INSTITUTIONAL INVESTOR DELIBERATION

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Abstract

We study institutional investors' deliberation on their voting choices using novel proprietary data from the second largest proxy advisor. Institutions engage in a two-stage process to produce voting choices: first, they design advance voting policies that are applied by third party proxy advisors; and second, they devote attention to, and deliberate on, specific ballots as they arise. We model the investor's decision on whether and how to invest in its voting choices. We then introduce a new measure of manual submission of votes and show how this serves as a proxy for fund attention. We demonstrate empirically that funds devote more attention to the ballots in their portfolio that are more important and controversial and that comprise a larger share of their portfolio. We also conduct a difference-in-difference analysis to show how special meetings and meetings connected to activists cause an increase in fund attention. On the first stage of the institutions' process, we show that the vast majority of funds use customized recommendation policies that differ substantially from proxy advisor benchmark recommendations. We connect the use of customized recommendations not only to deviations from benchmark recommendations, but to consistent ideological differences from benchmark recommendations on social responsibility proposals. Our results suggest that the controversial practice of auto-submission, wherein funds programmatically submit their ballots, is best understood as a cost saving mechanism, saving deliberation for important ballots. A regulatory focus on prohibiting auto-submission of votes may therefore be misplaced—instead, enhancing funds' incentives to create detailed *ex ante* policies may yield better results, given that funds effectively 'self-regulate' their use of proxy advice.

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I. Introduction

Before investors can decide how to vote on a corporate matter, they must decide how to decide how to vote. Paying close attention to issues at one's portfolio companies is costly, and so an investor must determine how much total attention to pay to its portfolio, what form the attention should take, and how to allocate this attention across its portfolio companies. The investor's decisions on these matters are not necessarily optimal for its portfolio firms: corporate stewardship through shareholder voting is a public good, but investors internalize all the costs and only a fraction of the benefits of making good voting choices. Thus, a shareholder's decision to invest minimally in voting decision-making might be optimal for the shareholder but suboptimal for the firm and for social welfare.

For this reason, investor decision-making processes are the subject of substantial academic interest, much of it focused on concerns that investors' stewardship of their portfolio companies is suboptimal (Bebchuk, Cohen, and Hirst (2017), Iliev and Lowry (2015), Iliev, Kalodimos, and Lowry (2022)). One particular method of producing votes has drawn particular consternation from regulators, academics, and industry groups: robo-voting, the practice of mechanically voting the recommendations of proxy advisors.[1] Proxy advisors are third party subscription services that provide recommendations to institutional investors on how to vote in corporate meetings (Choi et al. (2009)); their recommendations are highly influential on voting outcomes (Malenko and Shen (2016). But little is known about how institutions make their voting choices, and whether—or to what extent—they cast ballots without deliberation.

In this paper, we describe, both qualitatively and empirically through novel data, how institutional investors who use proxy advisors deliberate and make voting choices. We show that determining one's voting choices is a two-part process: first, shareholders set advance policies which become their default votes, and second, shareholders strategically invest attention to key votes that are contested and/or important for their portfolios. By setting policies—which, we show, usually differ from their proxy advisor's benchmark policies through the widespread use of customization—they achieve portfolio-wide economies of scale.[2]

[1] See, *e.g.*, SEC (2019) at pages 66 and 119; Exxon (2012); Doyle (2020).

[2] Institutional investors effectively create for themselves a system of efficient default rules—arguably the aim of corporate law as a whole. Easterbrook and Fischel (1996).

We present a model of fund rational inattention, in which funds choose how much to invest in deliberation and how to allocate this deliberation across securities. Our main empirical contributions are to document the widespread customization of investor voting policies; to introduce a new variable that proxies for automatic voting; and to empirically demonstrate how the relationships between customization, automatic voting, and fund, firm, and proposal characteristics are consistent with fund vote selection process that weighs costs and benefits across the portfolio and over time. Our results suggest that, at the voting stage, funds are rationally inattentive: there is some threshold of importance of a proposal for a security in its portfolio under which a vote will not devote specific attention to the proposal. Furthermore, funds reduce the costs of rational inattention before the voting stage by investing in customized policies that scale across their whole portfolio.

We note that such rational inattention would seem to be an intractable consequence of the shareholder collective action problem, though policy changes that alter the cost of inattention may shift the threshold at which a fund devotes attention. On a proposal to which a fund does not provide specific attention, its pre-established voting rule likely determines its vote. As compared to, say, random voting or down-the-line voting with management, voting in line with a third-party adviser's fund-specific customized recommendations on proposals which do not meet an investor's threshold for specific attention may be a relatively elegant solution, though our results do not speak specifically to that question.

Several papers study shareholder deliberation on voting by using high rates of agreement with proxy advisors to classify a minority of funds as robo-voters and the rest as active voters. We take a different approach by directly measuring auto-submission or manual submission of ballots and placing auto-submission in the context of the broader fund deliberation process.[3] Many prominent critics of the proxy voting system have argued that disabling the automatic submission of votes would lead to more informed voting, but to date no empirical research has

[3] We define auto-submission as an attribute of a voter's specific ballot; a ballot is auto-submitted when a voter allows one's pre-populated default voting choices to be cast on that ballot without manually hitting a button. We loosely define robo-voting as an attribute of a voter; a voter robo-votes when it auto-submits a high fraction of votes without deliberation, and we discuss more specific definitions of robo-voting used in the literature in Section V.

been able to examine this important claim.[4] We show that most funds appear to auto-submit some of the time, few funds auto-submit all of the time, and, for most funds, auto-submission is done in conjunction with the use of customized policies that, presumably, generate funds' preferred voting choices on most proposals.

Though our primary interest is in understand institutional investor voting deliberations, our paper relates closely to recent regulatory and policy debates. In 2019, the US Securities and Exchange Commission proposed regulations that would have substantially regulated proxy advisors, in part based on concerns about robo-voting and over-reliance on proxy advisor recommendations.[5] Following a contentious notice-and-comment period, the SEC in 2020 passed a less restrictive final rule governing proxy advice. In 2022, the SEC passed a new rule substantially undoing the 2020 regulation. Regulation has not been the only arena in which this area has been contested at the SEC. In 2022, the SEC announced a settlement with an institutional investor for voting with proxy advisor recommendations without confirming they were in the investor's clients' best interest, drawing a sharp dissent from two Commissioners.[6]

The paper proceeds as follows. We begin by presenting a model illustrating the tradeoffs funds face in investing in voting choices, treating fund deliberation as a multi-stage process that allocates resources to each voting decision and determines how much of each voting decision to keep in-house or to rely on outside advice. Funds will invest more attention in more important, controversial proposals in securities than own more of; funds with larger stakes and fewer securities will invest more attention as compared to other funds; and funds can benefit from *ex ante* policies applied by third parties that can benefit from economies of scale and scope.

[4] Business Roundtable, RE: Amendments to Exemptions from the Proxy Rules for Proxy Voting Advice Release No. 34-87457; File Number S7-22-19, (2020).

[5] Among other things, the 2019 Rule considered the possibility of requiring the disabling of automatic voting mechanisms. SEC, Amendments to Exemptions from the Proxy Rules for Proxy Voting Advice, Release No. 34-87457; File No. S7-22-19 (2019). The 2019 Rule also relied on claims that "a substantial percentage of proxy votes are typically cast within a few days or less of . . . release of [the] proxy voting advice." *Id*.

[6] Hester M. Peirce & Mark T. Uyeda, Statement Regarding In the Matter of Toews Corporation (Sept. 20, 2022) ("Toews instructed the third-party service provider always to vote all client proxies in favor of the proposals put forth by the issuers' management and against any shareholder proposals . . . We are concerned that the Order may be misconstrued regarding an adviser's fiduciary duties with respect to voting proxies on behalf of its clients, as well as the specific requirements imposed by the proxy voting rule.").

Next, we turn to our empirical analysis. We use publicly available data to show that, given the high degree of agreement between the proxy advisers and management, measures of robo-voting using agreement rate of an institutional voter and the proxy advisers may misstate the extent of truly automated voting. In fact, these measures also show a comparable degree of "managerial" robo-voting.

We then show statistics describing, for institutional investors that use Glass Lewis voting services, their policies regarding auto-submission and manual submission. We document the timing of fund votes and show that there is only a small spike in proxy voting immediately following the release of Glass Lewis's recommendations. We show that funds cast a disproportionate fraction of their votes on their auto-submission deadline.

We use funds' submission date as a proxy for manual or auto-submission to evaluate funds' choices of attention. We find that funds strategically choose which ballots in their portfolios to allocate attention to and show that funds devote attention to the larger holdings in their portfolios, to contested ballots, and to more important meetings. Using a difference-in-differences setup, we show a causal relationship between in-house attention and special meetings and meetings connected to activist investors. Although we only have a proxy for manual submission, our results show that attention to votes is not monolithic, but in fact depends on the fund, the firm, the stake, and the ballot, consistent with a rational allocation of fund resources.

Finally, we study the use of customized proxy advice. We show that 80% of funds acquire custom recommendations from proxy advisers, a departure from the extant literature which focuses on proxy adviser house recommendations, and provide evidence suggesting that customized recommendations differ, on average, on 21% of ballots from benchmark proposals. We show that more customized recommendations are associated with larger institutional investors, consistent with our predictions. We show shareholders who receive customized recommendations are more likely to evince a systematic ideological difference on SRI proposals from the proxy adviser benchmark recommendations.

Our results underscore the extent to which "robo-voting" may not be a useful framework to understand the issue of fund deliberation. Given that funds own many securities, may trade algorithmically rather than by specific human judgment, and sometimes employ small staffs, it is almost certain that at least some funds cast at least some ballots without discussing the ballot items in question. Our paper focuses on the deliberation process more holistically, including the extent of customization of recommendations from proxy advisers, and more narrowly, including which meetings are given more in-house attention by funds. Our results are consistent with funds balancing costs and benefits when deciding (i) acquisition of outside research, (ii) how much in-house attention to provide to proposals, and (iii) which proposals to allocate in-house attention to.

Our results have implications for the academic and policy discussion on shareholder monitoring of firms and on free-riding in voting. First, our results suggest that regulators should be focused on fund deliberation, rather than focusing on *ex post* measures of fund "robo-voting" based on benchmark recommendations. Our results suggest that the use of custom recommendations could increase fund deliberation and reduce the influence of proxy advisor benchmark recommendations.

Second, while we do find evidence that auto-submission appears to be correlated with traditional notions of "robo-voting"—*i.e.*, agreement with the benchmark recommendation—our results suggest that eliminating auto-submission may not be a productive policy, as we find meaningful variation in vote timing consistent with economic considerations.

On balance, regulators should carefully weigh the costs of limiting auto-submission and related features (*e.g.*, pre-population), which could increase the costs of voting and decrease the utility of proxy adviser services. This could paradoxically lead to less deliberation, through less use of add-on services like custom recommendations, and more reliance on proxy adviser house recommendations.

Our paper is organized as follows. In Section II, we provide background as to the mechanics of how institutional shareholders cast their ballots. In Section III, we construct a model of fund deliberations. In Section IV, we describe our data. In Section V, we evaluate measures of robo-voting, describe the extent to which they capture deliberation, and connect vote timing to auto-submission. In Section VI, we show empirically how funds allocation attention across the ballots in their portfolio. In Section VII, we present our results on customized recommendations. Section VIII concludes.

II. Background: Mechanics of Institutional Voting

In this section, we describe the mechanics of institutional vote execution.[7]

Institutional investors generally contract with a voting execution firm to execute their proxy votes. Three firms facilitate the vast majority of fund votes: Broadridge, Glass Lewis, and ISS, with proprietary software ProxyEdge, Viewpoint, and ProxyExchange, respectively. The latter two firms also offer proxy recommendations, either standard "house" or "benchmark" recommendations or client-specific custom recommendations based on tailored guidelines. An institution that subscribes to proxy recommendations may or may not also subscribe to the proxy advisor's voting execution services.

Institutions typically have multiple subsidiary voting units, generally funds or separately managed accounts, which have distinct portfolios and submit separate ballots. Voting units, which we generally refer to as funds for simplicity, may have customized recommendations and distinct voting execution policies distinct from other voting units at their institution.

For an institution that subscribes to voting execution services, Broadridge informs the voting execution firm of the number of shares held, for each issuer, by each of the institution's funds.[8] A fund can use its voting execution software to view the proposals on the ballot for each issuer in its portfolio, make selections, and submit its ballot. The fund may arrange for pre-population of its ballots, and may deviate from the pre-populated ballot by altering its voting choices within the software. For a fund that subscribes to both voting execution services and proxy advice, the default voting rule may be the proxy advisor's house recommendation or the client's custom recommendation, but the fund could choose a different pre-population or no pre-population at all. The fund may also arrange with the voting services firm for auto-submission: a date, some number of days prior to the meeting's voting deadline, in which the fund's votes are submitted if the fund has not manually submitted its ballot by that point.

[7] This section is based on SEC filings, information from intermediary voting service firm websites, and conversations with employees of ISS, Glass Lewis, and Broadridge.

[8] Brav et al. (2020) describes in detail the process by which Broadridge obtains that information.

Following the submission of shareholder ballots from investors through ISS and Glass Lewis's systems, these firms deliver the ballots from these institutional clients to Broadridge via the latter's Consolidated Data Feed.[9] Broadridge's Vote Audit Department checks for errors in the incoming voting numbers from ISS and Glass Lewis via the Consolidated Data Feed and from its own ProxyEdge (Broadridge 2010). Broadridge then reconciles the shares cast with share ownership with Depository Trust and Clearing Corporation ("DTCC"),[10] reviewing any large discrepancies. Broadridge subsequently transmits the voting results to the issuer or the issuer's transfer agent (Broadridge (2010a), Broadridge (2010b)).

Glass Lewis provides both proxy advisory services and voting services. Clients of Glass Lewis proxy advisory services may receive its benchmark recommendations or customized recommendations. For customized recommendations, the institution determines the rules upon which it wants recommendations made for the proposals it votes on, which may vary across the institution's funds, portfolio securities within a fund, and meeting and proposal types within a security. For example, in deciding whether to vote against an incumbent for a board seat, a fund can choose a threshold number of board meetings the incumbent has missed as a factor to be used in their custom recommendation.

Glass Lewis institution ballots are pre-populated with the institution's specific recommendations. Clients of Glass Lewis voting services have a series of options regarding vote execution, which may vary across institution's funds. Each fund chooses whether its ballots should automatically submit when the fund itself does not manually submit the ballot, and, if so, when the automatic submission should occur. The most common selection is three days before the meeting's voting deadline, which is four days before the meeting; other funds choose immediate submission upon receipt of the recommendation. Funds may choose more detailed vote execution options that may vary across its securities or meeting types; immediate auto-submission of ballots may be overridden using more detailed customization options.

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[9] See Datafeed License Agreement, available at https://www.sec.gov/Archives/edgar/data/1408198/000119312512474287/d438973dex1055.htm.

[10] The DTCC is a securities depository through which shares are held in street name, to minimize the paperwork involved in transferring shares (Brav et al. (2022)).

III. Hypothesis Generation and Model

A. Intuition

By what process do shareholders produce their votes? An extensive literature has shown that proxy advisor benchmark recommendations are influential (Malenko and Shen (2016); Bubb and Catan (2022)). So do institutional investors "set it and forget it?"

We posit institutional investors engage in a two-stage process. First, they set an advance voting policy, consisting of rules and standards to be applied by a third party. The advance policy setting-stage produces much of the variation in voting by institutions. As observed by Bubb and Catan (2022), choosing between management recommendations, Glass Lewis, and ISS is, by itself, a substantive policy choice between three substantially distinct ideological poles. We note, and will show later in our data, that rather than using benchmark recommendations, most proxy advisor customers tailor the advice they receive by using customized recommendations—a point we do not believe has been made before in the academic literature. Customized recommendations are a way of producing voting policies that accord more tightly with the fund's preferences or beliefs.

The second part of the institutional investor two-stage process is producing proposal-by-proposal voting choices. Because advance voting policies are produced in advance and converted into proposal-level recommendations by a third party, on some proposals these recommendations will necessarily deviate from what the fund would prefer if the fund had complete information about the proposal. Whether or not they receive outside recommendations or set advance policies, funds may (or may not) research and deliberate on specific proposals to produce votes consistent with their preferences and beliefs.

The two-stage process permits funds to vote as closely as possible to their preferences and beliefs with minimal cost. We can think of this process in the context of a director reelection. A fund with small stakes in many firms may achieve economies of scale by purchasing an outside advisor's recommendations, which may be based on, *e.g.*, the number of meetings the director missed. By customizing the recommendations, the fund can set a different threshold for missed meetings, adjusting the policy to fit its preferences. But if the director election is important to the fund's portfolio, it may prefer to devote specific attention to it and possibly deviate from its recommendation.

Such a vote-generation process produces testable predictions. A fund with small stakes in many firms would benefit from investment in a consistent advance voting policy, to exploit economies of scale. Conversely, a fund with a large stake in a single security would gain relatively little benefit from customizing third-party recommendations and instead should devote attention to the security's shareholder meeting. We can also think about within-fund predictions: a fund should devote more attention to its more important proposals.

In the rest of this section, we create a model designed to demonstrate a firm's incentives on decision-making. Our goal is to illuminate our intuitions and formalize our testable predictions on how fund attention is allocated within and across funds.

B. Model Set-up

We begin with a single-period model of how a single fund allocates attention across its portfolio, starting with minimal assumptions and then assuming a specific functional form for greater expositional clarity. We next adjust the model to allow for comparison across different funds. Finally, in the appendix, we broaden the model to allow for the fund's decision on setting advance policies.

Consider a single fund's choice on whether to devote attention to shareholder meetings for the securities in its portfolios. The fund owns J securities, indexed by j, each security conducting a referendum with a single proposal. The change in value of each security from its proposal passing as compared to failing is given by π_j.

The fund decides the level of investment $I_j \geq 0$ on specific, in-house attention for each of the J firms in its portfolio, for total cost $C(\sum I_j)$. Devoting in-house attention to a security yields a signal η_j regarding π_j. We write the distribution of π_j as $\pi_j \sim h(\pi_j; \alpha_j, \eta_j)$, a function of some known security-specific parameter α_j and the signal the fund received η_j. The distribution of the signal η_j is thus necessarily also dependent on α_j: $\eta \sim g(\eta_j; I_j, \alpha_j)$). The fund votes in favor of the proposal iff π_j is expected to be positive conditional on η.

The fund's dollar stake in the security is given by s_j and the influence of its vote on the outcome P_j is treated as fixed and exogeneous.[11] The fund's information set for security j at the time of voting can be written as $\Theta_j = \{P_j, s_j, h(\pi_j; \alpha_j, \eta_j)\}$.

C. *General Fund Optimization Problem*

The fund's problem of allocating attention across its securities is given by:

$$\max_{\{I_1,\dots,I_j,\dots,I_J\}} \sum_{j=1}^{J} \left[V(I_j; \Theta_j) \right] - C(\sum I_j) \qquad (1)$$

in which $V(I_j; \Theta_j)$ is the fund's payoff from its vote. $V(I_j; \Theta_j)$ is given by:

$$V(I_j; \Theta_j) = \int_{\mathrm{E}(\pi_j|\eta, \alpha_j)>0} P_j s_j \mathrm{E}(\pi_j|\eta, \alpha_j) g(\eta|I_j; \alpha_j) d\eta$$
$$+ \int_{\mathrm{E}(\pi_j|\eta, \alpha_j)<0} P_j s_j \mathrm{E}(-\pi_j|\eta, \alpha_j) g(\eta|I_j; \alpha_j) d\eta \qquad (2)$$

The first integral in Equation 2 represents the expected payoff from voting in favor of the proposal and the second integral represents the expected payoff from voting against the proposal.

D. Specific Functional Form with Predictions

Equations 1 and 2 describes the general case; in this subsection, we make specific assumptions on functional form to permit clearer exposition.

We allow the firm's benefit from the "correct" proposal result π_j to take values σ_j and $-\sigma_j$ with (unknown) probabilities p_j and $1 - p_j$. σ_j reflects the variance in outcomes (or the importance of the proposal to the security value).

The probability that the proposal is "good", p_j, is given by the beta distribution. The beta distribution can be understood as a series of n_j weighted coin tosses, each with success

[11] For votes where nothing but the passage or failure of the proposal matters, P_j is the fund's probability of being the pivotal voter. For votes that are purely symbolic, where every vote counts equally regardless of outcome, P_j is the fund's fraction of voting shares. For simplicity, we refer to this term as the likelihood of pivotality, since votes are generally viewed as being about passage or failure of the proposal.

probability p_j, in which each toss increases n_j by one and each "successful" toss increases α_j by 1. The expected value of p_j, given n_j tosses and a_j successes, is $\frac{\alpha_j}{n_j}$.[12]

We constrain in-house investment to be a binary decision $I_j \in \{0,1\}$: if the fund acquires a signal, η (that is, if the fund chooses to invest, $I_j = 1$), it flips a (weighted) coin whose result gives more information about the distribution of p_j. A positive signal $\eta = 1$ adds to the posterior parameter $\alpha_j = \alpha_j^0 + I_j \eta_j$; and, following any signals, the shareholder will vote for the proposal iff $\alpha_j > \frac{n_j}{2}$.

Define $x_j \equiv 2\left|\alpha_j - \frac{n_j}{2}\right|$, representing the degree of certainty the fund has in its choice. The fund will have no benefit from an additional signal if $x_j^0 > 1$, since in such a case, the fund's prior information is extreme enough in one direction that an additional signal in either direction could not change its vote. Thus, we focus on scenarios in which $x_j \leq 1$, so that $x_j = 1$ represents certainty as to how the fund will vote and $x_j = 0$ represents a toss-up.

Rewriting the fund's information set as Θ_{jn}, where $n_j^0 \geq 1$ denotes the number of signals in the fund's prior distribution, the fund's expected payoff when it acquires a signal is:

$$V(I_j = 1; \Theta_{jn}) = P_j s_j \sigma_j \frac{x_j^2 + n_j^0}{n_j^0(n_j^0 + 1)} \qquad (3)$$

The fund's expected payoff when it does not acquire a signal is:

$$V(I_j = 0; \Theta_{jn}) = P_j s_j \sigma_j \frac{x_j}{n_j^0} \qquad (4)$$

The payoff from voting increases with x_j, *i.e.*, with the certainty that the fund is making the correct voting choice. But what is the value of the increased certainty in Equation (3) as compared to Equation (4)? Combining Equations 3 with 4, the additional payoff from acquiring a signal is given by:

$$\Delta V_{jn} = P_j s_j \sigma_j \frac{1}{n(n+1)}(1 - x_j)(n - x_j) \qquad (5)$$

ΔV_{jn}, the expected benefit of a signal, is a monotonically decreasing function of prior certainty x_j. Intuitively, if a fund votes based on the prior parameters alone, then there is a

[12] We do not require α to be an integer; the beta distribution generalizes to non-integer parameters.

chance that its vote will be value-destroying. By acquiring an additional signal, it reduces that chance. The additional signal is most valuable when the fund is least certain about how to vote.

Pursuant to the model, each fund rank orders the benefits of in-house attention to each security in its portfolio. Equation (5) yields the following predictions about the within-fund allocation of resources:

Prediction 1: a fund is more likely to invest in in-house attention for those proposals

(i) *in which it holds a larger stake* s_j*;*

(ii) *which have greater importance to the firm* σ_j*; and*

(iii) *for which it is less ex ante certain* x_j*.*

We note that the above predictions are for a single fund within a single period. It follows from the model that, holding all else fixed, a shock to s_j, σ_j, or x_j would also yield an increase in attention.

E. Predictions on cross-fund allocation of stewardship resources

With additional simplifying assumptions, the model also yields predictions regarding the allocation of research resources *across* funds. We convert from a discrete to a continuous model by making the following assumptions:

- A fund owns a continuous mass of securities of magnitude J_a with continuous distribution of certainty x, with distribution $f(x)$.
- The cost function C is non-concave, as is standard for cost functions, reflecting a fund's limited stewardship resources.
- Each security in a fund has equal stake value $\frac{S}{J}$ where S is the total portfolio value of the fund.
- Pivotality P_j and importance σ_j are nonincreasing functions of *ex ante* certainty x.[13]

[13] As we note later, many events connected to uncertainty, such as a controversial proposal, are also connected to a fund's likelihood of being pivotal (because the vote is closer) and the proposal's importance.

Then $\Delta V(x) \equiv P(x)\sigma(x)\frac{1}{n(n+1)}(1-x_j)(n-x_j)$ is a decreasing function of x. The fund chooses x^* to maximize:

$$J\int_0^{x^*}\frac{S}{J}\Delta V(x)f(x)dx - C\big(JF(x^*)\big)$$

In which x^* represents the fund's threshold for devoting in-house attention to a ballot. The first order condition is given by:

$$\frac{S}{J} = \frac{C'\big(JF(x^*)\big)}{\Delta V(x^*)} \quad (6)$$

The right-hand side of Equation (6) is strictly increasing in x^*. A fund that picks a higher threshold x^*(*i.e.*, more investment) must have a higher S/J. (Equation (6) therefore gives a unique fund-specific threshold x^* below which the fund invests stewardship resources, and yields the following predictions about fund-level per-firm investment in stewardship:

Prediction 2:

(i) *As total portfolio value S increases, holding fixed the number of firms J, a fund's per-firm investment in stewardship increases; and*

(ii) *As total number of firms J increases, holding fixed portfolio value S, a fund's per-firm investment in stewardship decreases.*

F. *Outside recommendations*

We may further expand the model by transforming it into a two-stage model, where the above decision of in-house allocation of attention is the second stage and the first stage involves the acquisition of outside advice. For brevity, we move this section to the Appendix. Our main conclusions are as follows: first, if we assume the cost of in-house attention increases with the number of securities faster than the cost of third-party advice—a natural assumption, due to the economies of scale and economies of scope in proxy advice—then funds with more securities should acquire greater outside advice. Second, it is ambiguous whether in-house attention is a substitute or complement of outside advice at the fund level. The intuition behind the latter conclusion is as follows: although outside advice increases the number of signals and therefore may increase the certainty of a fund's vote, reducing the value of in-house attention, on *ex ante* uncontroversial proposals on which the fund would not expend in-house attention, the outside advice may send a signal that pushes the proposal into controversial territory, inducing the fund to spend in-house attention on it. For example, a fund which may not pay attention to what appears to be a routine director election may focus on it if an outside recommender's custom advice recommends a vote against the proposal.

IV. Data

We use novel proprietary data from two sources, ISS and Glass Lewis, as well as non-proprietary data.

Our primary dataset, provided by Glass Lewis, contains information on shareholder meetings held between 2011 and 2017 for each of the voting service customers of Glass Lewis. The data are provided at the fund-ballot level, in which we use "fund" to refer to the voting unit (such as a mutual fund or separately managed account). For each ballot cast by each fund, the data include the fund's number of shares in the issuer, the date on which it cast its ballot, and whether its ballot deviated from the benchmark Glass Lewis recommendations. We also observe, for each shareholder meeting, the date on which Glass Lewis's recommendation was issued.

Each institution and each voting unit have anonymized identification numbers, so we observe across the years of the sample each fund's full portfolio (as a snapshot as of the record date of shareholder meetings, similar to Brav et al. (2020)). With respect to proxy recommendations, we observe, for each fund, if they receive the Glass Lewis benchmark recommendations; one of five customized packages (Catholic, ESG, MacBride, Public Pension, or Taft Hartley), or has an otherwise customized policy.

We also observe limited information on the vote execution policy of the institution's funds. With respect to vote execution, other than a handful of exceptions, all funds choose either immediate submission upon release of the recommendation, submission three days prior to the meeting deadline, or no automatic submission. For each institution, we observe a list of all distinct selections made by any of the institution's funds, but not which funds make which selection. Thus, for an institution with a uniform vote execution rule across its funds, we observe that rule. However, if, for example, some of an institution's funds choose to auto-submit their votes three days before the meeting deadline and others do not permit auto-submission, then we observe that the institution has funds with those two selections, but do not observe which funds make which choice.

For the customization levels and vote execution policies, we have current (or when the client became inactive, if earlier), not 2011 through 2017 when their voting data are from. Conversations with Glass Lewis employees indicated that fewer than five percent of customers switched any of their settings over this time period. Because of this source of error, and since customers may further customize their vote execution beyond this customer-level-setting—with variation across funds, securities and/or meeting types—we consider our customer-level customization and vote execution data to be a potentially fuzzy indication of the fund's choices.

We also have proprietary data from ISS consisting of the dates on which ISS recommendations were issued for meetings dating from 2003 to 2017.

We use several public data sources. For information on shareholder meetings, we use ISS Voting Analytics. For information on securities, we use CRSP monthly stock file. For activist events, we use data from FactSet SharkRepellent, and we define a firm's shareholder meeting as connected to an activist if there is a proxy campaign at that firm for which the campaign meeting date matches the date of the meeting.

Table 1 provides summary statistics on our main dataset, the Glass Lewis votes merged with public data on issuers and meetings.

Our results are necessarily limited by the limitations of the data. We note a few such limitations here. First, with the exception of our work in Section V.A, all of our empirical results are studied using Glass Lewis customers. To the extent Glass Lewis customers differ from those who use another proxy advisor or who do not use proxy advisors at all, the external validity of our work will suffer. Our understanding from conversations with ISS is that customized policies are widespread. Second, as noted, we do not observe the customized recommendations themselves, and our only information about how funds voted on a ballot is whether their vote on any proposal on the ballot deviated from Glass Lewis benchmark recommendations. We can address specific questions using this data but cannot present, say, the overall number of recommendations that differ from Glass Lewis benchmark recommendations. Similarly, we do not observe whether a vote is manually submitted or auto-submitted, and we certainly cannot observe the fund's process for deliberating on it; we use a proxy for it and provide evidence justifying this proxy.

V. Measurement of Robo-voting

In this section, we discuss the measurement of robo-voting. In the past, academics have used a fund's rate of agreement with proxy advisors to assess robo-voting, designating a fund as a robo-voter if it has a sufficiently high rate of agreement with proxy advisor benchmark recommendations.[14] Iliev and Lowry (2015) first showed widespread agreement with proxy advisor recommendations and connected this to fund deliberation. Although they greatly broadened our understanding of the fund voting process, we note the inherent limitations of such metrics: funds may deliberate and manually vote but still follow their proxy advisor's recommendations; funds may auto-submit out of line with the benchmark recommendations through their use of custom recommendations; and funds may auto-submit but not frequently enough to be designated robo-voters. All of these, we will show, are likely extremely common. In fact, we show that the vast majority of funds appear to auto-cast at least some ballots.

A. Measuring Robo-Voting Using Ex Post Agreement with Proxy Advisors

We use *ex post* observed voting choices from ISS Voting Analytics over the time period 2003 through 2019 to consider the extent to which publicly available voting decisions can accurately capture robo-voting, and we discuss the construction and interpretation of such measures. In particular, we find that, by the definitions used by other metrics, there are more "management" robo-voters than ISS robo-voters.

We first note that robo-voting measures have the capacity to be misleading due to the high rates of agreement between proxy advisers and management; for example, we calculate 83% of all ballot items have ISS' recommendation identical to the management recommendation.

[14] Iliev and Lowry (2015) and Doyle (2018) classify a fund as a robo-voter if it agrees with ISS on more than 99% of proposals (including shareholder proposals). Shu (2020) uses a stricter standard: a 99.9% agreement rate with ISS on proposals in which ISS and management disagree.

The top panel of Figure 1 contains a histogram of agreement rate with ISS.[15] The vast majority of funds vote in agreement with ISS more than 80% of the time, and—consistent with those papers—a small minority of funds vote with ISS more than 99% of the time. However, this high rate of agreement is due at least in part to ISS's high rate of agreement with management. The middle panel of Figure 1 contains a histogram of agreement rate with management and shows that the vast majority of funds vote in agreement with management more than 80% of the time, suggesting that mechanical voting with proxy advisers is no more severe than mechanical voting with management.

Shu (2020) refines this measure by limiting to proposals in which ISS disagrees with management. As in Shu (2020), the bottom panel of Figure 1 limits to proposals in which ISS disagrees with management. However, this histogram continues to show that high rates of agreement with ISS are no more common than high rates of agreement with management, with a bi-modal distribution clustered near 0% and 100% agreement with ISS.

We note that Iliev and Lowry (2015), the Doyle (2018), and Shu (2020) all require a high rate of agreement to avoid falsely misclassifying funds as robo-voters, but with the resulting consequence that the focus is on a relatively small group of qualifying funds that generally have few assets.[16] Such a classification likely yields few false positives but appears to place a heavy emphasis on a small group of outlier institutions.

Such measures may be improved by adjusting for the extent to which many votes are routine or unimportant for a fund. Another potential refinement of these measures would focus on proxy contests, which generally have greater economic significance than shareholder proposals and which more often feature disagreements between ISS and management. Figure 2 shows histograms of agreement with ISS and management on proxy fights. Consistent with the idea that proxy fights have greater economic significance, we find far more variation in voting

[15] This reflects the Iliev and Lowry (2015) and Doyle (2018) definitions of robo-voting.

[16] Under the Iliev and Lowry (2015) and Doyle (2018) definitions, we identify 87 institutions that robo-vote with ISS and 83 that robo-vote with management out of 713 in our sample; raising the threshold to 100% agreement, we are left with 41 institutions robo-voting with ISS and 42 robo-voting with management; using the Shu (2020) definition we identify 23 ISS robo-voters and 67 management robo-voters.

agreement when we focus only on proxy contests, though we still find clusters at 0 and 100% agreement with ISS recommendations.[17]

For funds that do not vote down the line with management or a proxy advisor, their *ex post* voting choices do not paint a complete picture of their deliberation processes. For one thing, we have little sense of within-fund variation—looking at *when* funds agree with the proxy advisor might say more about the proxy advisor's judgment than the fund's. In addition, as we have shown, funds have many options of "whom" to robo-vote *with*; for a fund that votes some of the time with ISS, some with Glass Lewis, some with management, and some with none of the above, the fund's votes with ISS tell us little about robo-voting. In the next subsection, we introduce and validate a measure related to the mechanics of vote submission, which uses proprietary data from Glass Lewis.

B. Distribution of Vote Timing

As we described in Section II, most Glass Lewis customers designate the time at which their ballot should auto-submit if they have not manually submitted the ballot, whereas a minority of institutions have a manual submission policy and cannot auto-submit.

Table 2 shows the distribution of funds' auto-submission rules.[18] 26.6% of funds do not permit auto-submission—these funds cannot auto-submit or robo-vote, as the term is conventionally understood.[19] 1.9% of funds are scheduled to auto-submit immediately following the release of the Glass Lewis recommendations.[20] 69.7% of funds are scheduled to auto-submit using Glass Lewis's default date, three days before the meeting deadline, which is four days

[17] Applying Shu (2020)'s thresholds, we find 34 institutions that vote with ISS recommendations ≥99.9% of the time for proxy fights and 14 that vote contrary to ISS recommendations (≤0.01%) for proxy fights.

[18] Our data on auto-submission rules is at the institution level; the Table presents it by funds. Some institutions have multiple rules, and we cannot see which institutions they apply to. In Column 1 of Table 2, as well as in Figure 3 and Appendix Figure 1, we limit to institutions that have only a single rule, so we know precisely the rule of each institution. In Column 2, we include institutions with multiple voting roles, and apportion their constitutent funds a fraction of each voting rule.

[19] These funds could, of course, still vote a high percentage of the time in line with proxy advisor recommendations.

[20] Taken literally, this policy would seem to cause funds to always auto-submit. However, as Appendix Figure 1, Panel B(iii) shows, only 54.0% of ballots cast by funds in this subcategory are cast on the day of or after the release of Glass Lewis recommendations. Funds with this policy may designate firms or ballots for whom the policy would not apply, which may explain why fewer than 100% of ballots are submitted immediately.

before the shareholder meeting, which we will write as $t-4$ for clarity. Only 1.7% of funds are scheduled to auto-submit on a specific day relative to the meeting date other than $t-4$.

Data on the timing of actual votes cast shows that funds submit a large portion of their ballots on their auto-submission deadlines, especially $t-4$. Figure 3 presents histograms of the vote submission date of Glass Lewis customers with respect to the meeting date. Each panel presents a different subgroup. Funds scheduled to auto-submit three days before deadline (four days before meeting) have a discontinuous spike in submissions on day $t-4$, not reflected in the other groups. 74.6% of ballots cast by funds in that subcategory are submitted on day $t-4$.[21] Figure 3 provides evidence that the auto-submission dates are a major determinant of vote timing.

This finding is borne out by looking at funds with immediate submission policies. In Appendix Figure 1, we present additional histograms of vote submission with respect to the record date, the release of Glass Lewis recommendations, and the release of ISS recommendations. Appendix Figure 1 shows that, among the 1.9% of Glass Lewis customers whose policy is to auto-submit immediately—and only among that group[22]—there is a large mass of votes submitted at the Glass Lewis recommendation release date, consisting of 54.0% of ballots cast by funds in that category.[23] Figure 3 and Appendix Figure 1 make two things clear: a large portion of votes are submitted on fund auto-submission date, and a large portion are not.

[21] There is also a small mass of votes six days prior to the meeting date, from shareholder meetings that are held on Mondays, since the deadline for a Monday meeting is on Friday. 79% of meetings in the sample are held on Tuesday, Wednesday, or Thursday, with 8% on Monday.

[22] Our finding that the vast majority of ballots are cast well after the recommendation is issued appears to suggest that the SEC's assertion that there is a "high incidence of voting that takes place very shortly after a proxy voting advice" (SEC, 2020) does not hold true for Glass Lewis customers.

[23] Although we do not include a histogram for them, there are a small group of funds with auto-submission dates other than $t-4$. Just like funds with auto-submission dates on $t-4$, these funds commonly submit their ballots on day $t-4$. We suspect this is due to a data error and are looking into the cause of the discrepancy. Appendix Figure 1 also divides funds with an immediate auto-submission policy by whether they receive Glass Lewis benchmark or customized recommendations. The comparison between the two groups suggests that funds with customized recommendations receive their recommendations one day later than those who receive benchmark recommendations.

C. Vote Timing as a Proxy for Manual Submission

The institutional submission policies and the data on timing of fund ballots yields useful information about how ballots were submitted. First, we can see that some funds have policies that do not allow auto-submission. Second, for those funds that permit auto-submission, since we can observe their auto-submission dates and when they actually submit their ballots, we know that ballots submitted on days other than the auto-submission date were *not* auto-submitted.

Of course, submitting on the auto-submission date is not identical to what we are truly interested in—whether funds simply allow their pre-populated default choices to go through without deliberation. For example, a fund may have made a selection in advance and allowed it to be submitted on the auto-submission date. Thus, submission on the auto-submission date is an imperfect proxy for deliberation.[24] But submission on the auto-submission date is a more direct measure of fund deliberation than voting choices that fall in line with proxy advisor recommendations, with the added bonus that we can study it for all funds, not just the handful with extremely high rates of agreement with a proxy advisor, and it is informative about individual ballots.

How closely related is manual voting to voting out of line with one's proxy advisor's pre-populated recommendations? We can examine how our measurement of manual voting interacts with voting out of line with the fund's recommendations for the subset of shareholders for whom we have that information.[25]

We define our proxy for auto-submission as casting a ballot exactly 4 days before the meeting (or 6 days before a Monday meeting) or on the day of or the day after the Glass Lewis recommendation was released (and manual submission as other ballots).

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[24] Specifically, we expect our measure to be a strict over-estimate of true auto-submission. A fund that casts its ballot on the auto-submission date may have deliberated on the ballot and then, after deciding to vote with its recommendations, chosen to cast its ballot by leaving it alone on the Glass Lewis website. By contrast, a fund that casts its ballots outside of the auto-submission date must have exercised at least some deliberate action.

[25] Our data includes a binary variable for each fund ballot indicating whether the ballot was cast fully in line with Glass Lewis benchmark recommendations, which, for those funds that receive Glass Lewis benchmark recommendations rather than custom recommendations, is equivalent to indicating whether the ballot was cast in line with that fund's recommendations.

To validate our proxy, we focus on funds which receive Glass Lewis benchmark recommendations, as opposed to custom recommendations. Table 3, Column 1, shows that, among this group, 97.0% of auto-submitted ballots are voted down the line with Glass Lewis benchmark recommendations. This result suggests very strongly that our measure of auto-submission captures auto-submitted votes.[26] By contrast, as Table 3, Column 2 shows for the same funds, only 76.0% of ballots marked as manual submissions are voted down the line with Glass Lewis benchmark recommendations.[27]

Because opposition to one's proxy advisors' advice is itself tied to deliberation, this provides some validation that manually submitted votes feature more deliberation than votes cast on the fund's auto-submission date.[28]

We next turn to the relationship between manual voting—*i.e.*, casting a ballot outside of the fund's auto-submission date—and features of the fund, firm, and meeting. We will see that the results validate the model in Section III and, in doing so, further validate our measure.

VI. Empirical Analysis of Auto-Submission

A. Distribution of Manual Submission

We first evaluate how manual submission is distributed across funds. Figure 4 presents a histogram of each fund's percentage of time manually submitting, defined in Section V. The 18.1% of funds that require manual submission are dropped, so Figure 4 undercounts the true level of manual submission.

Figure 4 reveals certain new insights. First, even among funds that allow auto-submission, 7.2% always manually submit. Second, consistent with prior papers on robo-voting, 12.5% of these funds always auto-submit. Third, and most notably, over 80% of funds auto-submit some but not all of the time.

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[26] The 3% of ballots we mark as auto-submissions that are voted counter to recommendations are a measure of the fuzziness of our metric.

[27] Table 3, Column 3 shows that the difference is highly significant. We weight each fund equally. If we weighted each vote equally, the respective numbers would be 95.4% and 76.1%, respectively.

[28] Importantly, manual submissions are not just capturing opposition to one's proxy advisor recommendations. As we will see in the next section, manual voting is correlated with the variables predicted by the model in Section III even controlling for Glass Lewis opposition to management. And later in that section we show that manual submission is capturing something distinct from fund opposition to proxy advisors.

These results lead us to two questions, as suggested by the model: why do some funds auto-submit more than others; and, for most funds, why do they auto-submit some ballots and not others?

B. *Which Ballots Do Funds Manually Submit?*

We begin by looking within-fund. A given fund in a given year may manually submit some ballots and submit others on its auto-submission date. In this subsection, we empirically evaluate the fund's decision of which to manually submit.

Recall from the model in Section III that we would expect, all else equal, that funds would be more likely to invest attention into, and thereby manually submit ballots for, securities in their portfolio for which they hold larger stakes; ballots with greater importance to the value of the security; and ballots for which the correct answer is less certain.

Pursuant to the model, we estimate equations of the form:

$$y_{aijt} = \beta_0 + \beta_1 \log(s_{aijt}) + \beta_2 x_{ajt} + \beta_3 \sigma_{jt} + \theta_{at} + \psi_{aj} + \varepsilon_{aijt} \quad (7)$$

In which a indexes the fund, i indexes the institution, j indexes the security, t indexes years, y_{aijt} is a binary variable representing whether fund a manually cast a ballot for security j (proxied using votes not on the auto-submission date), s_{aijt} is fund a's dollar stake in firm j, x_{jt} is a vector of variables representing how controversial the election is (that is, based on $ex\ ante$ signals, how uncertain is the correct voting choice), σ_{jt} is a vector of variables representing how important the election is (*i.e.* the variance in firm outcomes), and θ_{at} contains fund-firm fixed effects, and ψ_{aj} contains fund-security fixed effects.

For our dependent variable y_{aijt}, we define auto-submission as ballots that were cast exactly 4 days before the meeting (or 6 days before a Monday meeting) or on the day of or the day after the Glass Lewis recommendation was released. As shown in Section V, fund auto-submissions take place on these days, so this variable should be correlated with fund manual submission.

For *ex ante* uncertainty of the correct voting choice, x, we use recommendations by proxy advisers contrary to management recommendations: ISS or Glass Lewis benchmark recommendations opposed to at least one management proposal on the ballot, or ISS or Glass

Lewis benchmark recommendations in favor of at least one shareholder proposal. We also include proxies for poor performance—Tobin's Q and Return on Assets—and major events—special elections and meetings connected to activists—which are measures of the importance of the election, σ.[29]

Table 4, Column 1 presents the results of regressions estimating Equation 7 with Fund-Year fixed effects. Table 4, Column 1 shows results overwhelmingly consistent with the model presented in Section III. Column 1 directly tests the model's within-fund predictions and shows that in-house attention is higher for a firm's larger stakes, meetings where ISS and/or Glass Lewis oppose management proposals or support shareholder proposals, firms that have been performing poorly as measured by Tobin's Q, special meetings, and meetings connected to activists. Consistent with the model's predictions, funds manually submit proposals that are especially important for the fund or the firm.

Table 4, Column 2, includes fund-firm fixed effects in addition to fund-year fixed effects, to focus on within-fund variation; which we discuss below. Because much of fund voting decision-making is done at the institution level, in Columns 3 and 4, we use institution-year and institution-fund fixed effects and get very similar results.

C. Omitted Variable Bias and Causal Estimation

One potential objection to our analysis is that firms may have unobserved differences that drive our regression results. Column 2 of Table 4 exploits the panel nature of the data by adding fund-firm fixed effects (that is, looking within fund-firm over time), curing omitted variable bias to the extent that omitted variables are invariant at the fund-firm level. Firm fixed effects alone would be sufficient to cure bias related to firm-invariant omitted variables; by using fund-firm fixed effects, we also control for any composition effects driven by selling or acquiring the security. The results in Column 2 are qualitatively identical to those in Column 1, except they also find more manual submission at firms with lower ROA.

[29] We note that the variables representing importance may also be connected to ex ante uncertainty of the voting choice. We do not take a strong position on whether these variables are properly channeled through x or σ, which are likely closely connected to each other. The model's predictions are identical regardless of which channel the variables run through.

To deepen the within-fund-firm analysis of Column 2, we take a closer evaluation of the causal relationship between manual voting and one-time firm events—special meetings and meetings connected to activists. We limit to firms that experience the event in question a single time during the sample period and designate the year of the event as $D_{jt}^{0} = 1$ and the years leading up to and following the event as $D_{jt}^{t-\tau} = 1$ if firm j experiences the event in year τ.

Then we can write the following difference-in-differences equation:

$$y_{aijt} = \alpha_0 + \beta_{-4} D_{jt}^{-4} + \cdots \beta_0 D_{jt}^{0} + \cdots + \beta_3 D_{jt}^{3} + \Gamma Z_{aijt} + \theta_t + \psi_{aj} + \varepsilon_{jt} \qquad (8)$$

The vector Z_{aijt} contains the control variables from Equation (7). As before, we cluster at the institution level. The equation yields the causal impact of the event on manual voting on the assumption that, but for the event, manual voting would have parallel trends for the event group and the non-event group. This assumption is non-verifiable, though we can buttress the assumption by evaluating whether there are any pre-trends for the treated group. With fund-firm fixed effects, no pre-trends, and a stark difference for the event group in the event year, the regressions results may be interpreted as the causal impact of the event or of omitted fund-firm-varying variables closely connected to the event.

Figure 5, Panel A(i) graphically shows the results a regression estimating Equation 8 for special meetings. The meeting one year prior to the special meeting is the benchmark (omitted) group in the regression and are represented by the horizontal red line at 0, so all coefficients are estimated in comparison to that meeting. There is large jump in manual voting for the Special Meeting, which persists afterward. Figure 8 shows no evidence of a pre-trend.

In Figure 5, Panel (ii), we include an alternative version of estimates of Equation 8 which omits the fund-firm fixed effects. Because this regression does not include fund or institution fixed effects, we also control for the institution-level variables that will later appear in Equation (9). Interestingly, both Panel A(i) and Panel A(ii) show a large spike in manual voting for the special meeting, but in the version without fund-firm fixed effects, the jump disappears immediately afterwards instead of persisting.

Similar to Panel A, Figure 5, Panel B(i) shows the results of a regression estimating Equation 8 for meetings connected to activists. Again, there is no evidence of a pre-trend, and there is large, clear jump in manual voting for the meeting connected to an activist, which disappears immediately afterward. Figure 5, Panel B(ii) estimates the regression without fund-firm fixed effects, with similar results.

We conclude that special meetings and meetings connected to activists see large jumps in manual voting that appear to be the causal results of those meetings.

D. Does Manual Submission Capture Attention?

Is our proxy for attention, manual submission of the ballot, capturing an element of deliberations that is not captured by the ex post voting outcoming? One potential concern is that manual submission of the ballot may be merely capturing deviations from one's pre-populated ballot, but may not capture true variation in deliberation. For example, a fund may provide equal in-house attention to all ballots, but, when it desires to deviate from its pre-populated ballot, may manually log in to its account (and, while logged in, manually submit its ballot).

The two motivations cannot be fully disentangled—active deliberation and deviation from one's prepopulated ballot are closely connected concepts. That said, in this subsection we attempt to assess whether deviation from one's pre-populated ballot is driving our results, and tentatively conclude that our measure is distinct from mere deviations from one's pre-populated ballot.

Our empirical strategy is as follows. First, limit to institutions for which we observe their recommendations from Glass Lewis, and repeat our regression of manual submission on covariates. Second, repeat the regression including as a right hand side variable whether the firm deviated from its pre-populated recommendations, and look to see whether the results change.

The results are in Appendix Table 1A. In the Columns marked "A", we replicate Table 4, but limiting to institutions who receive benchmark recommendations (so that, for these institutions, we observe the precise recommendations they actually receive). For this subset with relatively few clusters, many of our results from Table 4 become insignificant, though some results remain statistically significant.

In the Columns marked "B", we repeat this process, but include, as a control, whether the ballot deviated from Glass Lewis benchmark recommendations (which, for these institutions, is equivalent to deviation from the fund's prepopulated recommendations). Effectively, the Table tests, within ballots that deviated from their recommendations and within ballots that did not deviate from their recommendations, whether manual submission is correlated with the right-hand side variables. If our left-hand-side variable were mostly capturing deviation from pre-population, we would expect that the R^2 would climb sharply when controlling for deviation from pre-population, and that the coefficients on the relationship of the other right-hand-side variables would drastically attenuate. Instead, the results when controlling for deviation from recommendations are qualitatively very similar to those when not controlling for deviations, and movement between Columns is a small fraction of the standard errors. Adding deviation from the pre-populated ballot does not substantially increase the R^2.

We repeat the process again using all institutions in Appendix Table 1B. For this Table, opposition to the benchmark does not fully capture deviation from one's pre-populated ballot (to the extent that customized institutions have different recommendations) but we would expect it to be highly correlated with deviation from one's pre-populated ballot (to the extent that customized recommendations resemble benchmark recommendations). Again, including deviation from the benchmark does not substantially change the regression results. We conclude that our regressions capture a relationship between manual submission and our right-hand side variables that is not merely determined by deviation from one's pre-populated ballot.

E. Manual Submission of Ballots Across Funds and Institutions

In this subsection, we assess what factors explain variation across funds in total manual submission rates.

In addition to making predictions about which ballots funds will allocate attention to, the model in Section III makes cross-fund predictions. Specifically, the model predicts that attention paid to specific ballots should increase with the fund's average stake size and decrease with the number of securities in its portfolio. The histogram in Figure 4 shows substantial variation across funds in total auto-submission. In this Section, we use regression analysis to see if the correlates of fund-level auto-submission are consistent with the model's predictions.

Aggregating ballots to the fund-year level, we regress:

$$\bar{y}_{ait} = \gamma_0 + \gamma_1 \log(s_{ait}) + \gamma_2 J_{ait} + \theta_t(\psi_i) + \varepsilon_{ait} \quad (9)$$

In which a indexes the fund, i indexes the institution, j indexes the firm, t indexes time, $\bar{y}_{ait}$ reflects the fraction of the fund's ballots that were manually submitted, s_{ait} is the fund's average stake size, J_{at} is the fund's total number of firms in its portfolio, θ_t reflects year fixed effects, and ψ_i reflects institution fixed effects.

Table 5 contains the results. In Column 1, consistent with the model's predictions, funds with fewer securities and greater stake sizes manually submit more, but these estimates are only significant at the 10% and 5% levels, respectively. In Column 2, we include institution fixed effects, and find a null result on stake size but non-zero estimate on the number of securities which is significant at the 1% level. In Column 3, we aggregate at the institution level instead of the fund level and find strongly significant results on both, suggesting that the degree of auto-submission is set at the institution level.

We conclude that funds are rationally apathetic in their voting choices. Across and within funds and institutions, they vary their attention based on the value of the attention to their portfolio.

However, we do not believe this is the end of the story. Funds anticipate their rational apathy and take steps to select their votes *ex ante* when they will not pay attention *ex post*. Effectively, they set their default options. We now turn to the study of how those default options are set.

VII. Custom Recommendations

In this Section, we study custom recommendations based on data on Glass Lewis proxy execution customers. As described in Section IV, we observe, at the fund level, whether the fund receives proxy adviser benchmark recommendations or custom recommendations. We address the following descriptive questions. First, how common is customization? Second, to what extent are customized recommendations different from benchmark recommendations? Third, which funds choose to customize? Fourth, do funds use customization as a substitute for the manual submission of ballots? And fifth, how does customization relate to disagreement with benchmark recommendations? On the last question, we tie customization into the literature on fund ideology, defined as in Bolton et al. (2020) as predictable voting across a wide set of issues as contrasted with other voters. We show that customization is not just used for funds that tend to disagree with benchmark recommendations. Rather, we show that funds are more likely to use customization when they deviate from proxy adviser benchmark recommendations on social orientation proposals in a consistent direction, suggesting that one use of customized proposals is to modify the ideology of the recommendations to better fit the ideological bliss point of the customer.

A. How Widespread is Customization?

We first turn to the extent of customization. The vast literature on proxy advisors focuses on benchmark recommendations. But, as we show, at least for the proxy advisor for which we have data, few customers use the benchmark recommendations.

Figure 6 shows the distribution of custom recommendations. Glass Lewis customers can either receive benchmark recommendations, a themed recommendation package (Catholic, ESG, MacBride, Public Pension, or Taft Hartley), or an otherwise customized package of recommendations. On an equal-weighted basis, nearly 80% of funds (21,117 out of 26,434) receive customized recommendations, with only 361 of those from themed packages. On a value-weighted basis, nearly 90% of funds receive customized recommendations.

B. How Customized Are Customized Policies?

Although the use of customized policies is ubiquitous, such widespread adoption would be less interesting if the policies barely deviated from benchmark recommendations. Since we do not observe the recommendations themselves, we cannot directly observe the degree of customization that funds use.

To evaluate whether customized recommendations deviate from benchmark recommendations, we can take advantage of our auto-submission measure and the fact that auto-submitted ballots are likely voted in line with pre-populated recommendations. Consider those funds that receive benchmark recommendations. As we showed in Section III, 97.0% of their ballots that are auto-submitted (according to our metric) are cast down the line with Glass Lewis benchmark recommendations. (The 3.0% from 100% reflects that our metric is not a perfect measure of auto-submission.)[30]

[30] Recall that we can observe whether a vote was cast in line with benchmark recommendations but we do not otherwise see how the fund voted.

Funds that receive customized recommendations also use auto-submission, and we therefore can observe how frequently auto-submitted customized votes deviate from the benchmark recommendations. We present those numbers in Table 6. The average auto-submitted ballot agrees with Glass Lewis recommendations 75.3% of the time for funds with customized recommendation. The 21.7% gap between funds with benchmark recommendations and those with customized recommendations is an estimate of the percentage of time that customized recommendations differ from benchmark recommendations on at least one item. Customization appears to produce substantial deviations from the benchmark recommendations.

C. *Which Funds Customize?*

Through customization, funds can determine their level of *ex ante* investment in voting decisions. All the funds in the data are customers of Glass Lewis recommendations, so all engage in at least some level of acquisition of third-party advice. In this Subsection, we explore the fund's decision to customize that third party advice.

As discussed in Section III, because of economies of scale, we should expect funds with more securities in their portfolios to rely more on *ex ante* advice than funds with fewer securities. Funds with larger stake sizes should have greater investment in all advice, both *ex ante* and proposal-specific.

In Table 7, we evaluate the relationship, at the fund level, between customization and fund characteristics. We find, consistent with predictions, that funds with more securities and greater average stake size are more likely to customize. Per Column 1, A fund with twice as high a stake size is 1.03 percentage points more likely to customize, and one with twice as many securities is 1.88 percentage points more likely to customize. Column 2 includes institution fixed effects and finds that the, within an institution, funds with more securities are not customized more, but funds with larger stake sizes are more likely to customize than other funds in the same institution. The inclusion of institution fixed effects brings the R^2 to 96%, an indication that the customization decision is largely made at the institution level. In Column 3 we aggregate to the institution level and find that institutions with larger stake sizes and more securities have higher (average) customization levels. The results confirm the predictions from our model: funds use customized recommendations to achieve economies of scale across their portfolios.

D. How Does Customization Relate to Manual Voting?

In the model in Section III, we presented the decision whether to manually vote as the second stage of a two-stage decision, where the first stage is the customization decision. In this subsection, we tentatively explore the inter-relation of the two, though data limitations give us fairly little confidence in the results.

In Section III, we noted that whether customization and ballot-specific deliberation are complements or substitutes is theoretically ambiguous. Intuitively, investing in customized recommendations should serve as a substitute for later devoting specific attention to proposals. We note two reasons why we might not find that in our empirics. The first is theoretical: as we discuss in Section III, addition signals on how to vote can make a fund uncertain about a proposal it would otherwise be certain about and induce additional investment in voting choices. In practice, this could manifest itself as customized recommendations serving as a "flag" for funds—an adverse recommendation potentially indicating to the fund that it should pay attention to the proposal. The second reason is the limits of our empirical design. To the extent funds have some unobservable factors that drive them to invest in voting choices, customization and manual voting would be positively correlated, even if they were truly substitutes.

Table 8 presents the results of a regression of manual voting on customization at the fund or institution level. For each fund, we calculate its manual voting rate across ballots. We find that manual voting is more common for funds with custom recommendations. As we note above, it is unclear whether this suggests that customization and manual voting are truly complements or rather are both driven by the same unobservable variables. Between Columns 1 and 2, we add in control variables but they do not alter the result.

We do not have an instrumental variable for customization, so our ability to investigate this question is limited. We note, however, that Table 7, Column 2 suggests that customization is overwhelmingly decided at the institution level but there is some within-institution variation in customization. In Column 3 of Table 8, we include institution fixed effects, so we compare manual voting and customization across funds within an institution. With institution-level fixed effects, the result reverses: the funds with more custom recommendations manually vote less. If funds within an institution do not differ in their unobservable motivation to invest in voting choices, this result would suggest that manual voting and custom recommendations are substitutes.

E. *How Does Customization Relate to Voting Choices?*

We have shown that customized recommendations appear to deviate from benchmark recommendations, but we have not discussed why funds might choose their own path. After all, a simple model of proxy advice might assume total agreement among funds with the same objectives. In this section, we study the role of ideology in customization of proxy recommendations.

The question we ask can be written as follows. We would expect that funds which disagree more with Glass Lewis benchmark recommendations would be more likely to customize their recommendations. But, for a given level of disagreement, we might expect that a fund that disagrees in a consistent *direction* (e.g., more pro-management than the benchmark recommendations) to be more likely to customize than a fund that disagrees in both directions.

A wide literature has now shown that mutual funds vote ideologically, *i.e.*, consistently on certain issues. (Bolton et al. (2020); Bubb and Catan (2020)). In Bolton et al. (2020)'s framework, the first dimension of ideological variation across fund families is social orientation, and the second dimension is management/governance orientation.[31] As a simple adaptation, we focus on shareholder environmental and social proposals as a proxy for social orientation and shareholder governance proposals as a proxy for governance.

Having established that shareholders with customized recommendations are more likely to deviate from benchmark recommendations, we are interested in whether they are more likely to customize when they *asymmetrically* disagree with the proxy adviser on a class of issues. Controlling for their overall levels of deviation, we are interested in whether Institution B is more likely to customize than Institution A.

[31] We focus on the Bolton et al. (2020) framework, as opposed to Bubb and Catan (2020)'s, since the latter's divisions into ISS-party voters and Glass Lewis-party voters is less relevant for our sample of Glass Lewis customers.

Since we only observe, for each fund's ballot, whether the ballot deviated on any proposal from the benchmark recommendations, we extract a representation of each institution's ideological orientations on SRI and governance proposals as follows. First, we limit to meetings with exactly one shareholder proposal (SRI or governance) and benchmark recommendation support for all management proposals. We then calculate, for each institution, its score in favor of $\kappa \in \{SRI, Governance\}$ as the difference in its agreement rate with the benchmark recommendation as between meetings in which the benchmark recommendation (i) favors the shareholder proposal, $\theta_{i\kappa}^{1}$, and (ii) opposes the shareholder proposal, $\theta_{i\kappa}^{0}$.[32] The institution's score for type κ is given by $\theta_{i\kappa}^{*} = \theta_{i\kappa}^{1} - \theta_{i\kappa}^{0}$. For example, $\theta_{i,SRI}^{*}$ near 0 mean that the institution is as likely to deviate from the benchmark in favor of an SRI proposal as it is to deviate in opposition to it; a score near 1 means it is far more likely to deviate in favor of an SRI proposal; and a score near -1 means it is far more likely to deviate in opposition to it. $|\theta_{SRI}^{*}|$ and $|\theta_{Governance}^{*}|$ are measures of a consistent ideological difference from the benchmark.

Next, we estimate the relationship between customization and voting habits. We begin by focusing on relationship between customization and the shareholder's number of securities, ballots, and deviations, and then add in its ideological consistency. We make no claims as to causality or directionality: an institution may use a customized policy because it votes a certain way, or it may vote a certain way because it uses a customized policy. Rather, our goal is to shed light on the customization technology by showing how those who customize differ in their portfolios and voting from those who do not. We re-estimate the cross-institution regression of Table 8, Column 3, this time including our measures of ideological difference and controls for the institution's number of ballots, number of ballots opposed, and overall deviation rate from Glass Lewis recommendations.

Table 9 contains regression results estimating the relationship between customization ideological difference. First, we note that a customer's total number of deviations is a strong predictor of customization. This accords with the cost structure of customization—since the cost of customized policies scale concavely with the number of securities in the portfolio, institutions

[32] We limit to institutions for which θ_{κ}^{1} and θ_{κ}^{0} are each based on 10 or more ballots cast.

that deviate from the benchmark on a large proportion of proposals get the most "bang for their buck" by customizing.

Table 9 shows that institutions with strong deviations on SRI ideology from Glass Lewis are significantly more likely to customize, consistent with customization as a tool to adjust the ideological bliss point of one's recommendations. An ideological difference on governance proposals is not significantly associated with greater customization.

VIII. Conclusion

In this paper, we broaden the understanding of fund deliberations on voting, showing that funds invest in customized recommendation packages and strategically choose where to devote their attention.

The strategic devotion of attention closely resembles a voter's decision to turn out. There is a rich literature on the voter turnout decision, and a separate literature on the voting choice decision. For funds, though, the line is blurred.

As we've discussed, funds turn out to vote nearly universally. This is very likely the product of policy decisions—the fiduciary duty to vote, and the disclosure of mutual fund votes—make it somewhat costly for funds to not turn out. But *how* funds vote is much harder to monitor, and therefore to enforce policy on. Fund turnout incentives can be altered by policy, but one can't make them pay attention. The SEC has considered banning pre-populated defaults (SEC (2019)), but it is hard to see how that would accomplish any more than generating menial work. Universal turnout does not eliminate the rational apathy problem but rather transforms it. Instead of deciding whether to invest in turning out, funds must decide how much to invest in their voting choice. In that way, the voting decision is a transmutation of the turnout decision, and can be modeled, as we did, with a turnout model.

Instead, we would propose that the existing system might function better than its critics have suggested. If funds will not devote full attention to each ballot for each security in their portfolio, devising a policy, outsourcing its application to specialized proxy advisors, and taking the wheel on important proposals may offer a useful practical solution.

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Table 1. Summary Statistics

This Table presents summary statistics based on the merger of Glass Lewis voting data with ISS Voting Analytics, CRSP, Compustat, and Factset SharkRepellent. For variables that recur for a given unit each year (for instance, an issuer's Tobin's q changes each year), we take, for each unit, the average across years (for instance, we average each issuer's Tobin's q across the years that the issuer is in the sample, then present summary statistics on the averages at the issuer level).

	N	Mean	25%	50%	75%
Meeting Variables					
ISS Opposes a Mgmt Prop (%)	32,167	35.7			
ISS Supports a Shareholder Prop (%)	32,167	6.5			
GL Opposes a Mgmt Prop (%)	32,167	17.7			
GL Supports a Shareholder Prop (%)	32,167	4.6			
Special Meeting (%)	37,956	11.9			
Meeting Connected to Activist (%)	37,956	0.5			
Issuer Variables					
Tobin's Q	4,760	1.913	1.044	1.387	2.202
Return on Assets	4,583	0.055	0.016	0.076	0.135
Fund Variables					
Portfolio Size ($)	28,092	1.48E+09	165,020.8	1,636,950	18,106,367
Number of Securities	28,092	47.51	4.67	23	43.33
Institution Variables					
Portfolio Size ($)	344	5.36E+09	83,035,792	4.51E+08	2.77E+09
Number of Securities	344	439.52	43	165.89	522.9
Number of Funds	344	83.36	6	16	53.5

Table 2. Distribution of Voting Rules

This Table presents information on funds' submission policies. The numbers represent the number of funds with certain submission policies; below the numbers are percentages of the total. In Column 2, we exclude funds in institutions that have multiple policies. In Column 2, a fund is allocated all of an institution's policies divided by the number of institutional policies (so if the fund is listed as having both "Submit Immediately" and "Submit on $t-4$" policies, we would count it as having 0.5 of each).

	(1) Fund-Level, Institutions with Single Policy	(2) Fund-Level, Policies Apportioned Across Funds at an Institution
No Auto-Submission	4785	8170
(%)	26.6	30.9
Submit Immediately	348	1319.167
(%)	1.9	5.0
Submit on $t-4$	12524	16421.5
(%)	69.7	62.2
Submit on Other Day	303	492.3333
(%)	1.7	1.9
N	17960	26404

Table 3. Validation of Auto-Submission Measure

This Table presents information on how funds on the auto-submission date tend to be voted in line with recommendations. The sample is limited to funds that receive the Glass Lewis benchmark recommendations. In Column 1, we limit to ballots that are auto-submitted by our measure; for Column 2, we limit to ballots that are manually submitted by our metric. We define auto-submission as casting a ballot exactly 4 days before the meeting (or 6 days before a Monday meeting) or on the day of or the day after the Glass Lewis recommendation was released. For each fund-ballot, we regress agreement with Glass Lewis benchmark recommendations on the intercept; we weight by the inverse of the number of fund ballots (so all funds are weighted equally). In Column 3, we use the full sample and regress on an indicator variable for manual submission, presenting only that coefficient. Standard errors clustered at the institution level are in parentheses. *, **, and *** represent significance at the 0.05, 0.01, and 0.001 levels, respectively.

	(1) Auto-Submissions	(2) Manual Submissions	(3) Difference
Ballots Voted Down the Line With Glass Lewis Benchmark Recommendations	96.981***	75.993***	20.988***
	(1.283)	(3.957)	(3.980)
N	733,059	165,999	899,058

Table 4. Manual Voting and Firm and Ballot Characteristics

This Table contains least squares regressions estimating equations of the form:

$$y_{aijt} = \beta_0 + \beta_1 \log(s_{aijt}) + \beta_2 x_{ajt} + \beta_3 \sigma_{jt} + \theta_{at} + \psi_{aj} + \varepsilon_{aijt}$$

In which a indexes the fund, i indexes the institution, j indexes the security, t indexes years, y_{aijt} is a binary variable representing whether fund a manually cast a ballot for security j (proxied using votes not on the auto-submission date), s_{aijt} is fund a's dollar stake in firm j, x_{jt} is a vector of variables representing how controversial the election is (that is, based on $ex\ ante$ signals, how uncertain is the correct voting choice), σ_{jt} is a vector of variables representing how important the election is (*i.e.* the variance in firm outcomes), θ_{at} contains fund-firm fixed effects, and ψ_{aj} contains fund-security fixed effects, which are only included in Column 2. In columns 3 and 4, we use institution-year and institution-security fixed effects instead, and calculate stake size by totaling up the stakes of each of the institution's funds.

For our dependent variable y_{aijt}, we define auto-submission as ballots was cast exactly 4 days before the meeting (or 6 days before a Monday meeting) or on the day of or the day after the Glass Lewis recommendation was released. The unit of observation is the fund-ballot. Standard errors clustered at the institution level are in parentheses. *, **, and *** represent significance at the 0.05, 0.01, and 0.001 levels, respectively.

Manual Vote	(1) Fund-Year FE	(2) Fund-Year and Fund-Firm FE	(3) Institution-Year FE	(4) Institution-Year and Institution-Firm FE
Log Stake Value	1.084***	0.302**	2.216***	1.372**
	(0.190)	(0.101)	(0.427)	(0.468)
ISS Opposes a Mgmt Prop	2.049***	2.017***	2.360***	1.901***
	(0.533)	(0.459)	(0.577)	(0.455)
ISS Supports a Shareholder Prop	5.244***	2.865**	5.013***	3.146***
	(0.910)	(0.899)	(0.972)	(0.845)
GL Opposes a Mgmt Prop	5.053**	4.716**	4.891**	4.969**
	(1.782)	(1.578)	(1.794)	(1.750)
GL Supports a Shareholder Prop	3.345**	3.101*	3.529**	3.015*
	(1.093)	(1.291)	(1.099)	(1.202)
Tobin's Q	-0.147*	-0.728***	-0.021	-0.879***
	(0.065)	(0.218)	(0.107)	(0.255)
Return on Assets	-3.516	-5.082*	-6.530**	-8.651**
	(2.012)	(2.331)	(2.191)	(2.973)
Special Meeting	12.877***	12.120***	13.100***	12.433***
	(2.984)	(3.190)	(3.034)	(3.226)
Activist Connected to Meeting	17.237***	16.141***	18.289***	17.313***
	(2.739)	(2.598)	(2.853)	(2.799)
Intercept	17.418***	27.905***	-5.399	10.911
	(2.573)	(1.431)	(7.203)	(7.476)
N	4,764,302	3,708,551	4,772,188	4,723,147
Num Clusters	323	309	327	321
R^2	0.55	0.73	0.50	0.69

Table 5. Manual Voting Rates Across Funds and Institutions

This Table presents statistics on the relation between manual voting and fund and institution characteristics, aggregated to the fund or institution level. We regress:

$$\bar{y}_{ait} = \gamma_0 + \gamma_1 \log(s_{ait}) + \gamma_2 J_{ait} + \theta_t(+\psi_i) + \varepsilon_{ait}$$

In which a indexes the fund, i indexes the institution, j indexes the firm, t indexes time, $\bar{y}_{ait}$ reflects the fraction of the fund's ballots that were manually submitted, s_{ait} is the fund's average stake size, J_{at} is the fund's total number of firms in its portfolio, θ_t reflects year fixed effects, and ψ_i reflects institution fixed effects. Columns 1 and 2 are aggregated to the fund level; Column 3 is aggregated to the institution level instead. All columns contain year fixed effects; Column 2 contains institution fixed effects. Standard errors clustered at the institution level are in parentheses. *, **, and *** represent significance at the 0.05, 0.01, and 0.001 levels, respectively.

Percent of Ballots Manually Voted	(1) Fund-Year Level	Fund-Year Level	(3) Institution-Year Level
Log Mean Stake Value	1.569	0.128	4.210***
	(0.864)	(0.245)	(1.063)
Log # of Securities in Portfolio	-2.347*	-1.318**	-3.953***
	(1.120)	(0.434)	(0.927)
Intercept	30.912*	44.928***	-7.279
	(13.421)	(2.847)	(16.867)
Fixed Effects	Year	Year and Institution	Year
N	78,756	78,740	1,621
Num Clusters	336	320	336
R^2	0.04	0.69	0.10

Table 6. Customization and Deviations from Benchmarks

This Table presents results on the relationship between fund customization policies and votes in agreement with Glass Lewis benchmarks. The sample is limited ballots that are auto-submitted by our measure. We define auto-submission as casting a ballot exactly 4 days before the meeting (or 6 days before a Monday meeting) or on the day of or the day after the Glass Lewis recommendation was released. In Column 1, we limit to ballots to funds that receive the Glass Lewis benchmark recommendations; for Column 2, we limit to ballots that receive custom recommendations. For each fund-ballot, we regress agreement with Glass Lewis benchmark recommendations on the intercept; we weight by the inverse of the number of fund ballots (so all funds are weighted equally). In Column 3, we use the full sample and regress on an indicator variable for custom recommendations, presenting only that coefficient. Standard errors clustered at the institution level are in parentheses. *, **, and *** represent significance at the 0.05, 0.01, and 0.001 levels, respectively.

	(1) Benchmark Recommendations	(2) Custom Recommendations	(3) Difference
Ballots Down the Line With Glass Lewis Benchmark Recommendations	96.981***	75.256***	21.725***
	(0.187)	(0.258)	(0.319)
N	733,059	2,750,449	3,483,508

Table 7. Customization and Fund Characteristics

This Table presents results on the relationship between fund customization policies and characteristics of the fund. The regressions are conducted at the fund level. On the left hand side is whether the fund has a customized voting policy. On the right hand side we include the log of the fund's mean stake size, averaged across years, and the log of the fund's number of securities, averaged across years. In Column 2, we include instutiton-level fied effects. In Column 3, we aggregate to the institution level, with the outcome variable being the average customization across ballots at the institution. Robust standard errors clustered are in parentheses. *, **, and *** represent significance at the 0.05, 0.01, and 0.001 levels, respectively.

	(1) Fund-Level	(2) Fund-Level	(3) Institution-Level
Log (Fund/Institution Mean Stake Size)	1.030***	0.181***	4.014**
	(0.108)	(0.029)	(1.440)
Log (Fund/Institution Number of Securities)	1.878***	-0.056	6.782***
	(0.174)	(0.032)	(1.374)
Intercept	62.313***	78.087***	-39.765
	(1.354)	(0.341)	(22.691)
Fixed Effects	None	Institution	None
N	26,035	26,005	336
R^2	0.01	0.96	0.10

Table 8. Customization and Manual Voting

This Table presents results on the relationship between fund customization policies and manual voting. We estimate least squares regressions estimating equations of the form:

$$y_{aijt} = \beta_0 + \beta_1 \log(s_{aijt}) + \beta_2 x_{ajt} + \beta_3 \sigma_{jt} + \beta_4 customization_a + \theta_t + \varepsilon_{aijt}$$

In which a indexes the fund, i indexes the institution, j indexes the security, t indexes years, y_{aijt} is a binary variable representing whether fund a manually cast a ballot for security j (proxied using votes not on the auto-submission date), s_{aijt} is fund a's dollar stake in firm j, x_{jt} is a vector of variables representing how controversial the election is (that is, based on $ex\ ante$ signals, how uncertain is the correct voting choice), σ_{jt} is a vector of variables representing how important the election is (*i.e.* the variance in firm outcomes), and $customization$ is an indicator that equals 1 if the fund does not use the Glass Lewis benchmark recommendations. In columns 1 and 2, we include year fixed effects; in Column 3, we include institution fixed effects.

For our dependent variable y_{aijt}, we define auto-submission as ballots was cast exactly 4 days before the meeting (or 6 days before a Monday meeting) or on the day of or the day after the Glass Lewis recommendation was released. The unit of observation is the fund-ballot. Standard errors clustered at the institution level are in parentheses. *, **, and *** represent significance at the 0.05, 0.01, and 0.001 levels, respectively.

Manual Vote	(1)	(2)	(3)
Custom Recommendation	17.310**	15.810**	-7.023*
	(5.625)	(5.434)	(3.232)
Log Stake Value		2.097***	0.516**
		(0.568)	(0.192)
ISS Opposes a Mgmt Prop		1.507	1.357
		(0.842)	(0.734)
ISS Supports a Shareholder Prop		9.511***	8.008***
		(2.143)	(1.291)
GL Opposes a Mgmt Prop		5.704**	5.570**
		(1.924)	(1.882)
GL Supports a Shareholder Prop		3.073*	2.835**
		(1.493)	(1.024)
Tobin's Q		0.694	-0.200
		(0.617)	(0.120)
Return on Assets		-5.290	3.309
		(5.864)	(3.023)
Special Meeting		12.682***	12.257***
		(3.089)	(3.054)
Activist Connected to Meeting		19.348***	17.433***
		(3.413)	(2.940)
Intercept	19.414***	-10.153	28.495***
	(3.729)	(6.895)	(3.955)
Fixed Effects	Year	Year	Institution
N	5,260,717	4,770,105	4,770,099
Num Clusters	337	334	328
R^2	0.04	0.07	0.44

Table 9. Customization and Ideological Divergence from Glass Lewis

This Table estimates the relationship between customization and institution-level ideology variables by estimating:

$$Customized_i = \alpha + \gamma_1|\theta^*_{SRI}| + \gamma_2|\theta^*_{Governance}| + \gamma_3 Z_i + \varepsilon_i$$

$|\theta^*_\kappa|$ represents an institution's degree of ideological difference from the proxy advisor benchmarks on $\kappa \in \{SRI, Governance\}$, calculated as follows. First, we limit to meetings that have exactly one shareholder proposal (SRI or governance) on the ballot and for which the benchmark Glass Lewis recommendation supports all management proposals. We then calculate, for each institution, its score in favor of $\kappa \in \{SRI, Governance\}$ as the difference in its agreement rate with the benchmark recommendation between meetings in which the benchmark recommendation (i) favors the shareholder proposal, $\theta^1_{i\kappa}$, and (ii) opposes the shareholder proposal, $\theta^0_{i\kappa}$. We limit to institutions for which θ^1_κ and θ^0_κ are each based on 10 or more ballots cast. The institution's score for type κ is given by $\theta^*_{i\kappa} = \theta^1_{i\kappa} - \theta^0_{i\kappa}$.

Customized Institution	(1)	(2)
$\lvert\theta^*_{SRI}\rvert$	34.29**	35.22**
	(11.28)	(11.95)
$\lvert\theta^*_{Governance}\rvert$	-23.48	-31.28
	(28.73)	(33.66)
Log (Institution Number of Ballots)	-6.49	-9.86
	(4.00)	(5.30)
Log (Institution Number of Deviations from Benchmark)	10.78***	9.08***
	(1.61)	(2.68)
Log (Institution Mean Stake Size)	-2.43	1.10
	(5.94)	(6.39)
Log (Institution Number of Securities)	2.98	2.13
	(1.66)	(1.70)
Log (Institution Number of Funds)		4.67
		(3.22)
Log (Institution Deviation Rate)		17.41
		(20.12)
Intercept	12.11	26.24
	(33.39)	(39.19)
N	138	138
R^2	0.48	0.49

Figure 1. Agreement Rates with Management and ISS

This Figure presents histograms, at the fund level, of agreement rates in fund voting. Agreement rates are calculated as the fraction of proposals the fund votes on in which it agrees with another party. The top panel presents agreement rates with ISS recommendations; the middle panel presents agreement rates with management recommendations; the bottom panel presents agreement with ISS recommendations when ISS disagrees with management.

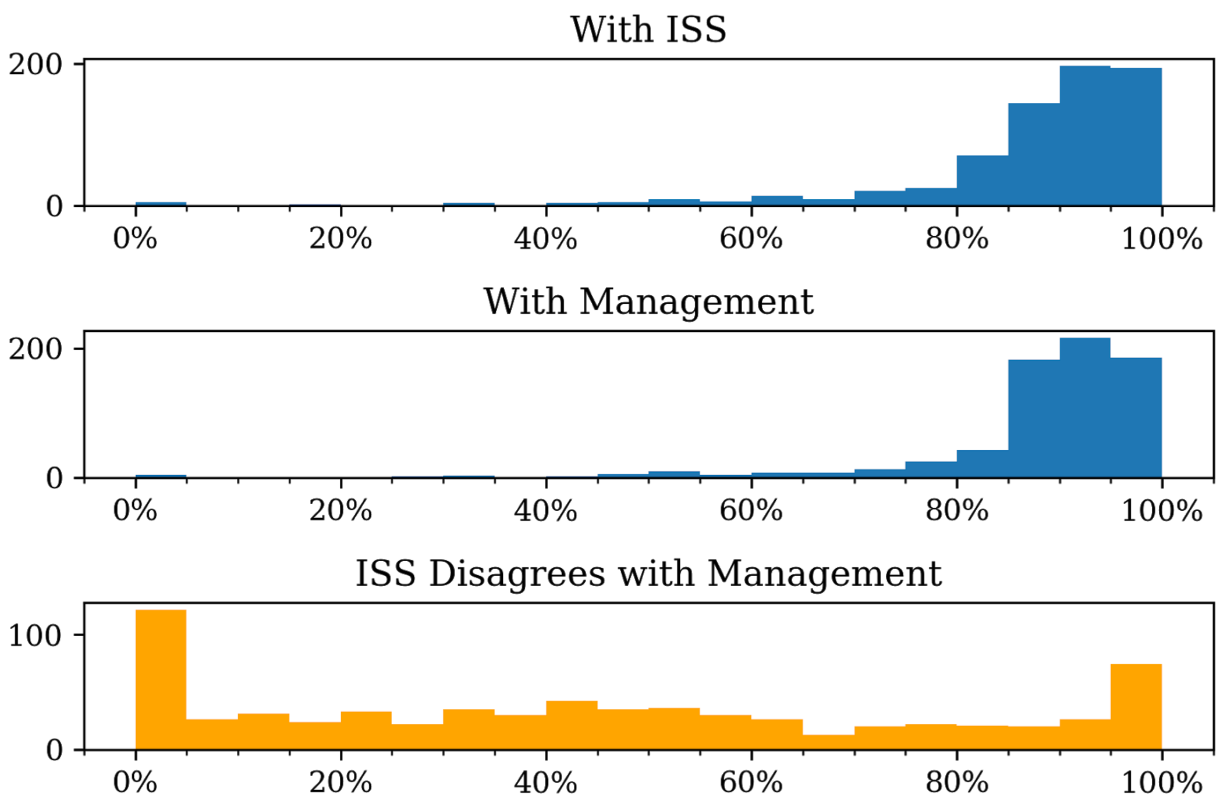


Figure 2. Agreement Rates with Management and ISS on Proxy Fights

This Figure presents histograms, at the fund level, of agreement rates in fund voting, limited to proxy fights. Agreement rates are calculated as the fraction of proposals on proxy fights that the fund votes on in which it agrees with another party. The top panel presents agreement rates with ISS recommendations; the bottom panel presents agreement rates with management recommendations.

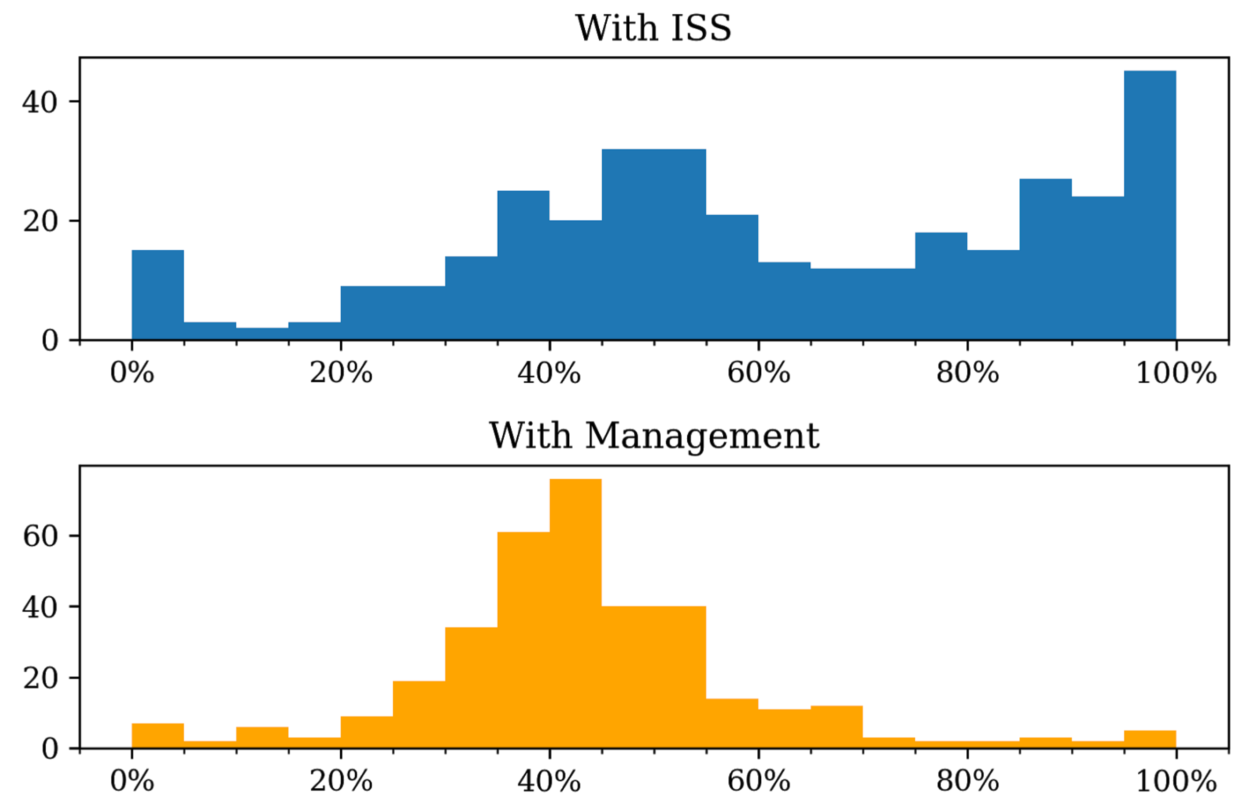
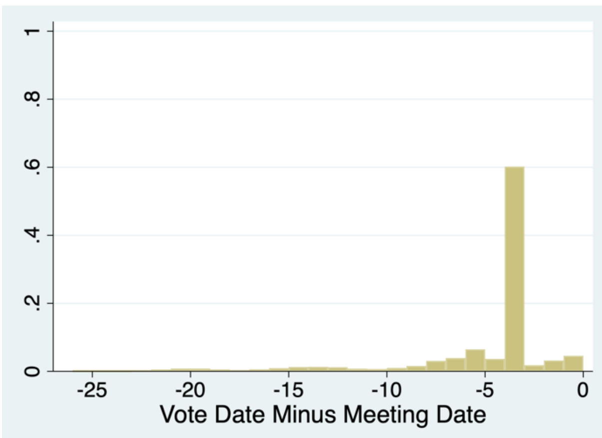


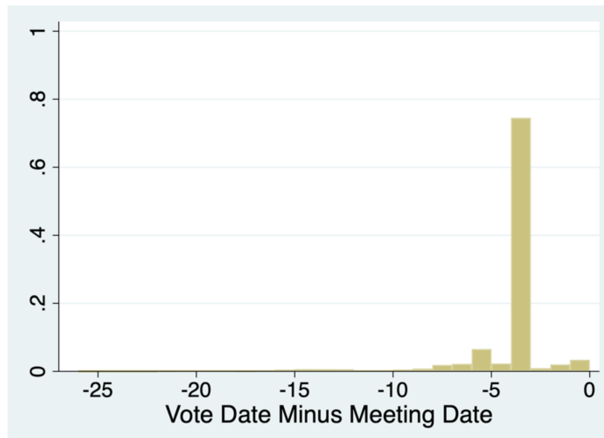
Figure 3. Vote Timing

This Figure contains a series of histograms on vote timing among Glass Lewis proxy execution customers for shareholder meetings in 2011 through 2017. Each fund-ballot is weighted equally. Each histogram presents the date on which a ballot was cast minus the meeting date, left-truncated at 26 days for visual clarity (1st percentile is 26 days). For this figure, we limit to institution with only a single submission policy, to ensure the panels are accurate. The first panel contains all funds; the second panel contains funds for which the institution has autosubmission 3 days prior to the meeting deadline for all funds; the third panel contains funds for which the institution has immediate autosubmission upon release of recommendations; and the fourth panel contains funds for which the institution permits no autosubmission.

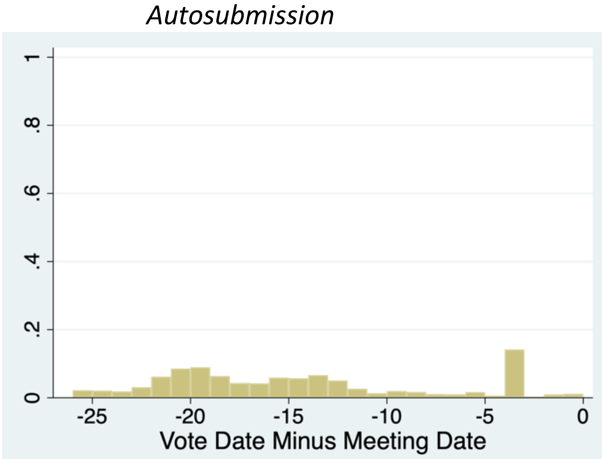
(i) All Funds



(ii) Funds With Autosubmission 3 Days Prior to Meeting Deadline



(iii) Funds with Immediate Autosubmission



(iv) Funds with No Autosubmission

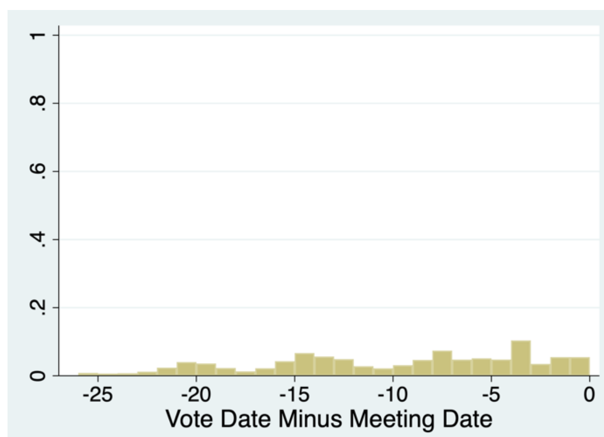


Figure 4. Rates of Manual Submission by Fund

This Figure contains a histogram of fund rates of manual submission, among Glass Lewis proxy execution customers for shareholder meetings in 2011 through 2017. For each fund, we calculate the percentage of ballots which were manually submitted, *i.e.* not auto-submitted. We define auto-submission as casting a ballot exactly 4 days before the meeting (or 6 days before a Monday meeting) or on the day of or the day after the Glass Lewis recommendation was released. We drop 4,786 funds (18.1% of the sample) whose submission policies do not permit auto-submission.

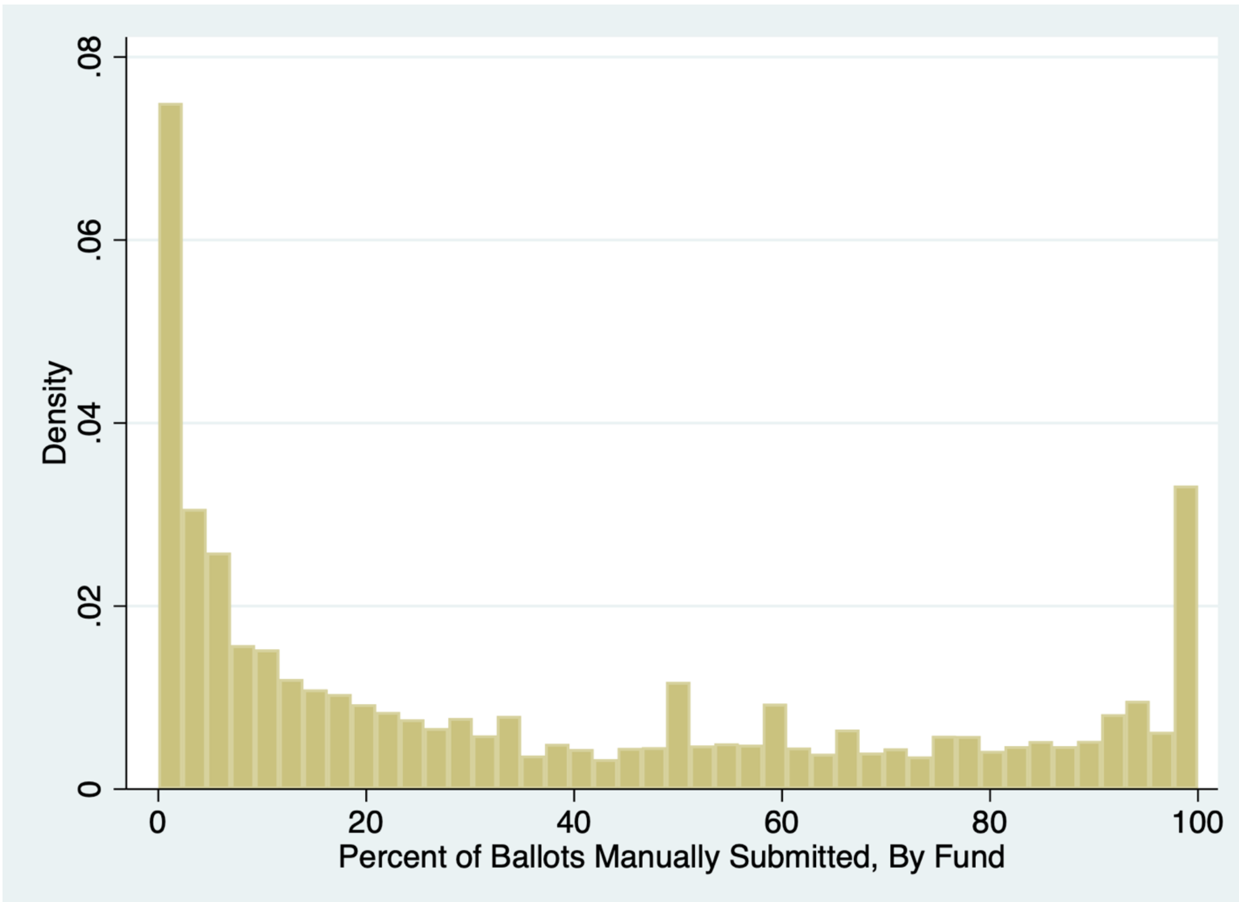


Figure 5. Coefficients of Event (and Previous and Subsequent Meetings) On Manual Submission

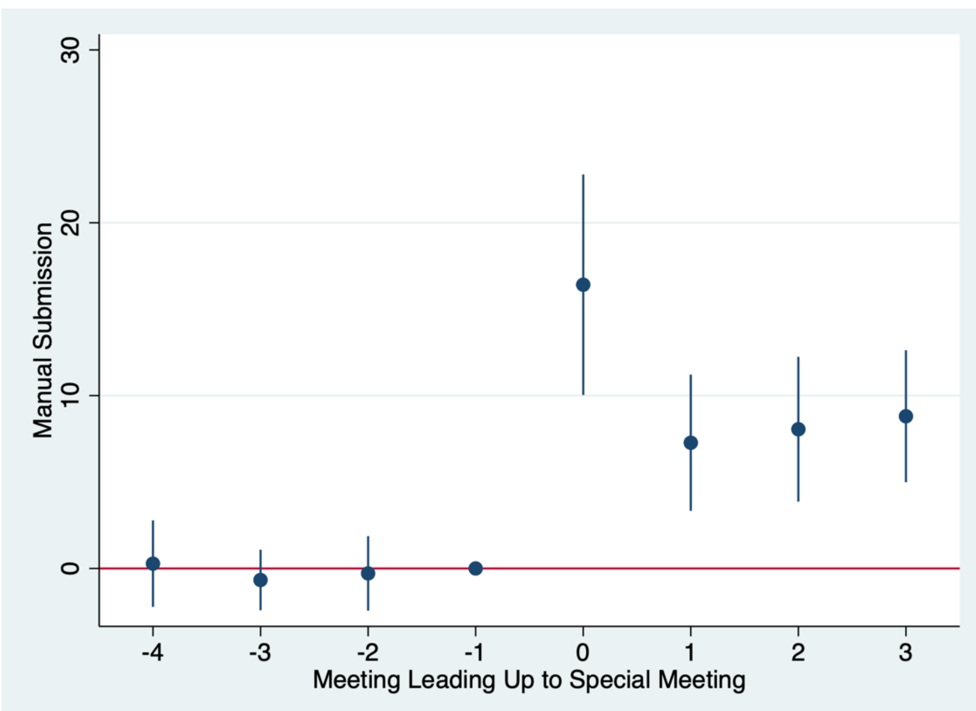
This Figure contains coefficients on $D_{jt}^{-4}, \dots, D_{jt}^{3}$ where D_{jt}^{0} represents the year of the event from the following regression:

$$y_{aijt} = \alpha_0 + \beta_{-4} D_{jt}^{-4} + \cdots \beta_0 D_{jt}^{0} + \cdots + \beta_3 D_{jt}^{3} + \Gamma Z_{aijt} + \theta_t + \psi_{aj} + \varepsilon_{jt}$$

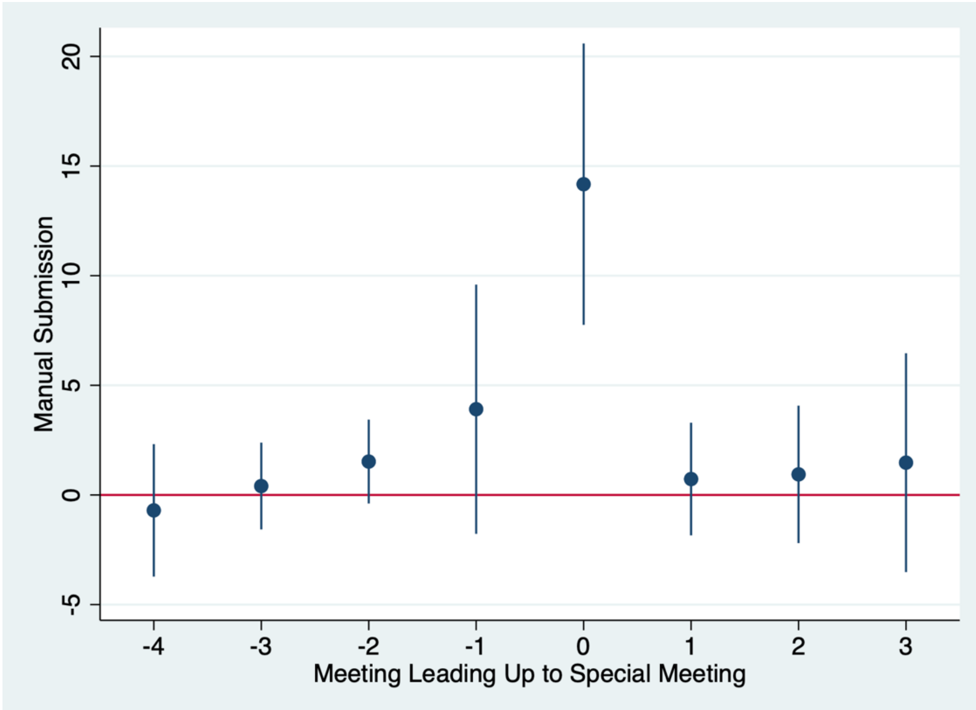
In which a indexes the fund, i indexes the institution, j indexes the security, t indexes years, y_{aijt} is a binary variable representing whether fund a manually cast a ballot for security j (proxied using votes not on the auto-submission date), D_{jt}^{0} reflects a special meeting or meeting connected to an activist, D_{jt}^{τ} reflects the meeting τ years after such meeting, Z is a vector of controls, θ_t is year fixed effects, and ψ_{aj} is fund-firm fixed effects. In Panel A we use special meetings; in Panel B we use meetings connected to an activist. The sample is limited to firms that have exactly one event in the period 2011 to 2017; the benchmark (omitted) group is the meeting prior to the event meeting. In Column (i), we estimate the equation above. In Column (ii), we do not include fund-firm fixed effects, and include the log of the institution's portfolio value and the log of the institution's number of securities owned in the regression. Standard errors are clustered at the institution level. Error bars reflect 95% confidence intervals.

Panel A: Special Meetings

A(i): Fund-Firm Fixed Effects

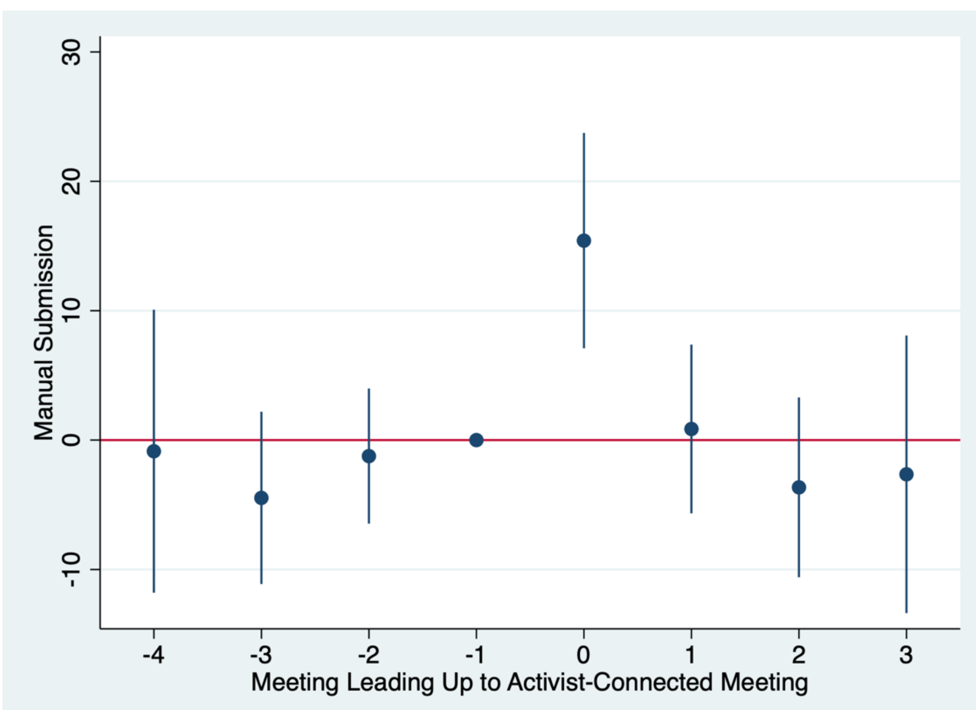


A(ii): No Fund-Firm Fixed Effects



Panel B: Meetings Connected to Activists

B(i): Fund-Firm Fixed Effects



B(ii): No Fund-Firm Fixed Effects

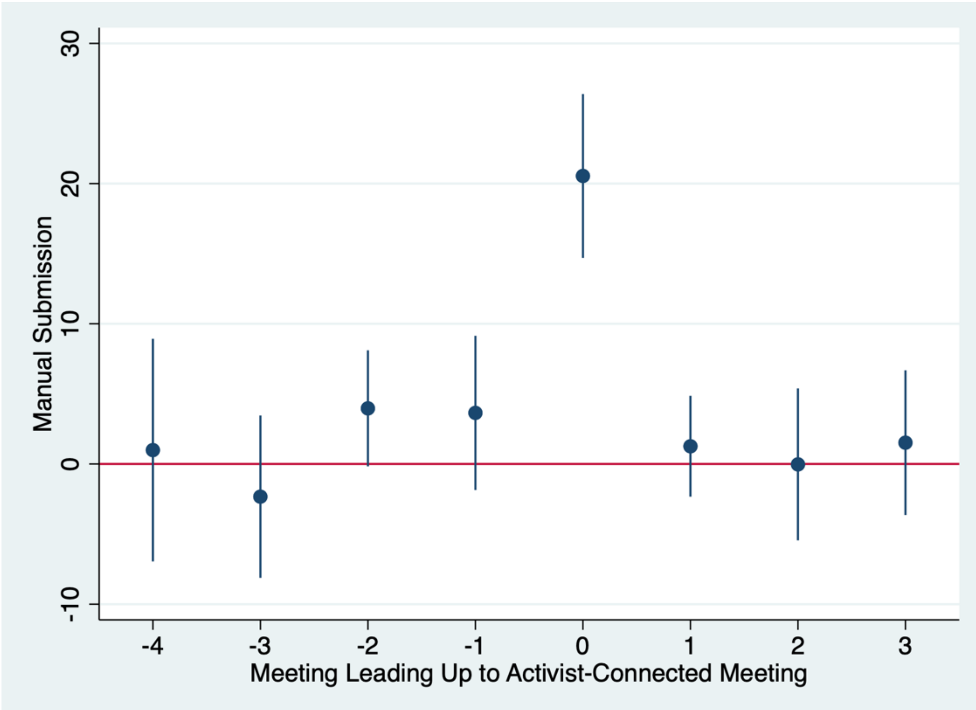
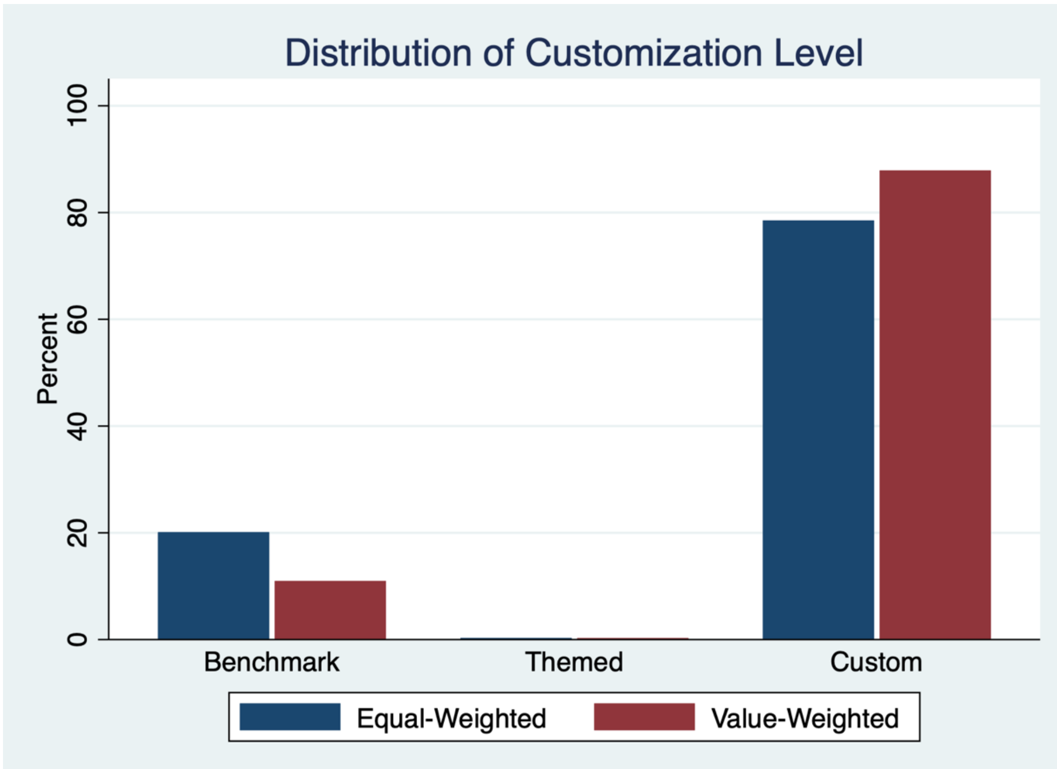


Figure 6. Frequency of Customized Recommendations

This Figure contains a histogram of customized policies, at the fund level, among Glass Lewis proxy execution customers. The blue bars weight each fund equally; the red bars weight each institution by the value of the fund's portfolio. We calculate the value of the fund's portfolio as the sum of stake value, as of the record date, for each firm in the portfolio in a given year, averaged across years that the fund appears in the data. Funds may either subscribe to Glass Lewis benchmark recommendations, "themed" recommendations (Catholic, ESG, MacBride, Public Pension, or Taft Hartley), or some other customized policy.



Appendix Table 1. Relationship Between Manual Voting and Regressors Among Benchmark Customers, Controlling For Deviations From Recommendations

Panel A: Benchmark Customers Only

Manual Vote	(1A)	(1B)	(2A)	(2B)	(3A)	(3B)	(4A)	(4B)
	Pooled Regression		Fund-Year FE		Fund-Year Level Aggregation		Fund-Year and Fund-Firm FE	
Deviated from Recs		27.643**		16.147				17.304
		(9.895)		(8.245)				(9.769)
Customer-Year Deviation Rate						73.677***		
						(16.664)		
Log Stake Value	1.858*	1.523	0.091	0.012			0.010	-0.010
	(0.897)	(0.815)	(0.135)	(0.138)			(0.053)	(0.056)
Log Portfolio Value	3.778	2.984			1.140	0.441		
	(2.432)	(2.119)			(1.443)	(1.306)		
Log # of Securities in Portfolio	-8.449*	-8.397*			-5.485**	-4.456**		
	(3.838)	(3.484)			(1.673)	(1.478)		
ISS Opposes a Mgmt Prop	2.212*	1.492*	1.052***	0.909**			0.243	0.267
	(0.863)	(0.728)	(0.288)	(0.329)			(1.062)	(0.918)
ISS Supports a Shareholder Prop	-2.245	-1.903	-1.320	-1.610			0.567	0.241
	(2.512)	(2.225)	(1.166)	(1.104)			(0.673)	(0.714)
GL Opposes a Mgmt Prop	2.269	0.853	2.642	1.695			2.971	1.799
	(2.059)	(1.935)	(1.680)	(1.380)			(2.100)	(1.264)
GL Supports a Shareholder Prop	3.074	3.027	3.126	3.037			0.954*	0.961*
	(1.935)	(1.832)	(1.797)	(1.727)			(0.404)	(0.435)
Tobin's Q	-0.449	-0.416	-0.075	-0.052			-0.583	-0.470
	(0.502)	(0.461)	(0.130)	(0.125)			(0.556)	(0.468)
Return on Assets	0.769	3.400	-1.757	-1.507			0.311	-0.209
	(4.112)	(3.769)	(2.497)	(2.279)			(3.204)	(2.394)

Special Meeting	4.972*	6.947***	5.358**	6.450***			3.987**	5.353***
	(2.063)	(1.985)	(1.629)	(1.686)			(1.455)	(1.367)
Activist Connected to Meeting	22.948*	19.976**	22.660*	20.728*			13.440**	13.171**
	(10.451)	(7.268)	(10.913)	(9.058)			(5.034)	(4.342)
Intercept	-31.572	-13.723	12.844***	12.478***	29.719	32.659	14.367***	13.161***
	(42.847)	(36.546)	(1.825)	(1.993)	(23.601)	(22.194)	(1.004)	(0.933)
N	849,010	848,918	847,890	847,798	716	716	680,180	680,088
Num Clusters	152	152	143	143	153	153	136	136
R^2	0.10	0.15	0.57	0.58	0.06	0.18	0.76	0.76

Panel B. All Institutions

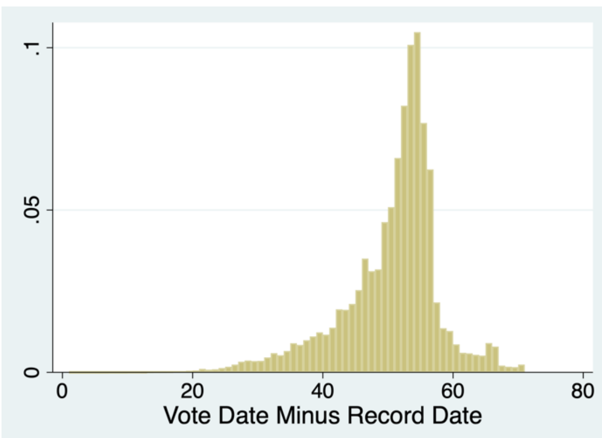
Manual Vote	(1A)	(1B)	(2A)	(2B)	(3A)	(3B)	(4A)	(4B)
	Pooled Regression		Fund-Year FE		Fund-Year Level Aggregation		Fund-Year and Fund-Firm FE	
Deviated from Recs		22.239^{***}		11.041^{**}				9.357^{**}
		(4.271)		(3.348)				(3.027)
Customer-Year Deviation Rate						54.930^{***}		
						(5.930)		
Log Stake Value	0.911	0.705	1.084^{***}	1.060^{***}			0.302^{**}	0.308^{**}
	(0.475)	(0.432)	(0.190)	(0.196)			(0.101)	(0.104)
Log Portfolio Value	9.730^{***}	8.890^{***}			4.210^{***}	3.468^{***}		
	(1.984)	(1.855)			(1.063)	(0.992)		
Log # of Securities in Portfolio	-16.357^{***}	-16.476^{***}			-8.163^{***}	-8.275^{***}		
	(3.399)	(3.122)			(1.399)	(1.245)		
ISS Opposes a Mgmt Prop	1.832^{*}	1.643^{*}	2.049^{***}	1.978^{***}			2.017^{***}	2.089^{***}
	(0.749)	(0.785)	(0.533)	(0.542)			(0.459)	(0.443)
ISS Supports a Shareholder Prop	8.608^{***}	6.489^{***}	5.244^{***}	4.393^{***}			2.865^{**}	2.514^{**}
	(1.926)	(1.785)	(0.910)	(0.876)			(0.899)	(0.908)
GL Opposes a Mgmt Prop	5.362^{**}	1.154	5.053^{**}	3.034^{**}			4.716^{**}	3.180^{**}
	(1.922)	(1.496)	(1.782)	(1.093)			(1.578)	(1.164)
GL Supports a Shareholder Prop	3.321^{*}	1.720	3.345^{**}	2.525^{*}			3.101^{*}	2.434^{*}
	(1.424)	(1.492)	(1.093)	(1.029)			(1.291)	(1.077)
Tobin's Q	0.102	0.127	-0.147^{*}	-0.109			-0.728^{***}	-0.652^{**}
	(0.479)	(0.442)	(0.065)	(0.066)			(0.218)	(0.204)
Return on Assets	-5.674	-3.470	-3.516	-2.905			-5.082^{*}	-5.196^{*}
	(4.200)	(3.742)	(2.012)	(1.828)			(2.331)	(2.221)

Special Meeting	13.574***	16.023***	12.877***	14.144***			12.120***	13.428***
	(3.121)	(3.157)	(2.984)	(3.191)			(3.190)	(3.324)
Activist Connected to Meeting	19.248***	21.929***	17.237***	18.640***			16.141***	16.858***
	(3.045)	(3.107)	(2.739)	(2.632)			(2.598)	(2.630)
Intercept	-92.737*	-74.858*	17.418***	15.229***	-7.279	-4.442	27.905***	25.619***
	(37.290)	(34.924)	(2.573)	(2.747)	(16.867)	(15.881)	(1.431)	(1.688)
N	4,770,105	4,769,269	4,764,302	4,763,466	1,621	1,621	3,708,551	3,707,693
Num Clusters	334	334	323	323	336	336	309	309
R^2	0.14	0.18	0.55	0.56	0.10	0.27	0.73	0.74

Appendix Figure 1. Additional Voting Timing Histograms

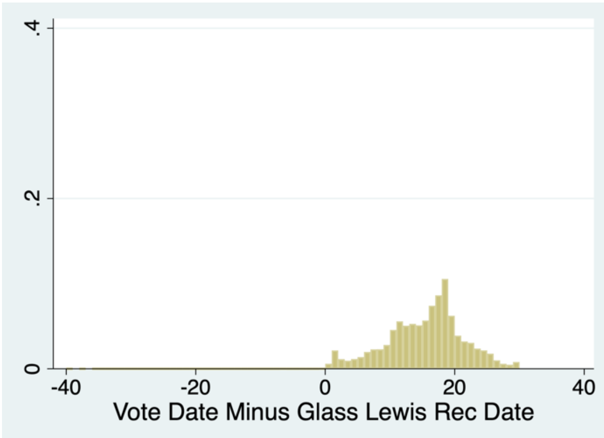
This Figure contains a series of additional histograms on vote timing among Glass Lewis proxy execution customers for shareholder meetings in 2011 through 2017. Each fund-ballot is weighted equally. For this figure, we limit to institution with only a single submission policy, to ensure the panels are accurate. Panel A presents the date on which a ballot was cast minus the record date, right-truncated at 81 days for visual clarity (99th percentile is 71 days). Panel B presents the date on which a ballot was cast minus the date on which Glass Lewis benchmark recommendations were released, right-truncated at 41 days for visual clarity (99th percentile is 31 days). Panel (B) is further subdivided into all funds; funds for which the institution has autosubmission 3 days prior to the meeting deadline for all funds; funds for which the institution has immediate autosubmission upon release of recommendations; funds which receive benchmark recommendations for which the institution has immediate autosubmission upon release of recommendations; and funds for which the institution has no autosubmission. Panel C presents the date on which a ballot was cast minus the date on which ISS benchmark recommendations were released, right-truncated at 41 days for visual clarity (99th percentile is 32 days).

Panel A. Timing With Respect to Record Date

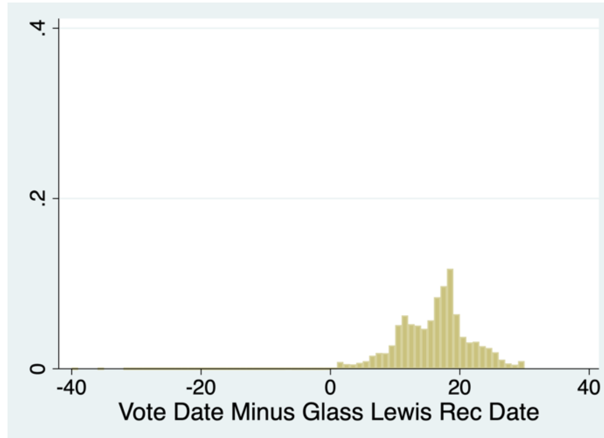


Panel B. Timing With Respect to Release of Glass Lewis Benchmark Recommendation

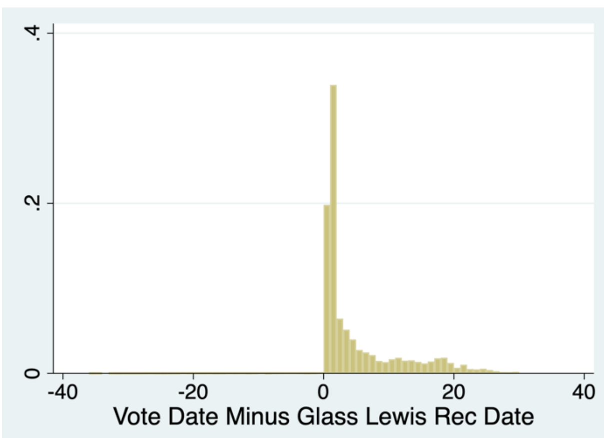
(i) All Funds



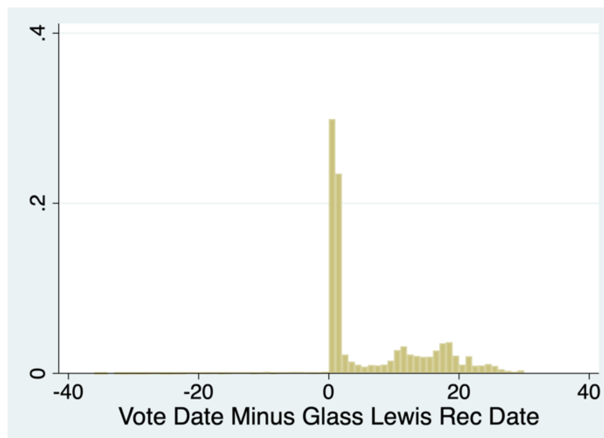
(ii) Funds With Autosubmission 3 Days Prior to Meeting Deadline



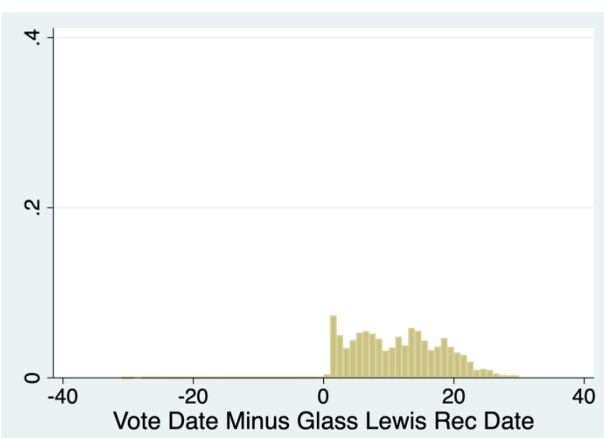
(iii) Funds with Immediate Autosubmission



(iv) Funds with Immediate Autosubmission and Benchmark Recommendations



(v) Funds with No Autosubmission



Panel C. Timing With Respect to ISS Benchmark Recommendation