discretionary guidelines producing less predictable recommendations. A striking exception appears in the "Vote For Without Exception" category, where alignment falls below 100% in several early sample years. This divergence is driven not by the AI deviating from the guideline, but by ISS issuing opposing recommendations on proposals that its guidelines unambiguously endorse, highlighting a disconnect between ISS's published standards and its actual recommendations. In Appendix Table D2, we report statistics on alignment by proposal type using ISS agenda item ID classifications. We note that there are no significant outliers across the major proposal categories, suggesting that disagreement between ISS and AI is in general distributed without a discernible pattern.

We next analyze the cases of alignment in a multivariate setting. Our dependent variable takes a value of one if ISS and AI issue the same recommendation on a particular proposal. We include several proposal characteristics as regressors, limited to those explicitly available to our AI proxy advisor. As measures of complexity and detail, we include the natural log of the number of tokens in a) the proposal and supporting statement, b) the opposition statement, and c) the ISS guidelines. We also control for the presence of a case-by-case proposal guideline. The models also include firm fixed effects to control for similar or recurring proposals within a firm, and year fixed effects for cross-sectional dependence in a given year. In several models, we also include proposal type fixed effects, which allows us to better isolate the degree to which a proposal's statements affect its recommendations.

Table 5 reports the results. These models use the recommendations generated by the PSOG model. We note a few key takeaways. First, the number of tokens in the proposal and supporting statement are generally associated with higher alignment, suggesting that the information presented in those statements is informative and relevant to the recommendation. The number of tokens in the opposition statement, however, generally associated with lower alignment, suggesting that AI and ISS may diverge in their assessment of risks or governance implications when management presents a more complex and nuanced defensive stance. The number of tokens in the guideline, which proxies for the complexity of the guideline, is unsurprisingly associated with lower alignment in Columns 3 and 4. In Columns 5 and 6, we include controls for "Case-by-Case" and "Case-by-Case + Generally" recommendation categories. These controls provide an alternative measure of the degree of vagueness and/or complexity in the guideline. Alignment is unsurprisingly lower in these recommendation categories. In the last column, we include controls for whether management refrains from making a recommendation, which is associated with higher alignment, and whether management puts a conflicting proposal up for vote, which has no effect on alignment.

We next analyze factors that affect the AI's propensity for issuing a "For" recommendation. We regress an indicator taking a value of one for an AI "For" recommendation onto the same set of controls from Table 5. Panel A of Table 6 reports the results. Our measure of detail and complexity in the Proposal and Supporting Statement (*# of Tokens in PS*) is associated with an increased likelihood of a "For" recommendation, suggesting that the AI is more supportive of a proposal when the sponsor provides a more thorough and complete explanation. In Columns 3 and 4, we find that the number of tokens in the guideline leads to a lower likelihood of a "For" recommendation; these increased tokens may be a result of exceptions and/or additional considerations laid out in the guideline that increase the guideline's subjectivity.

As a benchmark for comparing the AI's performance, we next run the same test on ISS recommendations. Panel B of Table 6 reports similar specifications, but with dependent variable taking a value of 1 if ISS issues a "For" recommendation. The results are broadly similar to the AI panel. We again find that a more detailed proposal and supporting statement, proxied for by *# of Tokens in PS (Ln)*, is associated with a significantly higher likelihood of ISS supporting the proposal. This positive effect, occurring in both the AI and ISS samples, could be driven by characteristics related to proposal quality. We also note the negative effect of *# of Tokens in G* in Column 3, similar to what we find in Panel A. We thus find no substantial discernible differences in the strictly text-based evaluation patterns of proposals between ISS and the AI advisor.

3.3. Discussion and Tests of Potential Lookahead Bias

AI models are often perceived as "black boxes," and readers may be skeptical of whether our AI model is relying on memorized ISS recommendations in its training data (i.e., "lookahead bias") instead of considering the specific content of the proposal and its applied guideline. As explained in Section 2.4, our prompt is designed to minimize this concern, and it is unlikely that training data included paywalled ISS recommendations on shareholder proposals that receive little attention from media. However, we acknowledge potential concerns may remain and address them in this section.

Before turning to direct tests, we note that a lookahead bias hypothesis would make several predictions that are inconsistent with results already reported. First, a model relying on memorized ISS recommendations should follow ISS when ISS departs from their own stated policy. However, in the "Vote For Without Exceptions" category of Table 4 during 2010-2012, where ISS opposed proposals that their guidelines unambiguously endorse, the AI advisor followed the guideline instead of ISS. Second, because publicly available online governance commentary grew substantially over our sample period, lookahead bias would suggest that alignment would rise over time as AI has more exposure to discussion of specific proposals. Instead, we find that alignment is stable throughout our 2009-2021 sample period (Table 4). We next proceed to a set of direct tests to address lookahead bias concerns.

We begin with a falsification test, reported in Panel A of Table 7, where we establish a set of falsified guidelines. For every ISS guideline, we replace "For" ("Against") with "Against" ("For"). We replace case-by-case guidelines with "Against." We then examine the ISS alignment with these falsified guidelines. If AI is relying on its training data instead of applying the guideline to the given proposal, we would expect little change in alignment. However, we find that alignment is substantially worse, decreasing to 37%, suggesting that the AI recommendations are indeed driven by the guideline and not the training data.

We next examine a subset of proposals for which lookahead bias would be most evident: those without a matched ISS guideline. These are more unique and specific proposals for which ISS does not state their voting policy. Without the matched guideline, AI is forced to rely entirely on its domain knowledge. If that knowledge includes ISS recommendations, we would expect AI alignment with ISS recommendations to be at a similar level to the approximately 75% that we observe in Table 3. But we instead find that alignment falls substantially, with AI recommendations aligning with ISS on only 42.81% of proposals.

As noted in Table 2, ISS policies have migrated to more case-by-case and generally vote for/against categories. We next examine the AI's ability to process guidelines by testing the effect this move to less explicit guidelines has on the confidence of AI. If AI is merely recalling previous ISS recommendations, then we would expect confidence to be unchanged when the guidelines become more complex. In order to evaluate the AI confidence level, we compute a relative confidence score by isolating the model's internal preference for the selected recommendation over its direct alternative (For vs. Against).[19] This score reflects AI model's certainty when it decides between the two possible outcomes. We include our estimate of AI confidence as the dependent variable for the models in Panel C of Table 7.

We note four important takeaways from Panel C of Table 7. First, the number of tokens in the opposition statement is associated with a significantly lower level of confidence. A more detailed and expansive set of arguments forces the AI to apply the guideline to a wider breadth of information. Second, the number of tokens in the guideline also significantly reduces the AI's confidence level. The token amount proxies for the level of complexity in the guideline, and increasingly complex guidelines force the AI to consider more factors. Third, we note that an ISS "case-by-case" or "generally for/against" guideline is also associated with lower confidence; a vague guideline is more difficult for AI to follow. Finally, we find that management abstaining from making a recommendation gives the AI greater confidence, allowing it to only consider the

[19] Internal preference is extracted directly from the language model's final-layer output vector, isolating the unnormalized scores assigned to the two candidate outcome tokens (For vs. Against). The confidence score is then calculated over these candidates, yielding a probability between 0.5 (maximum uncertainty) and 1.0 (absolute certainty) for the selected token.

arguments of the shareholder. Combined, these takeaways provide further evidence that AI integrates the provided guideline with proposal context and then navigates nuanced judgement rather than relying on superficial heuristics in its training data. If the AI model simply retrieves memorized patterns from its training data, guideline length and ambiguity would not systematically reduce its confidence.[20]

As a final test for potential lookahead bias, in Panels C and D of Appendix D1, we redact all organization names and their aliases from the proposal, supporting statement, and opposition statement, rather than restricting redactions solely to the target firm. This redaction reduces the chance that the model can rely on prior knowledge of a specific proposal, and the redacted results remain similar to Table 3. Combined, all of our results suggest that the AI model is relying on its judgement, and not retrieval of the actual ISS recommendation, as the primary determinant of its generated recommendations.

3.4. Alignment between AI Recommendation and Shareholder Voting

Although our AI proxy advisor generally produces recommendations that align with those of ISS, there are clearly cases of divergence. We next explore the nature of these disagreements. We introduce shareholder support levels as an unbiased third party by which to evaluate the performance of the AI proxy advisor relative to ISS.[21] Although many shareholders rely

[20] Our findings on guideline complexity and recommendation category have implications as AI tools become increasingly adopted by proxy voters. Although our AI advisor is generally in agreement with ISS, its alignment and confidence are both lower when ISS uses more complex and/or vague guidelines. AI advisors thus produce more predictable and consistent recommendations when provided guidelines that are more explicit in nature.
[21] Shareholder support rate is calculated using total votes cast (for, against, and abstentions), irrespective of firm-specific tallying conventions, to ensure cross-proposal comparability. Results are qualitatively unchanged when firm-specific conventions are applied.

exclusively on ISS recommendations (Iliev and Lowry, 2015), others exercise judgement, at least in some cases. Our tests focus on whether, in these cases of disagreement, voters are more likely to reach conclusions more aligned with the AI proxy advisor or with ISS.

Table 8 introduces univariate statistics of the final vote totals. In Panel A, we find that, within the sample of proposals that ISS supported ("ISS For"), proposals that AI also supported received support from 40.19% of shares outstanding, compared to a significantly lower 33.92% of shares outstanding for proposals that AI opposed. AI "For" recommendations in proposals opposed by ISS ("ISS Against") are similarly associated with an elevated level of shareholder support (12.94% in AI "For" compared to 9.17% in AI "Against"). In sum, the AI recommendation is consistently predictive of shareholder support; a positive (negative) voting recommendation from the AI proxy advisor is associated with higher (lower) support than results from a positive (negative) ISS recommendation alone. In Panel E of Appendix D1, we report a version of this test with redacted inputs to the AI model similar to the tests in Section 3.3. Our results are qualitatively similar, against suggesting that lookahead bias is not driving our findings.

Panel B of Table 8 reports the same analysis using Glass Lewis guidelines. Though the differences are narrower, the pattern remains. For proposals that Glass Lewis supports, AI support relates to a statistically insignificant increase in voting support. For proposals that Glass Lewis opposes, AI support is associated with a statistically significant 3.7% increase in shareholder voting support.

We next extend this analysis of support rates to a multivariate framework with the support rate as the dependent variable. We include controls for ISS/Glass Lewis recommendations, whether management declined to make a recommendation, whether management submits a conflicting proposal in the same ballot, the number of tokens in each statement, along with firm characteristics, sponsor identities, and firm, year, and proposal type fixed effects. Our variable of interest is the AI proxy advisor's recommendation. Table 9 reports the results.

Across Columns 1-5, an AI "For" recommendation is associated with a significantly higher level of support from shareholders. Among the controls, we also note the significantly positive effects of an ISS "For" recommendation and a "None" management recommendation, in line with their expected effects. These effects are consistent regardless of the fixed effects and controls included in the models. In Column 6-8, we introduce analysis incorporating Glass Lewis recommendations and guidelines and reach similar conclusions. In Column 6, we provide the Glass Lewis guidelines to the AI instead of ISS guidelines. In Column 7, we revert to the ISS guideline but restrict the sample to align with Column 6 and include controls for recommendations from both proxy advisors. In Column 8, we run the same specification but use Glass Lewis guidelines as the input to AI. Both columns lead to similar conclusions on the effect of the AI recommendation. Across all three columns, the effect of the Glass Lewis recommendation is significantly positive, as expected given their influence. However, the coefficient on the AI "For" indicator also continues to be positively related to the overall level of voting support regardless of the source of the guideline (ISS or Glass Lewis). Throughout all specifications, an AI "For" recommendation is associated with a significantly higher level of shareholder voting support. We conclude that the AI recommendation is capturing shareholder preferences beyond the effect of proxy advisor recommendations in isolation.[22]

We note that the additional controls included across the various specifications for guideline complexity (*# of Tokens in G*), case-by-case guidelines (*ISS Case-by-Case* and *ISS Case-by-Case*

[22] In Appendix Table D3, we report a similar analysis on the sample of 486 proposals without a matched guideline. Since there is no guideline, we use the PSO model to generate these recommendations. We find no significant effects in this small set of proposals.

+ *Generally* are not significantly related to shareholder support. Among the firm-level controls, shareholders of growth stocks with higher market-to-book show significantly higher support for shareholder proposals. Proposals tend to receive higher support when sponsored by pension and other non-SRI funds, whereas those sponsored by SRI funds receive lower support. However, this lower support may reflect the tendency of SRI funds to sponsor environmental and social (ES) proposals, which generally garner lower support than governance (G) proposals (Dikolli, Frank, Guo, and Lynch, 2022).

Panel B of Table 9 reports a similar analysis, but measures support only from actively voting mutual funds. We define active voters as mutual funds whose N-PX filings indicate that their votes deviate from ISS recommendations on more than 5% of votes, subject to a minimum of 200 proposals during the previous year. These voters are arguably more attentive and informed in their voting decisions. We continue to find similar results in this sample; the AI recommendations are associated with significantly higher voting support from more sophisticated mutual fund voters in nearly all specifications.[23]

3.5. The Role of Third-Party Governance Consultants

The role of third-party governance consultants in the proxy advisory business receives considerable scrutiny from both practitioners and regulators. A frequent criticism is that proxy advisors provide consulting services to the same firms for which they later issue voting recommendations. Although these advisors assert that their consulting and recommendation

[23] In untabulated tests, we run similar analysis on the sample of all mutual funds, and on the sample of mutual funds that deviate more than 5% from either ISS or Glass Lewis recommendations. We reach qualitatively similar conclusions in both of these analyses.

businesses are fully independent, the lack of transparency, particularly with respect to client identities, prevents any empirical verification of that claim. Even when consulting services are provided by third-party firms not directly affiliated with proxy advisors, the objective remains the same: to influence the recommendation decision in a way that aligns with management's preferences. As a result, consultant involvement may reflect one of several potential actions that could be associated with recommendation outcomes.

We introduce a novel way to analyze the impact of these consultants. Many firms disclose the presence of a third-party governance consultant in their proxy statement. These disclosures rarely identify the consultant by name, which prevents us from linking engagements to any particular provider. Accordingly, we do not interpret consultant disclosure as a direct measure of proxy advisor relationships, nor do we claim that ISS or Glass Lewis are providing services in any given case. Rather, we treat the consultant disclosure as an observable indicator of heightened corporate engagement around the proposal, while acknowledging that the underlying relationships and activities likely vary across firms and situations.

We first examine the characteristics of firms that disclose a governance consultant. Table 10 reports the results of a linear probability model where the dependent variable equals one if the firm discloses a consultant in their proxy statement. We find that the presence of a consultant is associated with longer (more tokens) opposition statements. This relation could be the result of the consultant taking an active role in writing the opposition statement, or it may simply reflect the fact that managers with the goal of influencing voting outcomes likely pursue multiple channels to achieve this goal. We also see a generally negative coefficient on the market-to-book ratio, consistent with undervalued companies being more likely to employ a governance consultant.

These patterns suggest that consultant disclosure is associated with proposals where managers mount a more extensive defense.

To examine whether recommendation outcomes differ in these settings, we compare ISS recommendations with our guideline-based AI benchmark that applies ISS's published voting guidelines to the proposal. Because the AI benchmark is designed to reflect the stated guidelines, divergences between ISS and AI in consultant-disclosure settings may be consistent with changes in the information environment surrounding the recommendation process. Such divergences could arise from multiple channels, including firms' engagement strategies, unobserved differences in firms that choose to retain consultants, and potentially the conflicts of interest discussed above.

Table 11 presents univariate statistics on the alignment between the ISS and AI recommendations, conditional on the presence of a third-party governance consultant. We identify 507 (11.11%) proposals that appear in proxy statements where the subject firm discloses the use of a third-party consultant. We then observe a statistically significant reduction of approximately 5.0% in ISS-AI alignment (a decrease from 75.6% to 70.6%) when a firm discloses a third-party governance consultant.

The directional breakdown provides further insight. Because management consistently opposes these shareholder proposals, the outcome most likely to have been affected by a third-party governance consultant is the case where the proxy advisor issues a recommendation *against* the proposal that AI *supports*. This pattern reflects a setting where ISS's recommendation is less supportive than the benchmark implied by published policies. In Panel A, we find that this outcome is significantly more likely to occur when a consultant is disclosed. The AI For/ISS Against outcome comprises 19.9% of firm-years with a consultant, compared to 12.3% of firm-years without a consultant, an increase of 7.6% in absolute terms and 61.8% (7.6%/12.3%) in relative terms.

We report a similar analysis using Glass-Lewis recommendations and guidelines in Panel B of Table 11. Although the effects are smaller, we continue to find a significantly elevated number of “AI For/Glass Lewis Against” outcomes in that smaller sample.

We further investigate these trends in a multivariate framework. In our specifications in Table 12, the dependent variable takes a value of 1 if the proposal receives the ISS Against/AI For outcome, and we include an indicator, *Third-party consultant*, taking a value of 1 if the firm discloses employing a third-party governance consultant. Throughout all six models, after controlling for proposal and firm characteristics, the third-party governance consultant indicator has a positive and significant effect on the likelihood of receiving the ISS Against/AI For outcome.[24]

Overall, we interpret these results as evidence that consultant-disclosure settings are systematically associated with greater divergence between ISS recommendations and the AI guideline-based benchmark. Because consultant disclosure may capture a range of contemporaneous firm actions, we do not attribute the pattern to any single source. At minimum, however, the evidence is consistent with the view that firms can affect the recommendation

[24] We acknowledge the possibility that a governance consultant may lobby ISS to make policy changes, and these policy changes could be implemented prior to the formal release of the ISS Voting Guidelines document. We test this possibility in Appendix D4, where we match each proposal to the relevant guideline from the following year. Our results are similar even when using next-year guidelines, suggesting that this possible explanation is not driving our results.

environment through some combination of engagement, information provision, and related tactics, in ways that are associated with recommendation outcomes.[25]

3.6. Real Outcomes

Our next set of tests aims to validate the AI-based recommendations by examining whether they are predictive of future outcomes at the firm. We split the sample of unsuccessful proposals into Environmental/Social (ES) proposals and Governance (G) proposals. Although ISS provides a resolution-type classification that distinguishes ES (SRI) and G (GOV) proposals, this classification is subject to nontrivial measurement error. To address this concern, we instead adopt the AI-based ESG classification developed in Lee (2025). We then use RepRisk incident data to examine the relation between AI recommendations and the likelihood of subsequent ES or G incidents at the firm.

In Table 13, we report Poisson regressions where the dependent variable is the count of ES or G incidents with high severity in the subsequent year following the meeting.[26] In the ES specifications in Columns 1 and 2, an AI "For" recommendation is predictive of subsequent ES incidents, suggesting that the AI advisor is able to capture information about underlying ES risk exposure that subsequently materializes in realized incidents. The predictive power is notably stronger than that of ISS recommendations in both models.

---

[25] We note that these consultant results are also inconsistent with a claim of lookahead bias driving our results. Under that view, AI memorization of ISS recommendations would push toward agreement with ISS. In the context of these consultant results, this would mean the model would have to be less aware of actual ISS recommendations on consultant firms than on non-consultant firms. However, we find that consultant-disclosing firms tend to be larger and more covered; if AI is only selectively aware of ISS recommendations, it would likely be at these larger and better covered firms.

[26] In each specification, a number of observations are dropped due to singleton categories induced by multiple fixed effects and perfect collinearity with a sparse dependent variable.

We report a similar set of tests on governance incidents in Columns 3 and 4. We find that neither the AI or the ISS recommendations are predictive of subsequent G incidents. A possible explanation is that ES incidents are discrete, externally observable, and extensively covered by media, whereas governance issues are often latent and materialize more gradually, making them less directly captured. Overall, Table 13 indicates that the predictive content of the AI recommendation is concentrated in the ES setting rather than generalizing to governance incidents.

4. Conclusion

Our study demonstrates that artificial intelligence can effectively replicate proxy advisor recommendations using only the available textual information from the proxy statement, AI's domain knowledge, and disclosed voting guidelines by ISS. The AI proxy advisor not only aligns with ISS a significant majority of the time, but its recommendations capture shareholder support beyond the ISS recommendation in isolation. These findings highlight the potential of AI tools to introduce transparency and consistency into a process often criticized for opacity and subjectivity.

Importantly, we find that discrepancies between ISS and AI recommendations are more likely when firms disclose hiring governance consultants. This divergence is especially pronounced in cases where ISS opposes a proposal that the AI supports, suggesting that consultants and contemporaneous firm actions may play a role in swaying recommendations on shareholder proposals that are likely unfavorably viewed by management. While our analysis cannot definitively identify the source of influence, it supports longstanding concerns about the dual roles and incentives of proxy advisors and their affiliates. As debates over proxy advisory reform continue, our findings offer evidence that AI may serve as a valuable benchmark or counterweight to traditional advisory firms.

References

Alexander, C. R., Chen, M. A., Seppi, D. J., & Spatt, C. S. (2010). Interim news and the role of proxy voting advice. *Review of Financial Studies, 23*(12), 4419–4454.

Bai, J., Boyson, N., Cao, Y., Liu, M., & Wan, C. (2025). Executives vs Chatbots: Unmasking Insights through Human-AI Differences in Earnings Conference Q&A. Working paper, available at https://ssrn.com/abstract=4480056.

Bethel, J. E., & Gillan, S. L. (2002). The impact of the institutional and regulatory environment on shareholder voting. *Financial Management, 31*(4), 29–54.

Blank, B., Hadley, B., & Lee, C. (2025). Pension Fund Activism Behind the Scenes: Evidence from Environmental and Social Proposals. Working paper, available at https://ssrn.com/abstract=4878044.

Cai, J., Garner, J. L., & Walkling, R. A. (2009). Electing directors. *Journal of Finance, 64*(5), 2389–2421.

Cao, S., Jiang, W., Wang, J., & Yang, B. (2024). From Man vs. Machine to Man + Machine: The art and AI of stock analyses. *Journal of Financial Economics, 160*, 103910.

Choi, S. J., Fisch, J. E., & Kahan, M. (2010). The power of proxy advisors: Myth or reality? *Emory Law Journal, 59*(4), 869–918.

Couvert, M. (2025). What Is the Impact of Mutual Funds' ESG Preferences on Portfolio Firms? Working paper, available at https://ssrn.com/abstract=3738666.

Del Guercio, D. & Hawkins, J. (1999). The motivation and impact of pension fund activism. *Journal of Financial Economics, 52*(3), 293–340.

Dicks, D. L. (2012). Executive compensation and the role for corporate governance regulation. *Review of Financial Studies, 25*(6), 1971–2004.

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

Ertimur, Y., Ferri, F., & Oesch, D. (2013). Shareholder votes and proxy advisors: Evidence from say on pay. *Journal of Accounting Research, 51*(5), 951–996.

Gillan, S., & Starks, L. (2000). Corporate governance proposals and shareholder activism: The role of institutional investors. *Journal of Financial Economics, 57*(2), 275–305.

Hu, E., Malenko, N., & Zytnick, J. (2025). Custom Proxy Voting Advice. Working paper, available at https://ssrn.com/abstract=4770971.

Iliev, P., & Lowry, M. (2015). Are mutual funds active voters? *Review of Financial Studies, 28*(2), 446–485.

Larcker, D. F., McCall, A. L., & Ormazabal, G. (2015). Outsourcing shareholder voting to proxy advisory firms. *Journal of Law and Economics, 58*(1), 173–204.

Lee, C. (2025). AI Meets ESG: Systematic ESG Classification of Shareholder Proposals. Working paper, available at https://ssrn.com/abstract=5933018.

Li, K., Mai, F., Shen, R., Yang, C., & Zhang, T., (2025). Dissecting Corporate Culture Using Generative AI. Working paper, available at https://ssrn.com/abstract=4558295.

Li, T. (2016). Outsourcing corporate governance: Conflicts of interest within the proxy advisory industry. *Management Science, 64*(6), 2951–2971.

Malenko, N., & Shen, Y. (2016). The role of proxy advisory firms: Evidence from a regression-discontinuity design. *Review of Financial Studies, 29*(12), 3394–3427.

McCahery, J. A., Sautner, Z., & Starks, L. T. (2016). Behind the scenes: The corporate governance preferences of institutional investors. *Journal of Finance, 71*(6), 2905–2932.

Shu, C. (2024). The proxy advisory industry: Influencing and being influenced. *Journal of Financial Economics*, 154, 103810.

Souther, M. (2026). Black-Box Stewardship: AI-Assisted Proxy Voting and Fiduciary Duty. Working paper, available at https://ssrn.com/abstract=6732498.

Table 1. Descriptive Statistics

This table reports summary statistics for all variables used in our study. Panel A reports statistics across the full sample of shareholder proposals, and Panel B reports statistics across the subset of proposal that have an explicitly stated ISS guideline. All variables and data sources are described in Appendix A.

Panel A. Full Sample (PSO Sample; N = 5,184)

Variable	Mean	SD	p25	p50	p75
Support Rate (%)	31.232	20.888	15.660	29.466	42.299
ISS For (0/1)	0.741	0.438	0	1	1
Management None (0/1)	0.019	0.138	0	0	0
Conflicting Proposal from Mgmt (0/1)	0.005	0.071	0	0	0
# Tokens in PS (Ln)	6.238	0.260	6.184	6.328	6.395
# Tokens in O (Ln)	6.605	0.607	6.303	6.657	6.997
Firm Size (Ln)	10.147	1.769	9.002	10.224	11.464
Cash Holdings	0.197	0.405	0.031	0.096	0.221
Dividend Yield	0.023	0.026	0.007	0.021	0.033
Market-to-Book	2.073	1.544	1.172	1.530	2.299
ROA	0.057	0.094	0.015	0.049	0.093
Past Stock Performance	0.144	0.447	-0.062	0.108	0.299
Institutional Ownership	0.736	0.199	0.647	0.749	0.852
Sponsor - Pension (0/1)	0.122	0.328	0	0	0
Sponsor - SRI Fund (0/1)	0.101	0.301	0	0	0
Sponsor - Other Fund (0/1)	0.199	0.399	0	0	0
Sponsor - Union (0/1)	0.072	0.258	0	0	0
Sponsor - Religious Group (0/1)	0.071	0.257	0	0	0
Sponsor - Special Interest Group (0/1)	0.052	0.223	0	0	0
Third-party Consulting (0/1)	0.112	0.316	0	0	0

Table 1. (Continued)

Panel B. Sample with ISS Guidelines (PSOG Sample; N = 4,565)

Variable	Mean	SD	p25	p50	p75
Support Rate (%)	33.838	20.340	20.666	31.632	43.933
ISS For (0/1)	0.803	0.398	1	1	1
Management None (0/1)	0.021	0.143	0	0	0
Conflicting Proposal from Mgmt (0/1)	0.006	0.075	0	0	0
# Tokens in PS (Ln)	6.239	0.259	6.186	6.328	6.395
# Tokens in O (Ln)	6.615	0.602	6.328	6.672	7.003
# Tokens in G for ISS (Ln)	4.588	0.827	4.263	4.654	5.037
ISS Case-by-case (0/1)	0.264	0.441	0	0	1
ISS Case-by-case + Generally (0/1)	0.768	0.422	1	1	1
Firm Size (Ln)	10.062	1.755	8.952	10.158	11.378
Cash Holdings	0.193	0.418	0.030	0.094	0.216
Dividend Yield	0.023	0.026	0.007	0.020	0.033
Market-to-Book	2.042	1.503	1.172	1.522	2.263
ROA	0.055	0.096	0.015	0.049	0.091
Past Stock Performance	0.146	0.452	-0.064	0.108	0.302
Institutional Ownership	0.740	0.200	0.652	0.754	0.856
Sponsor - Pension (0/1)	0.128	0.335	0	0	0
Sponsor - SRI Fund (0/1)	0.093	0.290	0	0	0
Sponsor - Other Fund (0/1)	0.194	0.395	0	0	0
Sponsor - Union (0/1)	0.068	0.251	0	0	0
Sponsor - Religious Group (0/1)	0.071	0.258	0	0	0
Sponsor - Special Interest Group (0/1)	0.042	0.200	0	0	0
Third-party Consulting (0/1)	0.111	0.314	0	0	0

Table 2. ISS Recommendations on Shareholder Proposals

Panel A reports the number of proposals each year, along with the ISS recommendations. In Panel B, we report statistics on ISS annually released guidelines. "Unique Guideline" represents an ISS guideline matched to one or more shareholder proposals in our sample. Guidelines are classified into vote "For," "Against," or "Case-by-case" categories according to the stated policy. Panel C reports the number of proposals falling within each guideline category by year. Panel D reports the support rate of ISS across those three categories. We define the PSO Sample as the set of observations with the text of the Proposal and Supporting Statement provided by shareholders, along with the Opposing Statement provided by management. The PSOG Sample is a subset of the PSO Sample, restricted to observations that can be matched with ISS's publicly available voting guidelines.

Panel A. Shareholder Proposals and ISS Recommendations by Year (PSO Sample; N = 5,184)

Year	# of Proposals	# of ISS For	# of ISS Against	% ISS For	% ISS Against
2009	441	334	107	75.74%	24.26%
2010	400	312	88	78.00%	22.00%
2011	256	181	75	70.70%	29.30%
2012	307	212	95	69.06%	30.94%
2013	365	264	101	72.33%	27.67%
2014	394	295	99	74.87%	25.13%
2015	463	362	101	78.19%	21.81%
2016	465	338	127	72.69%	27.31%
2017	421	307	114	72.92%	27.08%
2018	411	327	84	79.56%	20.44%
2019	403	299	104	74.19%	25.81%
2020	444	306	138	68.92%	31.08%
2021	414	302	112	72.95%	27.05%
Total	5,184	3,839	1,345	74.05%	25.95%

Table 2. (Continued)

Panel B. Unique ISS Guidelines (PSOG Sample; N = 4,565)

			# of Unique Guidelines in each Category									
Year	# of Proposals (PSOG)	# of Unique Guidelines	*Vote For Without Exceptions*	*Vote For With Exceptions*	*Generally Vote For*	*Case-by-case*	*Generally Vote Against*	*Vote Against With Exceptions*	*Vote Against Without Exceptions*	% For Guidelines	% Against Guidelines	% Case-by-case Guidelines
2009	388	52	3	2	21	15	7	0	4	50.00%	21.15%	28.85%
2010	343	46	25	9	4	7	0	0	1	82.61%	2.17%	15.22%
2011	234	41	21	9	4	6	0	0	1	82.93%	2.44%	14.63%
2012	277	48	27	8	5	6	0	0	2	83.33%	4.17%	12.50%
2013	323	48	1	4	19	20	3	0	1	50.00%	8.33%	41.67%
2014	365	54	1	4	20	21	6	0	2	46.30%	14.81%	38.89%
2015	428	53	1	4	23	21	3	0	1	52.83%	7.55%	39.62%
2016	393	49	1	4	20	21	2	0	1	51.02%	6.12%	42.86%
2017	347	43	1	3	17	19	1	0	2	48.84%	6.98%	44.19%
2018	380	43	2	2	16	19	2	0	2	46.51%	9.30%	44.19%
2019	367	42	1	2	17	18	3	0	1	47.62%	9.52%	42.86%
2020	375	47	2	3	16	23	2	0	1	44.68%	6.38%	48.94%
2021	345	42	2	2	15	19	4	0	0	45.24%	9.52%	45.24%
Total	4,565	608	88	56	197	215	33	0	19	56.09%	8.55%	35.36%

Table 2. (Continued)

Panel C: Proposals by Category (PSOG Sample; N = 4,565)

		# of Unique Proposals in each Category									
Year	# of Proposals (PSOG)	*Vote For Without Exceptions*	*Vote For With Exceptions*	*Generally Vote For*	*Case-by-case*	*Generally Vote Against*	*Vote Against With Exceptions*	*Vote Against Without Exceptions*	% For Proposals	% Against Proposals	% Case-by-case Proposals
2009	388	99	4	182	80	11	0	12	73.45%	5.93%	20.62%
2010	343	181	105	42	14	0	0	1	95.63%	0.29%	4.08%
2011	234	107	103	7	16	0	0	1	92.74%	0.43%	6.84%
2012	277	157	52	27	37	0	0	4	85.20%	1.44%	13.36%
2013	323	18	19	161	113	7	0	5	61.30%	3.72%	34.98%
2014	365	13	14	202	122	11	0	3	62.74%	3.84%	33.42%
2015	428	10	14	253	141	9	0	1	64.72%	2.34%	32.94%
2016	393	5	15	226	140	6	0	1	62.60%	1.78%	35.62%
2017	347	7	13	204	118	3	0	2	64.55%	1.44%	34.01%
2018	380	6	13	239	115	4	0	3	67.89%	1.84%	30.26%
2019	367	3	22	231	102	8	0	1	69.75%	2.45%	27.79%
2020	375	7	14	234	114	4	0	2	68.00%	1.60%	30.40%
2021	345	4	18	223	93	7	0	0	71.01%	2.03%	26.96%
Total	4,565	617	406	2,231	1,205	70	0	36	71.28%	2.32%	26.40%

Table 2. (Continued)

Panel D: ISS Support Rate within Guideline Category (PSOG Sample; N = 4,565)

Year	% ISS For in Vote For Without Exceptions	% ISS For in Vote For With Exceptions	% ISS For in Generally Vote For	% ISS For in Vote Case-by-case	% ISS For in Generally Vote Against	% ISS For in Vote Against Without Exceptions	% ISS For in No Guideline
2009	96.97%	100.00%	90.66%	73.75%	9.09%	8.33%	15.09%
2010	73.48%	96.19%	88.10%	64.29%	NA	0.00%	56.14%
2011	58.88%	90.29%	42.86%	93.75%	NA	0.00%	31.82%
2012	70.06%	78.85%	85.19%	91.89%	NA	0.00%	13.33%
2013	100.00%	100.00%	80.75%	75.22%	0.00%	0.00%	28.57%
2014	100.00%	100.00%	81.19%	78.69%	0.00%	0.00%	27.59%
2015	100.00%	100.00%	88.54%	76.60%	11.11%	0.00%	14.29%
2016	100.00%	100.00%	90.27%	70.00%	0.00%	0.00%	22.22%
2017	100.00%	100.00%	87.25%	72.03%	0.00%	0.00%	32.43%
2018	83.33%	92.31%	88.70%	74.78%	25.00%	0.00%	35.48%
2019	100.00%	90.91%	80.52%	74.51%	12.50%	0.00%	36.11%
2020	100.00%	92.86%	82.91%	66.67%	25.00%	0.00%	21.74%
2021	100.00%	100.00%	89.24%	68.82%	0.00%	NA	24.64%
Total	76.82%	92.86%	86.02%	73.94%	7.14%	2.78%	27.79%

Table 3. Summary for Alignment between ISS and AI

This table reports alignment between the ISS recommendation and the recommendation provided by the AI model. In Panels A, PSO refers to AI recommendations based on the text of the Proposal and Supporting Statement provided by shareholders, along with the Opposing Statement provided by management. In Panels B, PSOG refers to AI recommendations based on the text of the Proposal, Supporting Statement, Opposing Statement, alongside instructions to follow ISS's publicly available voting guidelines. In Panel C, PSOG-GL refers to AI recommendations based on the text of the Proposal, Supporting Statement, Opposing Statement, alongside instructions to follow Glass Lewis's publicly available voting guidelines. Panel D reports alignment for proposals that do not have a matched ISS guideline.

Panel A. Based on PSO Model (N = 5,184)

	ISS For	ISS Against
AI For	3,438	1,065
AI Against	401	280
Alignment	89.55%	20.82%
Overall Alignment		71.72%

Panel B. Based on PSOG Model (N = 4,565)

	ISS For	ISS Against
AI For	3,126	599
AI Against	541	299
Alignment	85.25%	33.30%
Overall Alignment		75.03%

Panel C. Based on PSOG-GL Model (N = 2,164)

	GL For	GL Against
AI For	1,103	576
AI Against	195	290
Alignment	84.98%	33.49%
Overall Alignment		64.37%

Table 4. Alignment between ISS and AI Recommendations

This table reports the annual alignment between voting recommendations generated by the AI model and those generated by ISS. The statistics are reported for the PSOG Sample, restricted to those observations where ISS's publicly available voting guidelines are available.

Year	Alignment (PSOG)	% Alignment in *Vote For Without Exceptions*	% Alignment in *Vote For With Exceptions*	% Alignment in *Generally Vote For*	% Alignment in *Vote Case-by-case*	% Alignment in *Generally Vote Against*	% Alignment in *Vote Against Without Exceptions*
2009	0.835	95.96%	100.00%	79.12%	75.00%	90.91%	91.67%
2010	0.799	73.48%	88.57%	92.86%	57.14%	NA	100.00%
2011	0.701	61.68%	86.41%	28.57%	37.50%	NA	100.00%
2012	0.704	70.06%	73.08%	88.89%	51.35%	NA	100.00%
2013	0.728	100.00%	89.47%	74.53%	60.18%	100.00%	100.00%
2014	0.723	100.00%	85.71%	76.73%	58.20%	100.00%	66.67%
2015	0.776	100.00%	92.86%	83.79%	61.70%	100.00%	100.00%
2016	0.746	100.00%	73.33%	80.09%	63.57%	100.00%	100.00%
2017	0.758	100.00%	92.31%	81.86%	61.02%	100.00%	100.00%
2018	0.747	100.00%	69.23%	76.57%	69.57%	75.00%	100.00%
2019	0.719	100.00%	86.36%	75.32%	58.82%	87.50%	100.00%
2020	0.728	100.00%	85.71%	77.35%	59.65%	75.00%	100.00%
2021	0.754	100.00%	66.67%	80.27%	62.37%	100.00%	NA

Table 5. Determinants of ISS-AI Alignment

This table examines the alignment between ISS recommendations and AI recommendations in a multivariate setting. The dependent variable takes a value of one if AI and ISS issue opposing recommendation on a particular proposal. All variables and data sources are described in Appendix A. Heteroskedasticity-robust standard errors are used, with t-statistics reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
# Tokens in PS (Ln)	-0.003	0.082**	0.022	0.091**	0.084**	0.084**	0.090**
	(-0.094)	(2.265)	(0.624)	(2.503)	(2.294)	(2.320)	(2.476)
# Tokens in O (Ln)	-0.047**	-0.038**	-0.032	-0.036*	-0.038**	-0.038**	-0.029
	(-2.322)	(-2.091)	(-1.594)	(-1.953)	(-2.061)	(-2.065)	(-1.411)
# Tokens in G (Ln)			-0.098***	-0.056***			-0.056***
			(-9.286)	(-3.369)			(-3.385)
ISS Case-by-case (0/1)					-0.054*		
					(-1.713)		
ISS Case-by-case + Generally (0/1)						-0.103***	
						(-3.240)	
Management None (0/1)							0.095*
							(1.862)
Conflicting Proposal from Mgmt (0/1)							-0.015
							(-0.176)
Meeting Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Proposal Type FE	No	Yes	No	Yes	Yes	Yes	Yes
Firm clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,295	4,277	4,295	4,277	4,277	4,277	4,277
Adj. R-squared	0.087	0.186	0.110	0.189	0.187	0.188	0.189

Table 6. Determinants of Recommendations

This table examines the determinants of recommendations from AI (Panel A) based on textual factors. The dependent variable takes a value of one if the AI recommends voting "For" the proposal. For comparison, Panel B reports the same specs but with the ISS recommendation as the dependent variable. All variables and data sources are described in Appendix A. Heteroskedasticity-robust standard errors are used, with t-statistics reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Panel A. AI Recommendations

	(1) AI For	(2) AI For	(3) AI For	(4) AI For	(5) AI For	(6) AI For	(7) AI For
# Tokens in PS (Ln)	0.098***	0.129***	0.109***	0.137***	0.130***	0.131***	0.136***
	(3.051)	(3.888)	(3.364)	(4.116)	(3.912)	(3.993)	(4.104)
# Tokens in O (Ln)	-0.017	-0.033**	-0.010	-0.031**	-0.033**	-0.033**	-0.028
	(-1.007)	(-2.192)	(-0.608)	(-2.040)	(-2.140)	(-2.144)	(-1.637)
# Tokens in G (Ln)			-0.044***	-0.050***			-0.050***
			(-4.183)	(-3.551)			(-3.562)
ISS Case-by-case (0/1)					-0.057**		
					(-2.105)		
ISS Case-by-case + Generally (0/1)						-0.128***	
						(-4.106)	
Management None (0/1)							0.055
							(1.166)
Conflicting Proposal from Mgmt (0/1)							-0.056
							(-1.105)
Meeting Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Proposal Type FE	No	Yes	No	Yes	Yes	Yes	Yes
Firm clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,295	4,277	4,295	4,277	4,277	4,277	4,277
Adj. R-squared	0.115	0.248	0.121	0.251	0.249	0.251	0.251

Table 6. (Continued)

Panel B. ISS Recommendations

	(1) ISS For	(2) ISS For	(3) ISS For	(4) ISS For	(5) ISS For	(6) ISS For	(7) ISS For
# Tokens in PS (Ln)	0.032	0.086***	0.044	0.085***	0.086***	0.085***	0.084***
	(0.889)	(3.474)	(1.225)	(3.452)	(3.473)	(3.436)	(3.406)
# Tokens in O (Ln)	-0.007	-0.005	0.000	-0.006	-0.005	-0.006	0.003
	(-0.389)	(-0.354)	(0.028)	(-0.376)	(-0.353)	(-0.382)	(0.161)
# Tokens in G (Ln)			-0.047***	0.008			0.008
			(-3.898)	(0.538)			(0.508)
ISS Case-by-case (0/1)					-0.002		
					(-0.073)		
ISS Case-by-case + Generally (0/1)						0.075***	
						(3.204)	
Management None (0/1)							0.092**
							(2.489)
Conflicting Proposal from Mgmt (0/1)							0.046
							(0.952)
Meeting Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Proposal Type FE	No	Yes	No	Yes	Yes	Yes	Yes
Firm clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,295	4,277	4,295	4,277	4,277	4,277	4,277
Adj. R-squared	0.129	0.398	0.135	0.398	0.398	0.399	0.398

Table 7: AI Ability to Process Guidelines and Avoid Lookahead Bias

This table examines AI's ability to correctly process the guidelines and avoid lookahead bias. In Panel A, we create falsified guidelines. In each guideline, we replace "For" ("Against") with "Against" ("For"). We replace all case-by-case categories with "Against." Panel A reports alignment with ISS recommendations using these falsified guidelines. Panel B reports alignment for the subset of proposals that do not have a matched ISS guideline, thus forcing the AI to rely only on its domain knowledge and the supporting and opposition statements. Panel C examines the determinants of the AI's confidence in its recommendation. Model confidence is measured by isolating the model's internal preference for the selected recommendation over its direct alternative (For vs. Against). The dependent variable is this probability, bounded between 0.5 (maximum uncertainty) and 1.0 (absolute certainty) for the selected recommendation. All variables and data sources are described in Appendix A. Heteroskedasticity-robust standard errors are used, with t-statistics reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Panel A: Falsified Guideline Recommendations

	ISS For	ISS Against
AI For	966	164
AI Against	2,701	734
Alignment	26.34%	81.74%
Overall Alignment		37.24%

Panel B. Proposals without a Matched Guideline (N = 619)

	ISS For	ISS Against
AI For	154	336
AI Against	18	111
Alignment	89.53%	24.83%
Overall Alignment		42.81%

Table 7. (Continued)

Panel C: AI Confidence Level

	(1) Confidence	(2) Confidence	(3) Confidence	(4) Confidence	(5) Confidence	(6) Confidence	(7) Confidence
# Tokens in PS (Ln)	-0.011	0.009	0.004	0.019**	0.011	0.012	0.018**
	(-1.157)	(0.989)	(0.453)	(2.237)	(1.177)	(1.367)	(2.153)
# Tokens in O (Ln)	-0.033***	-0.037***	-0.024***	-0.034***	-0.036***	-0.036***	-0.029***
	(-5.127)	(-6.373)	(-3.900)	(-5.968)	(-6.098)	(-6.478)	(-4.800)
# Tokens in G (Ln)			-0.058***	-0.062***			-0.062***
			(-16.199)	(-13.759)			(-13.828)
ISS Case-by-case (0/1)					-0.077***		
					(-7.663)		
ISS Case-by-case + Generally (0/1)						-0.151***	
						(-11.666)	
Management None (0/1)							0.071***
							(3.430)
Conflicting Proposal from Mgmt (0/1)							-0.014
							(-0.531)
Meeting Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Proposal Type FE	No	Yes	No	Yes	Yes	Yes	Yes
Firm clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,295	4,277	4,295	4,277	4,277	4,277	4,277
Adj. R-squared	0.178	0.315	0.251	0.353	0.329	0.351	0.354

Table 8: Voting Support Rates from ISS-AI Recommendations

This table reports statistics on shareholder alignment with voting recommendations from ISS and AI. The reported statistics are the average percent support across proposals in the sample, split based on whether ISS and AI support the proposal. In Panel A, the AI recommendation is provided with the voting guideline from ISS. In Panel C, the AI recommendation is instead provided with the voting guideline from Glass Lewis. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Panel A. Based on PSOG Model with ISS Guidelines (N = 4,565)

	ISS For	ISS Against
AI For	40.189	12.936
AI Against	33.917	9.166
Diff	6.272	3.770
t-stat	8.549***	5.929***

Panel B. Based on PSOG Model with Glass Lewis Guidelines (N = 2,164)

	GL For	GL Against
AI For	42.998	23.888
AI Against	41.443	20.215
Diff	1.555	3.673
t-stat	1.381	4.170***

Table 9. Determinants of Voting Support Rate

This table reports the determinants of shareholder voting support in a multivariate setting. In Panel A, the dependent variable is the percent of shares voting "For" each proposal. In Columns 1-7 (PSOG), the AI advisor is additionally provided with the voting guideline from ISS. In Column 8, the AI is provided the guideline from Glass Lewis. Panel B follows the same pattern, but the dependent variable is voting support from actively voting mutual funds. We define active voters as funds that deviate from ISS recommendations on more than 5% of votes, subject to a minimum of 200 proposals during the previous year, from N-PX filings. All variables and data sources are described in Appendix A. Heteroskedasticity-robust standard errors are used, with t-statistics reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Panel A: Overall Voting Support

	(1) ISS	(2) ISS	(3) ISS	(4) ISS	(5) ISS	(6) GL	(7) ISS	(8) GL
AI For (PSOG)	4.745***	1.279***	1.311***	1.273***	1.278***	2.126***	1.028**	1.706***
	(7.762)	(2.887)	(2.957)	(2.876)	(2.899)	(3.486)	(2.074)	(3.654)
ISS For	22.657***	19.572***	19.566***	19.572***	19.572***		16.874***	16.837***
	(34.906)	(29.570)	(29.653)	(29.564)	(29.561)		(25.979)	(26.107)
GL For						13.701***	11.690***	11.525***
						(16.674)	(19.384)	(19.478)
Management None	33.320***	17.264***	17.227***	17.243***	17.264***	21.189***	21.686***	21.397***
	(10.402)	(7.155)	(7.138)	(7.145)	(7.151)	(5.707)	(6.295)	(6.184)
Conflicting Prop. from Mgmt	6.126**	-6.355***	-6.380***	-6.352***	-6.354***	0.236	-1.492	-1.325
	(2.081)	(-3.589)	(-3.616)	(-3.590)	(-3.578)	(0.126)	(-0.812)	(-0.723)
# Tokens in PS (Ln)	-2.174**	-0.334	-0.391	-0.328	-0.334	1.581	-0.293	-0.017
	(-2.239)	(-0.451)	(-0.528)	(-0.443)	(-0.449)	(1.315)	(-0.322)	(-0.019)
# Tokens in O (Ln)	3.136***	0.624	0.607	0.624	0.624	0.654	1.114*	1.027*
	(4.875)	(1.242)	(1.206)	(1.243)	(1.242)	(1.064)	(1.931)	(1.774)
# Tokens in G for ISS (Ln)			0.334				-0.587	
			(1.093)				(-1.144)	
ISS Case-by-case				-0.227				
				(-0.299)				
ISS Case-by-case + Generally					-0.021			
					(-0.025)			

# Tokens in G for GL (Ln)						1.495		0.602
						(1.266)		(0.587)
Firm Size (Ln)	-1.269	-0.009	-0.004	-0.016	-0.009	-1.714	-1.671*	-1.734*
	(-1.474)	(-0.016)	(-0.006)	(-0.028)	(-0.016)	(-1.613)	(-1.854)	(-1.949)
Cash Holdings	0.911	0.688	0.668	0.685	0.689	-0.436	0.042	0.050
	(0.543)	(0.616)	(0.600)	(0.613)	(0.618)	(-0.242)	(0.023)	(0.029)
Dividend Yield	-12.159	-8.826	-8.598	-8.946	-8.838	-47.184***	-32.919***	-32.947***
	(-0.803)	(-0.702)	(-0.685)	(-0.716)	(-0.701)	(-4.155)	(-3.104)	(-3.142)
Market-to-Book	0.718*	0.607**	0.614**	0.608**	0.607**	1.031***	1.120***	1.189***
	(1.851)	(2.169)	(2.193)	(2.175)	(2.170)	(2.761)	(3.035)	(3.289)
ROA	6.473	5.197	5.134	5.206	5.198	3.557	0.028	0.306
	(1.537)	(1.589)	(1.575)	(1.591)	(1.590)	(0.849)	(0.007)	(0.080)
Past Stock Performance	0.898	0.101	0.094	0.101	0.101	1.006	1.747**	1.734**
	(1.621)	(0.258)	(0.239)	(0.256)	(0.257)	(0.979)	(1.983)	(1.984)
Institutional Ownership	3.071	1.851	1.860	1.851	1.851	-0.074	1.311	1.006
	(1.637)	(1.084)	(1.090)	(1.084)	(1.083)	(-0.039)	(0.722)	(0.564)
Sponsor - Pension	-0.775	1.805***	1.791***	1.808***	1.806***	-0.017	0.143	0.230
	(-0.794)	(2.723)	(2.700)	(2.724)	(2.726)	(-0.017)	(0.163)	(0.254)
Sponsor - SRI Fund	-7.443***	-2.855***	-2.821***	-2.862***	-2.856***	-1.266	-1.338	-1.286
	(-7.650)	(-3.587)	(-3.544)	(-3.595)	(-3.591)	(-0.976)	(-1.221)	(-1.184)
Sponsor - Other Fund	0.611	2.664***	2.648***	2.665***	2.664***	1.274	1.356*	1.391*
	(0.767)	(4.204)	(4.185)	(4.201)	(4.204)	(1.341)	(1.717)	(1.793)
Sponsor - Union	-2.054**	1.155	1.116	1.158	1.156	1.553	1.435	1.526
	(-2.195)	(1.351)	(1.295)	(1.354)	(1.358)	(0.944)	(1.131)	(1.196)
Sponsor - Religious Group	-5.710***	0.399	0.390	0.394	0.399	-1.005	-0.336	-0.368
	(-6.759)	(0.573)	(0.559)	(0.566)	(0.572)	(-0.797)	(-0.358)	(-0.379)
Sponsor - Special Interest	-4.939***	2.094**	2.102**	2.093**	2.095**	-1.393	-0.586	-0.605
	(-4.265)	(2.444)	(2.453)	(2.444)	(2.442)	(-0.865)	(-0.490)	(-0.510)
Meeting Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Proposal Type FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,295	4,277	4,277	4,277	4,277	2,021	2,021	2,021
Adj. R-squared	0.640	0.818	0.818	0.818	0.817	0.762	0.846	0.846

Panel B: Support from Active Voter Mutual Funds

	(1) ISS	(2) ISS	(3) ISS	(4) ISS	(5) ISS	(6) GL	(7) ISS	(8) GL
AI For (PSOG)	5.911***	1.380**	1.385**	1.320**	1.355**	2.532***	0.938	2.268***
	(6.387)	(2.231)	(2.227)	(2.130)	(2.196)	(3.724)	(1.593)	(3.464)
ISS For	18.457***	14.427***	14.426***	14.426***	14.442***		9.967***	9.880***
	(20.366)	(18.077)	(18.082)	(18.159)	(18.074)		(10.697)	(10.825)
GL For						21.764***	20.747***	20.488***
						(24.443)	(24.502)	(24.510)
Management None	36.819***	9.888***	9.883***	9.706***	9.870***	17.037***	17.401***	16.976***
	(8.321)	(3.322)	(3.318)	(3.255)	(3.313)	(5.920)	(6.039)	(5.809)
Conflicting Prop. from Mgmt	7.588*	-12.639***	-12.643***	-12.638***	-12.604***	1.275	0.063	0.342
	(1.901)	(-5.466)	(-5.469)	(-5.483)	(-5.419)	(0.368)	(0.019)	(0.102)
# Tokens in PS (Ln)	-2.061	-0.024	-0.033	0.043	-0.010	-1.107	-2.484**	-2.035*
	(-1.371)	(-0.023)	(-0.033)	(0.041)	(-0.010)	(-0.927)	(-2.253)	(-1.853)
# Tokens in O (Ln)	4.251***	0.270	0.267	0.268	0.270	0.996	1.109	1.078
	(3.556)	(0.429)	(0.423)	(0.426)	(0.429)	(1.325)	(1.504)	(1.464)
# Tokens in G for ISS (Ln)			0.055				0.195	
			(0.132)				(0.311)	
ISS Case-by-case				-2.261*				
				(-1.903)				
ISS Case-by-case + Generally					-0.589			
					(-0.505)			
# Tokens in G for GL (Ln)						1.531		1.037
						(1.431)		(1.038)
Firm Size (Ln)	-2.110	-0.262	-0.261	-0.332	-0.255	-0.943	-0.888	-0.978
	(-1.602)	(-0.264)	(-0.263)	(-0.337)	(-0.257)	(-0.733)	(-0.729)	(-0.808)
Cash Holdings	-0.125	-0.678	-0.682	-0.708	-0.660	-0.713	-0.690	-0.596
	(-0.049)	(-0.513)	(-0.515)	(-0.532)	(-0.500)	(-0.369)	(-0.393)	(-0.338)
Dividend Yield	5.787	8.522	8.561	7.297	8.183	-24.446*	-17.100	-18.304

	(0.305)	(0.547)	(0.550)	(0.473)	(0.527)	(-1.796)	(-1.575)	(-1.625)
Market-to-Book	0.612	0.183	0.184	0.193	0.185	0.458	0.407	0.491
	(0.948)	(0.466)	(0.468)	(0.495)	(0.472)	(1.165)	(1.061)	(1.241)
ROA	0.598	-0.116	-0.128	0.005	-0.102	-3.472	-6.437	-5.610
	(0.107)	(-0.030)	(-0.033)	(0.001)	(-0.026)	(-0.805)	(-1.631)	(-1.402)
Past Stock Performance	0.312	-0.493	-0.494	-0.500	-0.499	0.403	0.830	0.832
	(0.265)	(-0.799)	(-0.801)	(-0.813)	(-0.812)	(0.342)	(0.730)	(0.743)
Institutional Ownership	2.109	-1.777	-1.777	-1.758	-1.792	-0.324	0.586	0.171
	(0.837)	(-0.823)	(-0.822)	(-0.818)	(-0.829)	(-0.141)	(0.268)	(0.080)
Sponsor - Pension	-0.076	2.668***	2.665***	2.690***	2.681***	1.211	1.345	1.404
	(-0.050)	(2.758)	(2.752)	(2.800)	(2.774)	(1.026)	(1.142)	(1.190)
Sponsor - SRI Fund	-12.008***	-5.232***	-5.227***	-5.290***	-5.242***	-3.513***	-3.406***	-3.348***
	(-6.542)	(-4.450)	(-4.455)	(-4.545)	(-4.460)	(-2.673)	(-2.911)	(-2.889)
Sponsor - Other Fund	2.082	4.261***	4.258***	4.248***	4.262***	2.905**	2.981***	2.953***
	(1.507)	(4.284)	(4.287)	(4.260)	(4.282)	(2.473)	(2.699)	(2.690)
Sponsor - Union	-3.437***	1.030	1.023	1.061	1.074	1.639	1.617	1.652
	(-2.631)	(0.955)	(0.948)	(0.987)	(1.006)	(1.088)	(1.109)	(1.141)
Sponsor - Religious Group	-8.105***	0.658	0.656	0.611	0.649	-0.783	-0.245	-0.296
	(-5.758)	(0.693)	(0.692)	(0.644)	(0.682)	(-0.594)	(-0.208)	(-0.250)
Sponsor - Special Interest	-7.092***	2.560**	2.561**	2.552**	2.566**	0.154	0.810	0.748
	(-3.909)	(2.087)	(2.087)	(2.090)	(2.091)	(0.110)	(0.617)	(0.570)
Meeting Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Proposal Type FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,241	4,223	4,223	4,223	4,223	1,984	1,984	1,984
Adj. R-squared	0.510	0.795	0.795	0.796	0.795	0.841	0.857	0.858

Table 10: Determinants of Third-Party Governance Consultant Disclosure

This table reports the determinants of a firm disclosing the use of a corporate governance consultant. The dependent variable takes a value of one if the firm mentions the use of a corporate governance consultant in their proxy statement. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

	(1)	(2)
Management None (0/1)	0.041	0.037
	(1.413)	(1.288)
Conflicting Proposal from Mgmt (0/1)	0.058	0.053
	(1.036)	(0.902)
# Tokens in PS (Ln)	-0.004	-0.002
	(-0.252)	(-0.099)
# Tokens in O (Ln)	0.038***	0.035**
	(2.609)	(2.171)
Firm Size (Ln)	-0.005	-0.009
	(-0.258)	(-0.423)
Cash Holdings	0.039	0.040
	(0.862)	(0.903)
Dividend Yield	-0.065	-0.037
	(-0.260)	(-0.154)
Market-to-Book	-0.013*	-0.013*
	(-1.879)	(-1.832)
ROA	-0.019	-0.012
	(-0.250)	(-0.156)
Past Stock Performance	0.027**	0.025*
	(1.986)	(1.936)
Institutional Ownership	-0.000	-0.019
	(-0.009)	(-0.405)
Sponsor - Pension (0/1)	-0.005	-0.007
	(-0.371)	(-0.467)
Sponsor - SRI Fund (0/1)	-0.030	-0.031
	(-1.338)	(-1.235)
Sponsor - Other Fund (0/1)	0.013	0.009
	(0.751)	(0.472)
Sponsor - Union (0/1)	0.003	-0.007
	(0.186)	(-0.380)
Sponsor - Religious Group (0/1)	-0.039***	-0.046***
	(-2.760)	(-3.144)
Sponsor - Special Interest Group (0/1)	0.015	0.019
	(0.884)	(0.913)
Meeting Year FE	Yes	Yes
Firm FE	Yes	Yes
Proposal Type FE	No	Yes
Firm clustering	Yes	Yes
Observations	4,295	4,277
Adj. R-squared	0.587	0.588

Table 11. Third-Party Governance Consultants and ISS-AI Alignment

This table reports the effect of corporate governance consultants on voting recommendations. *Alignment Rate* reports the proportion of proposal in which ISS and AI are aligned in their recommendations. *Third-Party Consultant* includes proposals found in proxy statements where the subject firm discloses the use of a third-party governance consultant. Proposals from proxy statements without such disclosure are categorized as *None*. The *PSO* (*PSOG*) section reports the proportional outcomes for each combination of ISS and AI recommendations. PSOG-GL reports outcomes for AI recommendations based on Glass Lewis guidelines. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Panel A: ISS Guidelines

	Third-Party Consultant	None	Diff	t-stat
Alignment Rate (ISS)	0.706	0.756	-0.050	-2.327**
	(507)	(4,058)		
ISS For / AI For	0.635	0.691	-0.056	-2.473**
ISS For / AI Against	0.095	0.121	-0.027	-1.917*
ISS Against / AI For	0.199	0.123	0.076	4.137***
ISS Against / AI Against	0.071	0.065	0.006	0.514

Panel B. Glass Lewis Guidelines

	Third-party Consult	None	Diff	t-stat
Alignment (GL)	0.611	0.649	-0.038	-1.235
	(285)	(1,879)		
GL For / AI For	0.435	0.521	-0.086	-2.720***
GL For / AI Against	0.077	0.092	-0.015	-0.866
GL Against / AI For	0.312	0.259	0.053	1.812*
GL Against / AI Against	0.175	0.128	0.048	2.001***

Table 12. Determinants of ISS Against/AI For Outcome

This table reports the determinants if an ISS Against/AI For outcome in recommendations. This outcome is the one most likely to occur if a proxy advisor is biased by conflicts of interest. The dependent variable takes a value of one if the proposal receives an "Against" recommendation from ISS and a "For" recommendation from AI. In Columns 1-5, the AI recommendation is based on the voting guideline from ISS. In Column 6, the AI recommendation is based on the voting guideline from Glass Lewis. All variables and data sources are described in Appendix A. Heteroskedasticity-robust standard errors are used, with t-statistics reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels.

	(1) ISS	(2) ISS	(3) ISS	(4) ISS	(5) ISS	(6) GL
Third-party Consulting	0.092***	0.071**	0.071**	0.071**	0.072**	0.008
	(2.612)	(2.047)	(2.059)	(2.045)	(2.084)	(0.177)
Management None	-0.067**	-0.072**	-0.072**	-0.072**	-0.073**	-0.019
	(-2.201)	(-2.470)	(-2.471)	(-2.455)	(-2.498)	(-0.181)
Conflicting Proposal from Mgmt	-0.141**	-0.051	-0.051	-0.052	-0.048	0.285**
	(-2.220)	(-1.009)	(-1.004)	(-1.009)	(-0.948)	(2.267)
# Tokens in PS (Ln)	0.025	-0.015	-0.015	-0.016	-0.014	0.081
	(0.826)	(-0.564)	(-0.558)	(-0.566)	(-0.529)	(1.629)
# Tokens in O (Ln)	0.008	-0.001	-0.001	-0.001	-0.001	0.032
	(0.467)	(-0.086)	(-0.083)	(-0.087)	(-0.081)	(1.205)
# Tokens in G for ISS (Ln)			-0.001			
			(-0.061)			
ISS Case-by-case				0.003		
				(0.117)		
ISS Case-by-case + Generally					-0.050**	
					(-2.315)	
# Tokens in G for GL (Ln)						-0.090***
						(-2.658)
Firm Size (Ln)	0.040**	0.021	0.021	0.021	0.021	0.067*
	(2.384)	(1.306)	(1.305)	(1.307)	(1.338)	(1.919)
Cash Holdings	0.018	0.022	0.022	0.022	0.024	-0.040
	(0.411)	(0.522)	(0.523)	(0.523)	(0.555)	(-0.749)
Dividend Yield	0.773***	0.645*	0.644*	0.647*	0.615*	0.611

	(2.992)	(1.849)	(1.844)	(1.855)	(1.704)	(1.636)
Market-to-Book	-0.012	-0.008	-0.008	-0.008	-0.008	-0.029*
	(-1.345)	(-0.994)	(-0.997)	(-0.995)	(-0.968)	(-1.825)
ROA	-0.220**	-0.172**	-0.172**	-0.172**	-0.170*	-0.152
	(-2.271)	(-1.972)	(-1.967)	(-1.976)	(-1.961)	(-0.723)
Past Stock Performance	0.014	0.002	0.002	0.002	0.001	0.028
	(0.928)	(0.121)	(0.122)	(0.121)	(0.077)	(0.793)
Institutional Ownership	-0.019	0.039	0.039	0.039	0.038	0.068
	(-0.426)	(0.917)	(0.917)	(0.916)	(0.900)	(1.223)
Sponsor - Pension	-0.011	-0.023	-0.023	-0.023	-0.022	-0.051
	(-0.467)	(-0.999)	(-0.999)	(-0.999)	(-0.957)	(-1.190)
Sponsor - SRI Fund	0.003	-0.010	-0.010	-0.010	-0.010	0.056
	(0.098)	(-0.296)	(-0.298)	(-0.292)	(-0.322)	(0.937)
Sponsor - Other Fund	0.004	-0.019	-0.019	-0.019	-0.019	-0.062
	(0.159)	(-0.728)	(-0.726)	(-0.728)	(-0.731)	(-1.501)
Sponsor - Union	0.003	0.002	0.002	0.001	0.005	-0.027
	(0.102)	(0.051)	(0.054)	(0.050)	(0.171)	(-0.339)
Sponsor - Religious Group	0.047	-0.023	-0.023	-0.023	-0.024	-0.009
	(1.470)	(-0.606)	(-0.605)	(-0.605)	(-0.623)	(-0.157)
Sponsor - Special Interest Group	0.172***	0.018	0.018	0.018	0.018	-0.035
	(3.416)	(0.401)	(0.400)	(0.401)	(0.411)	(-0.601)
Meeting Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Proposal Type FE	No	Yes	Yes	Yes	Yes	Yes
Firm clustering	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,295	4,277	4,277	4,277	4,277	2,021
Adj. R-squared	0.099	0.251	0.250	0.250	0.251	0.310

Table 13: AI Recommendations and Subsequent ESG Incidents

This table reports Poisson regressions for future ESG risk incidents. The dependent variable in Columns (1) and (2) is the number of ES incidents reported for the firm in the RepRisk database. In Columns (3) and (4), the dependent variable is the number of Governance incidents in the RepRisk database. ES or Governance risk incidents with high severity are counted over the one-year period following the meeting. All variables and data sources are described in Appendix A. Heteroskedasticity-robust standard errors are used, with z-statistics reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

	(1) ES Risk	(2) ES Risk	(3) G Risk	(4) G Risk
AI For (PSOG)	0.361**	0.675***	0.111	0.186
	(2.362)	(3.306)	(0.556)	(0.790)
ISS For	0.066	-0.044	-0.081	0.286
	(0.528)	(-0.372)	(-0.588)	(1.341)
Firm Size (Ln)	-0.003	0.375	0.011	-0.067
	(-0.009)	(0.985)	(0.024)	(-0.157)
Cash Holdings	-4.221***	-3.395***	-1.467	-1.064
	(-3.115)	(-3.219)	(-0.621)	(-0.486)
Dividend Yield	25.089	29.963	-21.697	-20.906
	(1.150)	(1.636)	(-1.629)	(-1.578)
Market-to-Book	-0.078	-0.313	-0.137	-0.080
	(-0.292)	(-1.112)	(-0.392)	(-0.248)
ROA	6.817	8.119*	-0.786	-0.369
	(1.545)	(1.876)	(-0.238)	(-0.122)
Past Stock Performance	0.795	0.717	-0.066	-0.054
	(1.076)	(1.151)	(-0.156)	(-0.150)
Institutional Ownership	5.628	4.977	-1.051	-0.859
	(1.462)	(1.416)	(-1.539)	(-1.623)
Sponsor - Pension	-0.218	-0.654**	0.047	0.196
	(-1.391)	(-2.209)	(0.165)	(0.590)
Sponsor - SRI Fund	-0.178	-0.096	0.384	0.536
	(-0.621)	(-0.209)	(0.966)	(1.159)

Sponsor - Other Fund	-0.215	-0.373	-0.705**	-0.605**
	(-0.908)	(-1.064)	(-2.366)	(-2.205)
Sponsor - Union	0.654	-	-0.058	0.063
	(1.008)		(-0.167)	(0.169)
Sponsor - Religious Group	-0.393***	-0.293*	0.211	0.553**
	(-2.977)	(-1.902)	(1.611)	(2.492)
Sponsor - Special Interest Group	-0.774***	-0.678***	0.050	-0.085
	(-3.180)	(-3.579)	(0.083)	(-0.122)
Meeting Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Proposal Type FE	No	Yes	No	Yes
Firm clustering	Yes	Yes	Yes	Yes
Observations	315	303	759	734
Pseudo R-squared	0.424	0.469	0.338	0.355

Appendix A. Variable definitions

Variable	Definition	Data Source
PSO	This refers to the sample or model constructed from the text of the proposal (P), the sponsor's supporting statement (S), and the board's opposition statement (O).	SEC Proxy Statements
PSOG	This refers to the sample or model constructed from the text of the proposal (P), the sponsor's supporting statement (S), the board's opposition statement (O), and the matched guidelines (G).	SEC Proxy Statements; ISS/GL Annual Proxy Voting Guidelines
Support Rate (%)	The percentage value of vote support for the proposal from shareholder voting. The denominator includes votes for, against, and abstentions, irrespective of firm-specific tallying conventions, to ensure comparability of support rates across proposals.	ISS Shareholder Proposals
ISS For (0/1)	An indicator variable equal to one if the ISS issues a "For" recommendation for the proposal; zero otherwise.	ISS Voting Analytics
Management None (0/1)	An indicator variable equal to one if the board issues "No" recommendation for the proposal; zero otherwise.	SEC Proxy Statements; ISS Voting Analytics
Conflicting Proposal from Mgmt (0/1)	An indicator variable equal to one if management submits a proposal that directly conflicts with the given shareholder proposal; zero otherwise. A conflict is defined as cases in which a management-sponsored proposal and a shareholder-sponsored proposal on the same ballot have identical resolutions.	ISS Voting Analytics
# Tokens in PS (Ln)	The number of tokens in the proposal and its supporting statement combined (log-transformed).	SEC Proxy Statements
# Tokens in O (Ln)	The number of tokens in the board's opposition statement (log-transformed).	SEC Proxy Statements
# Tokens in G for ISS (Ln)	The number of tokens in the matched ISS guideline (log-transformed).	ISS Annual Proxy Voting Guidelines
# Tokens in G for GL (Ln)	The number of tokens in the matched GL guideline (log-transformed).	GL Annual Proxy Voting Guidelines
ISS Case-by-case (0/1)	An indicator variable equal to one if the matched ISS guideline includes case-by-case evaluation criteria in the given policy; zero otherwise.	ISS Annual Proxy Voting Guidelines
ISS Generally (0/1)	An indicator variable equal to one if the matched ISS guideline includes either ‘Generally Vote For’ or ‘Generally Vote Against’ conditions; zero otherwise.	ISS Annual Proxy Voting Guidelines
Firm Size (Ln)	The value of the subject firm’s market value of equity in millions of dollars (log-transformed).	Compustat
Cash Holdings	The value of the subject firm’s cash and cash equivalents scaled by its non-cash total assets.	Compustat
Dividend Yield	The value of the subject firm’s total dividend yield.	Compustat
Market-to-Book	The market value of the subject firm divided by its book value.	Compustat

ROA	The subject firm's income before extraordinary items scaled by its total assets.	Compustat
Past Stock Performance	The subject firm's buy-and-hold stock performance over the 1-year window prior to the meeting date.	CRSP
Institutional Ownership	The percentage of the firm's shares held by institutional investors at the end of the quarter prior to the filing date of the proxy statement.	13F
Sponsor (0/1)	A set of indicator variables based on the sponsor type of the shareholder proposals: pension funds, SRI funds, other funds, unions, religious groups, or special interest groups. When a proposal has co-sponsors, more than one indicator may have values.	ISS Shareholder Proposals
Third-party Consultant (0/1)	An indicator variable equal to one if the subject firm discloses, within its proxy statement, the use of a retained third-party consultant; zero otherwise. Keyword searches include terms related to third-party consultant and third-party advisor. Each identified case is then manually reviewed to confirm whether the consultant was retained by the subject firm for its corporate governance services, rather than merely mentioned in sections of the proxy statement submitted by other parties, such as director nominees for their biography or shareholder proposal sponsors.	SEC Proxy Statements
ES/G Risk	The number of risk incidents with high severity, specifically targeting the subject firm associated with the given shareholder proposal (sharp event only), measured over a one-year window following the meeting. Two-month lag is applied to reflect forward-looking ES/G risk rather than reactions to the meeting outcomes (i.e., months 2 to 14 after the meeting).	RepRisk
Meeting Year FE	Fixed effects based on meeting year, defined as starting on February 1st to align with the effective date of ISS Annual Proxy Voting Guidelines.	ISS Shareholder Proposals
Firm FE	Fixed effects based on firm identity, defined using ISS Company ID.	ISS Shareholder Proposals
Proposal Type FE	Fixed effects for shareholder proposal types, identified using ISS Agenda Item ID.	ISS Shareholder Proposals

Appendix B. Guideline Classification Examples

This table provides examples of ISS guidelines for each guideline category.

Category	Example Guideline
Vote For Without Exception	Vote FOR shareholder proposals calling for linkage of executive pay to non-financial factors including performance against social and environmental goals, customer/employee satisfaction, corporate downsizing, community involvement, human rights, or predatory lending.
Vote For With Exceptions	Vote FOR management or shareholder proposals to reduce supermajority vote requirements. However, for companies with shareholder(s) who have significant ownership levels, vote CASE-BY-CASE, taking into account: - Ownership structure; - Quorum requirements; and - Vote requirements.
Generally Vote For	Generally vote for proposals requesting a report on greenhouse gas (GHG) emissions from company operations and/or products and operations, unless: - The company already discloses current, publicly-available information on the impacts that GHG emissions may have on the company as well as associated company policies and procedures to address related risks and/or opportunities; - The company's level of disclosure is comparable to that of industry peers; and - There are no significant, controversies, fines, penalties, or litigation associated with the company's GHG emissions.
Vote Case-by-Case	Vote case-by-case on proposals regarding proxy voting mechanics, taking into consideration whether implementation of the proposal is likely to enhance or protect shareholder rights. Specific issues covered under the policy include, but are not limited to, confidential voting of individual proxies and ballots, confidentiality of running vote tallies, and the treatment of abstentions and/or broker non-votes in the company's vote-counting methodology. While a variety of factors may be considered in each analysis, the guiding principles are: transparency, consistency, and fairness in the proxy voting process. The factors considered, as applicable to the proposal, may include: - The scope and structure of the proposal; - The company's stated confidential voting policy (or other relevant policies) and whether it ensures a level playing field by providing shareholder proponents with equal access to vote information prior to the annual meeting; - The company's vote standard for management and shareholder proposals and whether it ensures consistency and fairness in the proxy voting process and maintains the integrity of vote results; - Whether the company's disclosure regarding its vote counting method and other relevant voting policies with respect to management and shareholder proposals are consistent and clear; - Any recent controversies or concerns related to the company's proxy voting mechanics; - Any unintended consequences resulting from implementation of the proposal; and - Any other factors that may be relevant.
Generally Vote Against	Generally vote AGAINST shareholder proposals to establish a new board committee, as such proposals seek a specific oversight mechanism/structure that

	potentially limits a company's flexibility to determine an appropriate oversight mechanism for itself. However, the following factors will be considered: - Existing oversight mechanisms (including current committee structure) regarding the issue for which board oversight is sought; - Level of disclosure regarding the issue for which board oversight is sought; - Company performance related to the issue for which board oversight is sought; - Board committee structure compared to that of other companies in its industry sector; and - The scope and structure of the proposal.
Vote Against Without Exception	Vote AGAINST proposals asking for a list of company executives, directors, consultants, legal counsels, lobbyists, or investment bankers that have prior government service and whether such service had a bearing on the business of the company. Such a list would be burdensome to prepare without providing any meaningful information to shareholders.

Appendix C. Prompts and examples

B.1. Prompt without ISS guidelines

Role:

You are an analyst at a proxy advisory firm that provides voting recommendations. Your task is to evaluate the following 'Shareholder Proposal' by objectively assessing the 'Supporting Statement' provided by the sponsor of the proposal and the 'Opposition Statement' provided by the company. Base your evaluation exclusively on information available prior to 2013-03-15. Provide a deterministic voting recommendation as either "For" or "Against", without any explanations.

Shareholder Proposal:

The shareholders ask the board of directors to adopt a policy that in the event of a change in control (as defined under any applicable employment agreement, equity incentive plan or other plan), there shall be no acceleration of vesting of any equity award granted to any named executive officer, provided, however, that the board's Compensation Committee (the "Committee") may provide in an applicable grant or purchase agreement that any unvested award will vest on a partial, pro rata basis up to the time of the named executive officer's termination, with such qualifications for an award as the Committee may determine.

For purposes of this Policy, "equity award" means an award granted under an equity incentive plan as defined in Item 402 of the SEC's Regulation S-K, which addresses executive compensation and named executive officer (or "executive") are those persons covered under Items 401 and 402 of the SEC's Regulation S-K. This resolution shall be implemented so as not affect any contractual rights in existence on the date this proposal is adopted.

Supporting Statement:

Abbott Laboratories (the "Company") allows executives to receive an accelerated award of unearned equity under certain conditions after a change of control of the Company. We do not question that some form of severance payments may be appropriate in that situation. We are concerned, however, that current practices may permit windfall awards that have nothing to do with an executive's performance.

According to last year's proxy statement, a change in control at the end of the 2011 fiscal year could have accelerated the vesting of $56 million worth of equity awards to Abbott Laboratories' top five executives, with the Chairman and CEO, Mr. White, entitled to $26 million.

In this regard, we note that the Company's stock programs use a "double trigger" mechanism for equity awards, meaning executives are entitled to receive the accelerated vesting of awards in a change in control only if there is a termination in employment as defined in the plan or agreement.

We are unpersuaded by the argument that executives somehow "deserve" to receive unvested awards. To accelerate the vesting of unearned equity on the theory that an executive was denied the opportunity to earn those shares seems inconsistent with a "pay for performance" philosophy worthy of the name.

We do believe, however, that an affected executive should be eligible to receive an accelerated vesting of equity awards on a pro rata basis as of his or her termination date, with the details of any pro rata award to be determined by the Committee.

Other major corporations, including Apple, Chevron, Dell, ExxonMobil, IBM, Intel, Microsoft, and Occidental Petroleum, have limitations on accelerated vesting of unearned equity, such as providing pro rata awards or simply forfeiting unearned awards.

We urge you to vote FOR this proposal.

Opposition Statement:

The Board of Directors recommends that you vote AGAINST the proposal.

Abbott's policies on treatment of outstanding equity awards upon a change in control serve the best interests of Abbott's shareholders by creating retention incentives that enable employees to avoid distractions and potential personal conflicts of interest at a critical juncture for the Company, thus promoting a continued focus on the business and reducing the risk of management turnover. The proposal would eliminate the Board's ability to exercise its business judgment in designing equity awards that it believes are in the best interest of Abbott's shareholders and competitive in the marketplace.

Responsive to discussions with investors in 2012, for future grants to its senior executives, the Compensation Committee eliminated the single-trigger provision of its equity award plans that accelerated the vesting of equity awards merely upon a change in control. Consequently, accelerated vesting will now be limited to the circumstance wherein, within six months prior to and through two years after a change in control, an award holder's employment is terminated without cause, or the executive resigns for good reason, as defined by the plan agreement, but simply put, results in the diminution of the executive's compensation or other material terms and conditions of employment.

This amendment, thereby, replaced the single-trigger approach the proponents oppose with a double-trigger, that is activated only when the executive experiences a real and significant loss without cause. The Board believes that this approach promotes stability and focus during an uncertain time by ensuring that executives do not risk a substantial loss by supporting a transaction that is in the best interest of shareholders, but would cause them to lose their jobs or suffer a material financial loss through no fault of their own.

The proposal seeks to substitute the proponent's view that the amount of time an executive is employed represents the extent to which an award is "earned" for the Compensation Committee's considered judgment. Contrary to the proponents, the Committee believes that an executive should not be deprived of the opportunity to realize the full value of a previously-granted equity award due following a change in control because the award (and the opportunity to vest in the award) is part of the executive's total compensation package. Abbott is committed to a pay-for-performance philosophy and as such roughly two-thirds of named executive officers' total compensation is comprised of equity awards whose value is realized over three to five years based on continued service and/or the achievement of pre-determined performance criteria. Putting executives in a position to lose the opportunity to earn these awards undermines the pay for performance objectives of this balance.

We note that the vast majority of S&P 500 companies provide single- or double-trigger accelerated vesting of equity upon a change in control, without pro-ration. Adoption of the proposal would put Abbott executives in a worse position than those at most other large public companies, including most of our peer companies, thus impairing our ability to attract and retain highly qualified executives.

Finally, the proponent's proposal that senior executives be treated differently than all other plan participants serves no legitimate shareholder interest and undermines the objectives stated above.

Accordingly, the Board of Directors recommends that you vote AGAINST the proposal.

Voting Recommendation:

B.2. Prompt with ISS guidelines

Role:

You are an analyst at a proxy advisory firm that provides voting recommendations. Your task is to evaluate the following 'Shareholder Proposal' by objectively assessing the 'Supporting Statement' provided by the sponsor of the proposal and the 'Opposition Statement' provided by the company. Apply the relevant 'Voting Recommendation Guidelines' as the primary analytical framework. Base your evaluation exclusively on information available prior to 2012-03-15. Provide a deterministic voting recommendation as either "For" or "Against", without any explanations.

Shareholder Proposal:

Shareholders of Abbott Laboratories (the "Company") urge the Compensation Committee of the Board of Directors (the "Committee") to adopt a policy requiring that senior executives retain a significant percentage of shares acquired through equity compensation programs until reaching normal retirement age. For the purpose of this policy, normal retirement age shall be defined by the Company's qualified retirement plan that has the largest number of plan participants. The shareholders recommend that the Committee adopt a share retention percentage requirement of at least 75 percent of net after-tax shares. The policy should prohibit hedging transactions for shares subject to this policy which are not sales but reduce the risk of loss to the executive. This policy shall supplement any other share ownership requirements that have been established for senior executives, and should be implemented so as not to violate the Company's existing contractual obligations or the terms of any compensation or benefit plan currently in effect.

Supporting Statement:

Equity-based compensation is an important component of senior executive compensation at our Company. While we encourage the use of equity-based compensation for senior executives, we are concerned that our Company's senior executives are generally free to sell shares received from our Company's equity compensation plans. Our proposal seeks to better link executive compensation with long-term performance by requiring a meaningful share retention ratio for shares received by senior executives from the Company's equity compensation plans. Requiring senior executives to hold a significant percentage of shares obtained through equity compensation plans until they reach retirement age will better align the interests of executives with the interests of shareholders and the Company. A 2009 report by the Conference Board Task Force on Executive Compensation observed that such hold-through-retirement requirements give executives "an evergrowing incentive to focus on long-term stock price performance as the equity subject to the policy increases".

In our opinion, the Company's current share ownership guidelines for its senior executives do not go far enough to ensure that the Company's equity compensation plans continue to build stock ownership by senior executives over the long-term. We believe that requiring senior executives to only hold shares equal to a set target loses effectiveness over time. After satisfying these target holding requirements, senior executives are free to sell all the additional shares they receive in equity compensation.

For example, our Company's share ownership guidelines have required the Chief Executive Officer (the "CEO") to hold 175,000 shares. In comparison, in 2010 our Company granted the CEO 200,000 performance-vesting shares and 295,000 stock options. In other words, the equivalent of one year's equity awards will be more than sufficient to satisfy the Company's share ownership guidelines for the CEO.

We urge shareholders to vote FOR this proposal.

Opposition Statement:

Sensible share ownership guidelines balance the importance of aligning executives' and shareholders' interests against the need to allow executives to prudently manage their personal financial affairs. The Board believes that Abbott's current share ownership guidelines strike that balance effectively. By contrast, the strict anti-diversification strategy in the proponents' proposal would not be considered prudent investment advice for any shareholder, including an executive, and would damage Abbott's ability to attract and retain senior management.

Abbott's current share ownership guidelines require the Chief Executive Officer to own 175,000 shares, the Chief Operational Officer to own 100,000 shares, and Executive Vice Presidents and Senior Vice Presidents to own 50,000 shares, which have been met or exceeded by all officers. Officers have only five years from the date they are appointed or elected to their positions to achieve the required levels of share ownership, which they hold in the form of equity awards and stock purchases through Abbott's 401(k) plan. To further align executives' interests with those of Abbott's shareholders, we have crafted our compensation program so that the majority of the named officer's compensation (approximately two-thirds) consists of long-term equity awards. Current and expected future equity grants are subject to vesting over a three-year or longer period, with performance vesting criteria for the majority of long-term equity awards. As such, the vast majority of executives' current income can only be earned in the future through meeting established performance criteria which are directly related to shareholder returns.

Executives have legitimate reasons to access their equity compensation when it vests and to diversify their investments. Our current share ownership guidelines are consistent with those adopted by peer companies and by public companies generally. The proposal that executives should be required to hold 75% of net after tax shares until retirement seems to gloss over these realities, especially the competitive marketplace for executive talent. The proposal is so restrictive that it could motivate critical executives to leave the Company prematurely in order to access the value of their equity compensation.

Additionally, to avoid even the potential appearance of inappropriate equity transactions, we require all executive officers to clear any transaction involving Abbott shares with the General Counsel prior to entering into the transaction. Abbott does not allow hedging or pledging of restricted shares.

Based on these facts, the Board of Directors recommends that you vote AGAINST the proposal.

Voting Recommendation Guidelines:

Vote CASE-BY-CASE on shareholder proposals asking companies to adopt policies requiring senior executive officers to retain all or a significant portion of the shares acquired through compensation plans, either:

- while employed and/or for two years following the termination of their employment; or

- for a substantial period following the lapse of all other vesting requirements for the award ("lock-up period"), with ratable release of a portion of the shares annually during the lock-up period.

The following factors will be taken into account:

- Whether the company has any holding period, retention ratio, or officer ownership requirements in place. These should consist of: a) rigorous stock ownership guidelines; b) a holding period requirement coupled with a significant long-term ownership requirement; or c) a meaningful retention ratio;

- Actual officer stock ownership and the degree to which it meets or exceeds the proponent's suggested holding period/retention ratio or the company's own stock ownership or retention requirements;

- Post-termination holding requirement policies or any policies aimed at mitigating risk taking by senior executives;

- Problematic pay practices, current and past, which may promote a short-term versus a long-term focus.

A rigorous stock ownership guideline should be at least 10x base salary for the CEO, with the multiple declining for other executives.

A meaningful retention ratio should constitute at least 50 percent of the stock received from equity awards (on a net proceeds basis) held on a long-term basis, such as the executive's tenure with the company or even a few years past the executive's termination with the company.

Voting Recommendation:

Appendix D1. Statistics Generated by Alternative Methodologies

This table mirrors Tables 3 and 8, but we provide results based on a series of alternative methodologies. In Panel A, we utilize a stricter prompt to only follow the guidelines. In Panel B, we instruct the AI to take on the role of a fund manager yet still follow the provided guidelines. In Panels C, D, and E, we redact all organization names and their aliases from the statements provided to AI.

Panel A. Strict Prompt to Follow Guidelines- PSOG Model (N = 4,565)

	ISS For	ISS Against
AI For	3,242	655
AI Against	425	243
Alignment	88.41%	27.06%
Overall Alignment		76.34%

Panel B. Prompt with Fund Manager's Fiduciary Duty- PSOG Model (N = 4,565)

	ISS For	ISS Against
AI For	2,948	551
AI Against	719	347
Alignment	80.39%	38.64%
Overall Alignment		72.18%

Panel C. Redacted PSO Model (N = 5,184)

	ISS For	ISS Against
AI For	3,566	1,113
AI Against	273	232
Alignment	92.89%	17.25%
Overall Alignment		73.26%

Panel D. Redacted PSOG Model (N = 4,565)

	ISS For	ISS Against
AI For	3,207	632
AI Against	460	266
Alignment	87.46%	29.62%
Overall Alignment		76.08%

Panel E: Shareholder Support Rates, Redacted PSOG Model (N = 4,565)

	ISS For	ISS Against
AI For	40.184	13.031
AI Against	32.850	8.473
Diff	7.334	4.558
t-stat	9.843***	7.187***

Appendix D2. Alignment between ISS and AI by Proposal Type

This table reports alignment between ISS recommendations and AI recommendations across proposal types, as defined by ISS (ISS Agenda Item ID), in our sample. The ISS Resolution column shows a representative label from the ISS data dictionary, although actual resolutions may vary in detail. ISS Resolution Type refers to a broader classification assigned by ISS, distinguishing between governance (GOV) and environmental/social (SRI) proposals. 'NA' indicates that no proposals are classified under that category.

ISS Agenda Item ID	ISS Resolution	ISS Resolution Type	PSOG Sample Alignment	# of Obs.
S0105	Limit Auditor from Providing Non-Audit Services	GOV	0.000	1
S0107	Require Independent Board Chairman	GOV	0.613	494
S0111	Allow Shareholder Meetings to be Held in Virtual-Only Format	GOV	0.500	2
S0115	Company-Specific -- Miscellaneous	GOV	NA	0
S0119	Reimburse Proxy Contest Expenses	GOV	0.000	1
S0126	Amend Articles/Bylaws/Charter -- Non-Routine	GOV	1.000	1
S0146	Adjust/Remove Exclusive Venue Provision	GOV	0.500	2
S0152	Approve Allocation of Income/Distribution Policy	GOV	NA	0
S0201	Declassify the Board of Directors	GOV	0.995	189
S0202	Establish Term Limits for Directors	GOV	0.833	6
S0205	Establish Other Governance Board Committee	GOV	0.600	15
S0206	Establish Environmental/Social Issue Board Committee	GOV	0.933	30
S0207	Restore or Provide for Cumulative Voting	GOV	0.773	66
S0209	Establish Director Stock Ownership Requirement	GOV	1.000	1
S0211	Establish Mandatory Retirement Age for Directors	GOV	1.000	1
S0212	Require a Majority Vote for the Election of Directors	GOV	0.945	219
S0215	Require Majority of Independent Directors on Board	GOV	1.000	2
S0216	Deliberations on Possible Legal Action Against Directors/(Internal) Auditors	GOV	NA	0
S0219	Limit Composition of Committee(s) to Independent Directors	GOV	NA	0
S0220	Require Director Nominee Qualifications (Excluding Environmental & Social)	GOV	0.455	11
S0221	Adopt Proxy Access Right	GOV	0.815	216
S0222	Company-Specific Board-Related	GOV	0.000	1
S0224	Require Environmental/Social Issue Qualifications for Director Nominees	GOV	0.571	21
S0225	Change Size of Board of Directors	GOV	1.000	2
S0226	Amend Proxy Access Right	GOV	0.854	103
S0227	Board Diversity	GOV	0.795	44

S0230	Require More Director Nominations Than Open Seats	GOV	1.000	1
S0232	Amend Articles Board-Related	GOV	0.286	7
S0234	Amend Articles/Bylaws/Charter - Removal of Directors	GOV	1.000	2
S0235	Amend Articles/Bylaws/Charter - Call Special Meetings	GOV	0.890	335
S0236	Amend Vote Requirements to Amend Articles/Bylaws/Charter	GOV	0.706	17
S0237	Amend Director/Officer Indemnification, Liability or Exculpation Provisions	GOV	1.000	2
S0238	Provide Right to Act by Written Consent	GOV	0.833	353
S0302	Submit Shareholder Rights Plan (Poison Pill) to Shareholder Vote	GOV	0.733	15
S0303	Eliminate or Restrict Shareholder Rights Plan (Poison Pill)	GOV	0.000	1
S0304	Provide for Confidential Voting	GOV	1.000	1
S0305	Proxy Voting Tabulation	GOV	0.216	37
S0308	Proxy Voting Disclosure	GOV	0.000	1
S0311	Reduce Supermajority Vote Requirement	GOV	0.848	145
S0316	Approve Recapitalization Plan for all Stock to Have One-vote per Share	GOV	0.681	72
S0318	Eliminate or Restrict Severance Agreements (Change-in-Control)	GOV	0.600	5
S0319	Reincorporate in Another State	GOV	0.700	20
S0321	Submit Severance Agreement (Change-in-Control) to Shareholder Vote	GOV	0.826	23
S0326	Amend Articles/Bylaws/Charter to Remove Antitakeover Provisions	GOV	0.833	6
S0332	Approve/Amend Terms of Poison Pill	GOV	1.000	1
S0352	Company-Specific--Governance-Related	GOV	0.636	11
S0353	Miscellaneous -- Equity Related	GOV	1.000	4
S0378	Amend Articles/Charter Equity-Related	GOV	NA	0
S0411	MacBride Principles	SRI	1.000	1
S0412	Human Rights Risk Assessment	SRI	0.714	42
S0414	Improve Human Rights Standards or Policies	SRI	0.530	83
S0421	Plant Closures and Outsourcing	SRI	0.500	2
S0423	Operations in Hgh Risk Countries	SRI	0.600	5
S0427	Data Security, Privacy, and Internet Issues	SRI	0.889	9
S0500	Stock Retention/Holding Period	GOV	0.496	121
S0501	Limit/Prohibit Executive Stock-Based Awards	GOV	1.000	2
S0502	Death Benefits / Golden Coffins	GOV	0.917	12
S0503	Increase Disclosure of Executive Compensation	GOV	0.500	6
S0504	Limit Executive Compensation	GOV	0.667	3
S0506	Submit SERP to Shareholder Vote	GOV	0.667	6
S0507	Report on Pay Disparity	GOV	0.462	26
S0510	Link Executive Pay to Social Criteria	GOV	0.435	62
S0511	Company-Specific--Compensation-Related	GOV	0.962	26

S0512	Performance-Based and/or Time-Based Equity Awards	GOV	0.769	13
S0515	Non-Employee Director Compensation	GOV	NA	0
S0516	Clawback of Incentive Payments	GOV	0.630	46
S0517	Advisory Vote to Ratify Named Executive Officers' Compensation	GOV	1.000	91
S0520	Pay for Superior Performance	GOV	1.000	4
S0521	Disclose Information on Compensation Consultant	GOV	1.000	3
S0524	Adopt Anti Gross-up Policy	GOV	1.000	6
S0525	Employment Contract	GOV	NA	0
S0526	TARP Related Compensation (INACTIVE)	GOV	0.667	3
S0527	Limit/Prohibit Accelerated Vesting of Awards	GOV	0.873	102
S0528	Adopt Policy on Bonus Banking	GOV	0.600	5
S0530	Adopt Policy on Succession Planning.	GOV	0.500	2
S0531	Adjust Executive Compensation Metrics for Share Buybacks	GOV	0.500	4
S0532	Use GAAP for Executive Compensation Metrics	GOV	NA	0
S0602	Fair Lending	GOV	0.400	5
S0610	Mandatory Arbitration on Employment Related Claims	GOV	1.000	3
S0617	Employ Financial Advisor to Explore Alternatives to Maximize Value	GOV	1.000	2
S0618	Seek Sale of Company/Assets	GOV	0.750	4
S0704	Prepare Tobacco-Related Report	SRI	1.000	1
S0708	Toxic Emissions	SRI	NA	0
S0709	Phase Out Nuclear Facilities	SRI	0.500	2
S0710	Facility Safety	SRI	0.333	9
S0711	Nuclear Safety (INACTIVE)	SRI	0.000	1
S0725	Weapons - Related	SRI	1.000	3
S0727	Review Foreign Military Sales	SRI	0.750	8
S0729	Review Drug Pricing or Distribution	SRI	0.625	8
S0730	Report on Environmental Policies	SRI	0.500	2
S0731	Community -Environment Impact	SRI	0.597	77
S0733	Reduce Tobacco Harm to Health	SRI	1.000	4
S0734	Review Tobacco Marketing	SRI	0.429	7
S0735	Prepare Report on Health Care Reform	SRI	0.500	6
S0736	Genetically Modified Organisms (GMO)	SRI	1.000	4
S0737	Toxic Substances (INACTIVE)	SRI	0.000	1
S0738	Product Toxicity and Safety	SRI	0.556	18
S0742	Report on Climate Change	SRI	0.692	65
S0743	GHG Emissions	SRI	0.765	115
S0744	Hydraulic Fracturing	SRI	0.846	13
S0745	Climate Change Action	SRI	NA	0
S0748	Proposals Requesting Non-Binding Advisory Vote On Climate Action Plan	SRI	1.000	1
S0777	Report on Sustainability	SRI	0.878	90

S0778	Wood Procurement	SRI	NA	0
S0779	Renewable Energy	SRI	0.481	27
S0780	Energy Efficiency	SRI	0.333	3
S0781	Recycling	SRI	0.828	29
S0782	Publish Two Degree Scenario Analysis	SRI	NA	0
S0805	Disclose Prior Government Service	SRI	0.364	11
S0806	Charitable Contributions	SRI	1.000	1
S0807	Political Contributions Disclosure	SRI	0.806	391
S0808	Political Lobbying Disclosure	SRI	0.619	265
S0809	Political Activities and Action	SRI	0.750	12
S0810	Company-Specific -- Shareholder Miscellaneous	GOV	0.800	5
S0811	Adopt Sexual Orientation Anti-Bias Policy	SRI	0.800	35
S0812	Report on EEO	SRI	0.879	58
S0815	Labor Issues - Discrimination and Miscellaneous	SRI	0.333	3
S0816	Holy Land Principles	SRI	NA	0
S0817	Gender Pay Gap	SRI	0.632	38
S0819	Workplace Sexual Harassment	SRI	0.500	2
S0890	Animal Welfare	SRI	0.182	11
S0891	Animal Testing	SRI	0.214	14
S0892	Animal Slaughter Methods	SRI	0.125	8
S0911	Miscellaneous -- Environmental & Social Counterproposal	SRI	0.286	14
S0913	Adopt a Policy on Ideological Board Diversity	SRI	NA	0
S0999	Miscellaneous Proposal -- Environmental & Social	SRI	0.353	17
GOV			0.778	3,049
SRI			0.695	1,516
Total			0.750	4,565

Appendix D3: Proposals without Matched Guidelines

This table reports analysis similar to Table 9, but on the sample of 486 proposals without matched guidelines. Since there is no guideline, the AI recommendation is based on the PSO model. Heteroskedasticity-robust standard errors are used, with t-statistics reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

	Unmatched	Unmatched
AI For (PSO; 0/1)	0.956	-0.732
	(1.053)	(-0.760)
ISS For (0/1)	21.168***	18.883***
	(14.289)	(10.534)
Management None (0/1)	76.683***	-
	(15.836)	
Conflicting Proposal from Mgmt (0/1)	-	-
# Tokens in PS (Ln)	0.865	-0.389
	(0.767)	(-0.317)
# Tokens in O (Ln)	1.521	1.387
	(1.429)	(1.285)
Firm Size (Ln)	-0.826	0.785
	(-0.624)	(0.527)
Cash Holdings	3.532	6.306
	(0.932)	(1.465)
Dividend Yield	16.060	-12.462
	(0.570)	(-0.476)
Market-to-Book	-0.789	-1.113
	(-1.072)	(-1.489)
ROA	-7.931	-2.866
	(-1.050)	(-0.427)
Past Stock Performance	-0.001	-1.347
	(-0.001)	(-1.407)
Institutional Ownership	5.191**	6.032**
	(2.225)	(2.614)
Sponsor - Pension (0/1)	6.312***	5.982***
	(3.903)	(3.814)
Sponsor - SRI Fund (0/1)	2.634*	1.802
	(1.741)	(1.121)
Sponsor - Other Fund (0/1)	-2.410*	-2.400
	(-1.912)	(-1.601)
Sponsor - Union (0/1)	3.266*	3.187
	(1.867)	(1.359)
Sponsor - Religious Group (0/1)	3.300*	2.617

	(1.716)	(1.455)
Sponsor - Special Interest Group (0/1)	-0.193	-0.985
	(-0.178)	(-0.828)
Meeting Year FE	Yes	Yes
Firm FE	Yes	Yes
Proposal Type FE	No	Yes
Firm clustering	Yes	Yes
Observations	486	469
Adj. R-squared	0.764	0.801

Table D4: Consultant Test using Next-Year Guidelines

This table mirrors Columns 3-7 of Table 10, but we prompt AI with guidelines from the following year instead of the current year (PSONG). We perform this test to address concerns that a governance consultant may lobby ISS to change guidelines, with those changes being incorporated before the subsequent release of the ISS policy document.

	(1) PSONG	(2) PSONG	(3) PSONG	(4) PSONG	(5) PSONG
Third-party Consulting (0/1)	0.084**	0.064*	0.063*	0.065*	0.063*
	(2.443)	(1.867)	(1.860)	(1.885)	(1.826)
Management None (0/1)	-0.077**	-0.088***	-0.088***	-0.087***	-0.084***
	(-2.461)	(-2.934)	(-2.924)	(-2.890)	(-2.839)
Conflicting Proposal from Mgmt (0/1)	-0.142**	-0.044	-0.044	-0.044	-0.040
	(-2.250)	(-0.937)	(-0.928)	(-0.930)	(-0.843)
# Tokens in PS (Ln)	0.028	-0.006	-0.008	-0.006	-0.008
	(0.891)	(-0.222)	(-0.312)	(-0.259)	(-0.327)
# Tokens in O (Ln)	-0.002	-0.012	-0.013	-0.013	-0.013
	(-0.106)	(-0.773)	(-0.790)	(-0.796)	(-0.785)
# Tokens in G for ISS (Next Year's; Ln)			0.010		
			(0.593)		
ISS Case-by-case (Next Year's; 0/1)				0.020	
				(0.767)	
ISS Case-by-case + Generally (Next Year's; 0/1)					0.055*
					(1.823)
Firm Size (Ln)	0.032*	0.015	0.015	0.015	0.015
	(1.915)	(1.015)	(1.007)	(1.032)	(1.007)
Cash Holdings	0.030	0.035	0.036	0.036	0.036
	(0.551)	(0.679)	(0.688)	(0.700)	(0.687)
Dividend Yield	0.791***	0.641*	0.636*	0.648*	0.648*
	(2.887)	(1.766)	(1.751)	(1.787)	(1.807)
Market-to-Book	-0.006	-0.003	-0.003	-0.003	-0.003
	(-0.735)	(-0.380)	(-0.362)	(-0.391)	(-0.427)
ROA	-0.207*	-0.160*	-0.162*	-0.160*	-0.162*
	(-1.924)	(-1.722)	(-1.743)	(-1.725)	(-1.736)
Past Stock Performance	0.016	0.001	0.001	0.001	0.001
	(1.352)	(0.105)	(0.104)	(0.113)	(0.098)
Institutional Ownership	-0.009	0.051	0.052	0.053	0.055
	(-0.222)	(1.233)	(1.254)	(1.259)	(1.304)
Sponsor - Pension (0/1)	-0.005	-0.015	-0.015	-0.015	-0.013
	(-0.206)	(-0.664)	(-0.638)	(-0.660)	(-0.572)
Sponsor - SRI Fund (0/1)	0.015	-0.000	0.000	0.001	0.001
	(0.434)	(-0.009)	(0.011)	(0.021)	(0.019)
Sponsor - Other Fund (0/1)	0.007	-0.014	-0.014	-0.015	-0.013

	(0.244)	(-0.543)	(-0.537)	(-0.557)	(-0.489)
Sponsor - Union (0/1)	-0.005	-0.010	-0.009	-0.010	-0.006
	(-0.155)	(-0.338)	(-0.300)	(-0.334)	(-0.196)
Sponsor - Religious Group (0/1)	0.051*	-0.028	-0.027	-0.028	-0.025
	(1.652)	(-0.747)	(-0.739)	(-0.745)	(-0.674)
Sponsor - Special Interest Group (0/1)	0.169***	0.011	0.013	0.011	0.012
	(3.327)	(0.238)	(0.265)	(0.239)	(0.252)
Meeting Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Proposal Type FE	No	Yes	Yes	Yes	Yes
Firm clustering	Yes	Yes	Yes	Yes	Yes
Observations	4,303	4,285	4,285	4,285	4,285
Adj. R-squared	0.096	0.263	0.263	0.263	0.264