

# Information and Preferences in Shareholder Voting<sup>\*</sup>

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## Abstract

We develop a structural model of shareholder voting under incomplete information about proposal quality. Preferences and information are not separately identified from individual voting patterns: correlated information and strategic voting jointly determine the mapping from preferences to votes. Our identification strategy uses proxy advisor recommendations as observable measures of public information and vote co-movement across shareholders to identify the information environment; preferences are then pinned down by the voting equilibrium. Despite higher support for management, blockholders' preferences towards passage of management proposals are close to dispersed shareholders': the gap reflects inference from pivotality. Differences in information quality affect voting outcomes more than differences in preferences.

**Keywords:** corporate governance, shareholder voting, institutional investors, strategic voting, structural estimation

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# 1. Introduction

Institutional investors occupy block positions in practically all listed firms in the US (Holderness, 2009). Through ownership and participation in shareholder voting, these investors may exert influence on corporate governance. Research has shown that large institutional blockholders exhibit higher propensities to support management in shareholder voting than other shareholders. This pattern is often interpreted as evidence that blockholders have a preference towards passage of management-supported proposals.

This interpretation, however, may conflate information and preferences. Investors vote without observing a proposal's effect on firm value; a rational investor forms beliefs about whether the proposal's passage is value-increasing by observing public information (via proxy statements and advisor recommendations), their own private information, and information embedded in the voting environment itself. Consequently, the same investor may vote differently across similar proposals than their unconditional preference for passage would imply.

In this paper, we develop a structural model in which firms are held by large blockholders and smaller, dispersed shareholders who vote on management-sponsored proposals. Proposal quality is uncertain at the time of the vote. Shareholders have heterogeneous information about proposal quality and may also have heterogeneous preferences for passage (i.e., private values), modeled as extra utility from the proposal passing that is independent of the proposal's effect on firm value (i.e., its common value).<sup>1</sup>

In equilibrium, each shareholder supports the proposal when their posterior belief about its value exceeds an endogenous, shareholder-specific threshold. Shareholders vote strategically, so their belief conditions on the event that their vote changes the outcome. The information conveyed by this event depends on each shareholder's own voting weight and the distribution of voting weights across other shareholders, and crucially on other shareholders' information and preferences. As a result, the inference effect of being pivotal varies widely across shareholders and proposals. We use the model to study how information and preferences jointly shape equilibrium voting and observed voting outcomes.

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<sup>1</sup>In the model and estimation, we allow blockholders to have heterogeneous private values and private-information quality, while assigning smaller, dispersed shareholders a common private value and information quality, which we interpret as those of the representative dispersed shareholder base.

A stylized example clarifies the model’s intuition and empirical relevance. A blockholder who supports more proposals than smaller shareholders may appear biased toward management. But a strategic voter conditions on the event that her vote is decisive, and this is itself informative about proposal quality. If other shareholders are more skeptical of management proposals, a close vote means many received favorable signals to nearly pass the proposal, which is more likely when the proposal is good. Pivotality therefore induces the blockholder to rationally support more proposals than they would absent a preference bias.

When signals are correlated (for example, through proxy advisor reports), the strategic effect attenuates. Shareholders draw on the same public information, so a close vote partly reflects that shared signal rather than independent private information, and the pivotal event is less informative. As a result, the same blockholder voting in favor would likely be more indicative of a preference towards management.

The identification problem extends beyond the stylized example: because both public information and strategic conditioning shape equilibrium voting, identical voting data can be consistent with different combinations of preferences and information.<sup>2</sup> Our main goal in this paper is to provide a solution to this identification problem and jointly estimate shareholders’ information quality and preferences towards proposal passage.

Identification proceeds as follows. First, we use proxy advisor recommendations as a proxy for public information, which broadly separate proposals into those public information indicates are good and those it indicates are bad for firm value. Second, the covariance between each blockholder’s vote and dispersed support within recommendation separates public from private information: conditional on the recommendation, a blockholder’s vote co-moves with dispersed support only through private information about quality, her own and the dispersed shareholders’, so these covariances pin down the precision of the advisor’s report and thus the split of each shareholder’s accuracy between public and private signals. Cross-blockholder co-voting provides overidentifying discipline on the same channel.

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<sup>2</sup>We formalize this observation: there is a continuum of information and preference parameters, indexed by the noise in the advisor’s report and with preferences re-solved in equilibrium, that generate identical individual voting patterns: the same joint distribution of dispersed support and the recommendation, and of each blockholder’s vote and the recommendation. Identification requires both structure on the information environment and moments beyond individual voting patterns. The source of non-identification, like in the example above, is that correlated information and strategic voting jointly determine the mapping from preferences to votes.

With the information environment identified, preferences are recovered from each shareholder’s equilibrium cutoff condition, which accounts for how public and private information quality, along inference from pivotality, jointly map beliefs into votes. The recovered private values therefore capture systematic differences in voting that cannot be explained by the information environment, allowing us to distinguish pro-management preferences from greater support arising through heterogeneous information effects. A major part of the paper establishes joint identification of the information environment and preferences.

This identification strategy speaks to the empirical literature on shareholder voting. Approaches that read preferences from observed votes directly, such as ranking shareholders by observed support (e.g., [Fichtner et al., 2017](#); [Bebchuk and Hirst, 2019](#)) or recovering latent preferences through dimensionality reduction of investor-by-proposal voting data (e.g., [Bolton et al., 2020](#); [Bubb and Catan, 2022](#)), are identified only under maintained assumptions about the information environment. Conversely, approaches that infer information from votes require assumptions about preferences. Our non-identification result makes this difficulty precise, and our estimation strategy jointly identifies and recovers the information and preference environments from observed voting data.

We estimate the model on Say-on-Pay (executive compensation) proposals from annual meetings held between 2018 and 2024.<sup>3</sup> We focus on six large mutual fund blockholders as the modeled actors: Vanguard, BlackRock, State Street, Dimensional, Fidelity, and T. Rowe Price. ISS recommendations serve as the proxy for public information, and we recover latent preferences and information parameters via the Generalized Method of Moments (GMM).

Our estimation recovers, for each shareholder, information parameters governing the precision of private and common signals and private values corrected for information effects. The resulting estimates imply sizable differences between observed and preference-implied support. BlackRock, for example, supports proposals 13.4 percentage points more often than dispersed shareholders, yet its preference-implied support differs by only 4 points; across the Big Three, preference-implied support rates of 83 to 85 percent sit within five points of

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<sup>3</sup>We focus on Say-on-Pay proposals because they are regularly required across public firms, providing a broadly comparable proposal type observed across a large cross-section of firms and years. They also generate substantially more variation in shareholder support than routine proposals, such as director elections, which are typically approved by overwhelming margins.

the 79.5 percent implied for dispersed shareholders. Blockholders' unconditional preferences place them much closer to dispersed shareholders than their support rates suggest; the wedge is strategic, driven by rational inference from pivotality rather than by taste.<sup>4</sup>

These results highlight a central prediction: higher observed support need not reflect stronger preferences, because strategic effects and information asymmetry let blockholders with more precise signals or greater holdings appear more pro-management than their preferences imply. The bias does not simply scale all blockholders equally: inverting observed support rates while ignoring pivotality reorders the preference ranking of the six blockholders.

A central question in the governance literature is whether blockholders vote differently from other shareholders because of differences in preferences or in information (e.g., [Matsumasa and Shu, 2022](#)). We implement counterfactuals that separately equalize information and preferences across investor types by assigning blockholders the same public and private information precision, and separately the same preferences, as dispersed shareholders.

Equalizing information quality has a larger effect on aggregate voting outcomes than equalizing preferences. In particular, removing blockholders' informational advantage increases outcome uncertainty: the close-vote rate rises from 13.4% to 18% overall and increases from 39.4% to 54.3% among more uncertain proposals (when ISS issues an "Against" recommendation), with the cross-proposal variance of total shareholder support nearly halving overall. This arises because (more) precise private signals allow blockholders to better distinguish good from bad proposals, pushing outcomes away from the passing threshold. Equal information quality removes this state-contingency and blockholders vote more uniformly on their pro-management baseline, supporting more bad proposals and fewer good ones.

Equalizing preferences, by contrast, has a smaller effect because blockholders' precise signals preserve the state-contingency of their votes regardless of the preference level. In this sense, differences in information matter much more than differences in preferences for voting outcomes. Policies that equalize influence across investors, such as pass-through voting, therefore risk discarding the information content of blockholder votes while delivering

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<sup>4</sup>Dimensional is a notable exception, with systematically lower raw support consistent with its distinct investment philosophy. It is reassuring for the model that the same framework can rationalize and fit this qualitatively different voting pattern alongside the Big Three and other large funds.

only limited gains from more closely aligning outcomes with underlying investor preferences (Malenko et al., 2026).

This paper makes three contributions. First, we prove that individual voting patterns cannot identify investor preferences separately from the information environment: a continuum of parameters generates identical patterns, which disciplines any empirical approach that reads preferences or information from votes while holding the other fixed. Second, we show that the joint behavior of blockholder votes and dispersed support restores identification and quantifies the impact of strategic inference on voting. Estimating the model, we find that blockholders' recovered preferences are much closer to those of dispersed shareholders than raw support rates suggest. Third, our counterfactual analysis demonstrates that information heterogeneity, not preference heterogeneity, has greater impact on aggregate voting outcomes, with direct consequences for policies that equalize influence across investors.

The paper is organized as follows. The rest of this section discusses the literature. Section 2 outlines the general model. Section 3 analyzes the model and illustrates the identification problem induced by public information and strategic voting. Section 4 presents the identification and estimation strategies, and describes the data used in the estimation. Section 5 presents results of the estimation. Section 6 concludes.

**Literature review.** Our model builds on the theory of corporate voting under incomplete information. Maug (1999) studies whether proxy voting aggregates shareholders' dispersed information and resolves their conflicts of interest, Bond and Eraslan (2010) analyze voting on proposals that are themselves strategically designed, Levit and Malenko (2011) examine non-binding votes, and Matsusaka and Ozbas (2017) model the allocation of approval and proposal rights. Closest to our information structure, Malenko and Malenko (2019) show that reliance on a common proxy-advisor signal can displace independent research, correlate shareholders' voting mistakes, and weaken information aggregation, the force behind our identification problem. Bar-Isaac and Shapiro (2020) study how many of her votes a blockholder optimally casts, Meirowitz and Pi (2022) the shareholder's choice between voting on her information and trading on it, and Levit et al. (2026) the voting premium in a model where shareholders trade before voting. Relative to this literature our contribution is empirical: we place block-

holder ownership, private values, and advisor-correlated information in a single equilibrium model and estimate it on voting microdata.

The mechanisms at the model’s core originate in the economics of voting, where rational voters condition on being decisive: the swing voter’s curse of [Feddersen and Pesendorfer \(1996\)](#), information aggregation in elections ([Austen-Smith and Banks, 1996](#); [Feddersen and Pesendorfer, 1997](#)), and jury verdicts under strategic voting ([Feddersen and Pesendorfer, 1998](#)), with [Bhattacharya \(2013\)](#) showing that aggregation can fail without preference monotonicity and [Barelli et al. \(2022\)](#) characterizing when large elections aggregate information.

A smaller literature estimates such models: [Iaryczower and Shum \(2012\)](#) separate the information and ideology of Supreme Court justices, and [Kawai and Watanabe \(2013\)](#) infer strategic voting in general elections. Corporate voting differs from these one-person-one-vote settings along the dimensions we study: ownership-weighted votes make pivot probabilities non-negligible and heterogeneous across shareholders and firms, a common advisor correlates information, and shareholders hold private values over passage. Like [Iaryczower and Shum \(2012\)](#), we separate information from preferences in voting records, but show that with correlated public information this separation fails from individual voting patterns alone. [Zachariadis et al. \(2020\)](#) estimate a model of the shareholder’s turnout decision in which those whose preferred outcome is likely to prevail free-ride on others’ votes while shareholders in the minority mobilize disproportionately, so that participation itself shapes which proposals pass. We take turnout as given and model the direction of votes conditional on participation.

A growing empirical literature infers investor preferences from votes. [Bubb and Catan \(2022\)](#) and [Bolton et al. \(2020\)](#) recover latent preference dimensions by scaling institutional investors’ voting records, and [Yi \(2021\)](#) ranks firms by the governance needs revealed in funds’ votes. Votes are also read as measures of information and monitoring: [Matvos and Ostrovsky \(2010\)](#) document heterogeneity and peer effects in fund voting, [Iliev and Lowry \(2015\)](#) distinguish funds that research their votes from those that follow advisors, [Iliev et al. \(2021\)](#) measure this research directly from investors’ EDGAR downloads and find it concentrated on larger firms and linked to monitoring through voice and exit, and [Brav et al. \(2024\)](#) show in proxy contests that voting is an informative monitoring channel, with [Brav et al. \(2022\)](#) provid-

ing parallel evidence for retail shareholders. [Maug and Rydqvist \(2009\)](#) estimate a strategic voting model on proposal-level outcomes, and [Matsusaka et al. \(2019\)](#) and [Matsusaka et al. \(2021\)](#) show that proposal quality is heterogeneous and sometimes value-reducing. Our non-identification proposition clarifies what such measures can recover: any mapping from votes to preferences or information embeds assumptions about the other.

Because ISS recommendations serve as our observed public signal, the paper also connects to work on proxy advice. [Malenko and Shen \(2016\)](#) estimate the causal effect of ISS recommendations on votes in a regression discontinuity, [Ertimur et al. \(2013\)](#) document advisor influence in Say-on-Pay votes, [Matsusaka and Shu \(2022\)](#) ask whether proxy advice allows funds to cast informed votes, and [Hu et al. \(2024\)](#) document that most funds receive customized recommendations. On the supply side, [Malenko et al. \(2025\)](#) model advisors' incentives in designing recommendations, and [Blonien et al. \(2025\)](#) measure the quality of ISS recommendations directly. Rather than measuring advice quality or its causal effect, we estimate the advisor's precision inside the voting equilibrium, jointly with shareholders' private information and preferences; the model's implied effect of a flipped recommendation reproduces the regression-discontinuity magnitude of [Malenko and Shen \(2016\)](#) without targeting it.

Finally, our estimates speak to the debate over large passive investors in corporate governance. Critics argue that low-fee business models, conflicts of interest, and weak stewardship incentives tilt index funds toward management ([Bebchuk and Hirst, 2019](#)), and that passive funds' weak incentives to acquire firm-specific information leave their votes uninformed ([Lund, 2018](#)); others counter that the Big Three's scale gives them strong incentives to be informed ([Kahan and Rock, 2020](#)) and that competition for investor flows pushes passive managers to invest in stewardship ([Fisch et al., 2019](#)); the empirical evidence is likewise divided ([Appel et al., 2016](#); [Heath et al., 2022](#)), and [Brav et al. \(2023\)](#) survey the question. Our estimates recast this preference-based debate: the Big Three's information-corrected preferences lie close to dispersed shareholders', their higher support reflecting strategic inference from pivotality, not alignment with management.

## 2. Model

### 2.1. Ownership and Voting

Each firm  $j$  is owned by a set of investors, each indexed by  $i$ . Blockholders  $b \in \{1, \dots, N_B\}$  each own a fraction  $\psi_b$  of outstanding shares, such that total blockholder ownership is  $\sum_{b=1}^{N_B} \psi_b$ . The remaining shares  $\Psi_D = 1 - \sum_{b=1}^{N_B} \psi_b$  are held by  $N_D$  symmetric dispersed shareholders, each of whom owns a fraction  $\psi_D = \Psi_D/N_D$ .

The firm's management puts up a proposal of unknown quality on which shareholders vote. Examples include advisory votes on executive compensation or director elections. Proposal quality is captured by a common-value state,

$$x_j \sim N(0, 1), \tag{1}$$

such that  $x_j$  is unknown to shareholders at the time of voting but has a prior distribution that is common knowledge.<sup>5</sup> Management provides a recommendation for the proposal; voting in favor corresponds to supporting management's recommendation.

Each shareholder is characterized by a preference or private value parameter  $\delta_i \in \mathbb{R}$ . Let  $\Delta \equiv \{\delta_i\}$  denote the (common knowledge) set of preferences for all shareholders.<sup>6</sup> Shareholders with positive  $\delta_i$  receive greater utility when the proposal passes: they prefer passage of proposals regardless of their intrinsic quality. We interpret investors with positive  $\delta_i$  as being more inclined to support management. However, a positive  $\delta_i$  need not represent any literal bias towards management, it simply captures any preference that makes adoption more attractive, independent of its quality.

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<sup>5</sup>The standard normal prior is a location and scale normalization within the class of Gaussian information structures. Because shareholders observe only noisy signals of  $x_j$ , the location and scale of proposal quality are not separately identified from the payoff cutoffs and signal precisions introduced below. Normalizing  $x_j \sim N(0, 1)$  is therefore without loss of generality conditional on normality. The distribution of proposal quality may differ across proposal types, however, so we focus on a single proposal type in estimation.

<sup>6</sup>We take investors' preference parameters to be fixed and common knowledge, thereby isolating uncertainty about proposal quality. This assumption is not essential to the strategic inference mechanism explained below (investors would integrate over uncertainty about other investors' preferences when conditioning on being pivotal.) Pivotality would then convey information about both proposal quality and the realized composition of preferences (Feddersen and Pesendorfer, 1997). Allowing proposal-specific private preference shocks would be more consequential for our empirical setting, because such shocks may be difficult to distinguish from private information about proposal quality.

Given the outcome of the vote  $P_j \in \{0, 1\}$ , 1 indicates approval, shareholder  $i$ 's payoff is

$$U_i(P_j, x_j, \delta_i) = P_j \times (x_j + \delta_i), \quad (2)$$

in which payoffs are normalized to zero when the proposal fails. When the proposal passes, the payoff reflects two components: the common value  $x_j$ , which represents the proposal's impact on firm value and the private value  $\delta_i$ . All dispersed shareholders share the same preference parameter  $\delta_D$ , while each blockholder  $b \in \{1, \dots, N_B\}$  has its own  $\delta_b$ . The complete preference environment is thus  $\Delta = \{\delta_D, \{\delta_b\}_{b=1}^{N_B}\}$ . Note that

$$\Pr(x_j + \delta_i > 0) = 1 - \Phi(-\delta_i) = \Phi(\delta_i), \quad (3)$$

where  $\Phi(\cdot)$  is the standard normal CDF. This quantity gives each shareholder's baseline approval probability, absent any effect of (private or public) information. We refer to  $\Phi(\delta_i)$  as shareholder  $i$ 's preference-implied support rate.

We assume full vote turnout for analytical clarity.<sup>7</sup> The proposal passes,  $P_j = 1$ , if the total support rate exceeds the passing threshold  $\lambda^*$ , and fails,  $P_j = 0$ , otherwise. Under a majority rule, for example,  $\lambda^* = 0.5$ , whereas under a supermajority  $\lambda^* > 0.5$ .<sup>8</sup>

Let  $V_{bj} \in \{0, 1\}$  denote blockholder  $b$ 's vote, and let  $V_{Bj} = (V_{1j}, \dots, V_{N_Bj})$  denote the profile of blockholder votes. Given  $V_{Bj}$ , the share of total votes cast in favor by blockholders is  $s_{Bj} = \sum_{b=1}^{N_B} \psi_b V_{bj}$ . Let  $\tau_j \in [0, 1]$  denote the fraction of dispersed shareholders who vote for the proposal, so that dispersed shareholders contribute  $\Psi_D \tau_j$  to the vote. The total support rate is therefore

$$\lambda_j = s_{Bj} + \Psi_D \tau_j = \sum_{b=1}^{N_B} \psi_b V_{bj} + \Psi_D \tau_j, \quad (4)$$

and the proposal passes if  $\lambda_j \geq \lambda^*$ .

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<sup>7</sup>When we estimate the model, we allow for abstentions, though not at the strategic margin: abstentions enter mechanically as a reduction in the shares voted. For a model in which participation is strategic, see [Zachariadis et al. \(2020\)](#).

<sup>8</sup>Additionally, under the normal structure, the passing threshold  $\lambda^*$  is absorbed into the preference parameters  $\delta_i$ , so simple majority and supermajority rules are equivalent up to reparameterization.

## 2.2. Information Environment

Before voting, shareholders receive noisy signals about the proposal which causes them to update their beliefs about underlying quality  $x_j$ .

### 2.2.1. Public signals

We assume that before voting a proxy advisor produces a report about the proposal. We model this report as a continuous, noisy signal of the underlying state:

$$s_j = x_j + u_{Ij}, \quad u_{Ij} \sim N(0, \sigma_{u_I}^2), \quad (5)$$

where  $\sigma_{u_I}^2$  represents the quality of the proxy advisor's information. We interpret  $s_j$  as the proxy advisor's underlying research report. Blockholders observe this report directly, whereas dispersed shareholders form a noisier, group-specific public assessment of proposal quality based on the report and other public information. Dispersed shareholders use

$$\eta_{Dj} = s_j + v_{Dj}, \quad v_{Dj} \sim N(0, \sigma_{v_D}^2), \quad (6)$$

while blockholders observe the report  $s_j$  itself. The group-specific noise term  $v_{Dj}$  captures the additional imprecision with which dispersed shareholders observe or process the proxy advisor's report and related public disclosures. Since  $s_j = x_j + u_{Ij}$ , we can equivalently write the dispersed public signal in reduced form as

$$\eta_{Dj} = x_j + u_{Dj}, \quad u_{Dj} \equiv u_{Ij} + v_{Dj},$$

with  $u_{Ij}$  and  $v_{Dj}$  independent of each other and of  $x_j$ . Hence

$$\sigma_{u_D}^2 = \sigma_{u_I}^2 + \sigma_{v_D}^2,$$

and the precisions  $1/\sigma_{u_I}^2$  and  $1/\sigma_{u_D}^2$  summarize the effective quality of public information for block and dispersed shareholders, respectively.

That blockholders observe the report itself is an exclusion restriction: in the model, the report is the only public information common to blockholders, so any co-movement in their votes beyond what proposal quality itself induces must flow through the report. The restriction has a natural institutional foundation as proxy advisors sell their research to institutional clients (Malenko and Malenko, 2019), whereas dispersed shareholders typically encounter the advisor’s analysis indirectly; the noise term  $v_{Dj}$  captures this additional imprecision.<sup>9</sup>

The two groups’ public signals nonetheless remain imperfectly correlated,  $\text{Corr}(\eta_{Dj}, s_j | x_j) = \sigma_{u_I} / \sigma_{u_D} \leq 1$ , so dispersed support is not a sufficient statistic for the report and  $s_j$  retains an independent role in blockholder votes. Empirically, blockholder votes covary even conditional on dispersed support and the advisor’s recommendation; in the model this co-movement arises through the shared report, and in estimation we match each blockholder’s average co-voting with the other blockholders as overidentifying moments that discipline  $\sigma_{u_I}^2$ .

**Binary proxy advisor recommendations.** It is useful to note that, empirically, we observe a binary recommendation. We assume that this binary recommendation arises from the continuous report such that

$$S_j = \mathbb{1} [s_j > \xi],$$

where  $\xi$  is a fixed threshold which can be interpreted as the headline “For/Against” recommendation of a proxy advisor such as ISS.<sup>10</sup> In the data, the econometrician observes this binary signal  $S_j$  ex post, but not the underlying continuous report  $s_j$  or the noise in dispersed shareholders’ public signal. We assume that shareholders do not directly observe  $S_j$ ; instead, we summarize the effect of the proxy advisor’s analysis through the report  $s_j$  for blockholders and the public signal  $\eta_{Dj}$  for dispersed shareholders, and use the observed binary recommen-

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<sup>9</sup>The restriction is also what allows us to separately identify the advisor’s signal quality: for a fixed observed correlation between a blockholder’s vote and the advisor’s recommendation, the blockholder can be well informed about proposal quality only if the advisor’s signal is itself precise, and the extent to which blockholders’ votes track dispersed shareholder support *beyond* what the shared report explains then pins down  $\sigma_{u_I}^2$ . We develop this identification argument in the estimation section.

<sup>10</sup>We remain agnostic about whether the proxy advisor’s recommendation rule is biased toward or against management. Because  $\xi$  is a fixed threshold, any constant bias is absorbed into its estimated value, and our identification strategy goes through as long as the bias does not vary across proposals.

dation  $S_j$  in the estimation to help identify the information environment.<sup>11</sup>

### 2.2.2. Private signals

In addition to the public signals, each shareholder  $i$  receives a private signal

$$z_{ij} = x_j + \varepsilon_{ij},$$

where  $\varepsilon_{ij} \sim N(0, \sigma_{\varepsilon_i}^2)$  is independent across shareholders and proposals and independent of  $x_j$  and all public signal shocks. This private signal represents investor-specific information or analysis that may not be reflected in the public signals. Differences in the precision of these private signals,  $1/\sigma_{\varepsilon_i}^2$ , capture heterogeneity in shareholders' information quality.

Dispersed shareholders share a common private signal precision,

$$\sigma_{\varepsilon_i}^2 = \sigma_{\varepsilon_D}^2 \quad \text{for all dispersed } i, \quad (7)$$

reflecting that small investors rely on similar, relatively noisy sources of information. By contrast, each blockholder  $b$  may have a distinct information precision,

$$\sigma_{\varepsilon_i}^2 = \sigma_{\varepsilon_b}^2 \quad \text{for blockholder } b. \quad (8)$$

This structure implies that all shareholders start from a common prior and update using both public and investor-specific information. Dispersed shareholders observe  $(\eta_{Dj}, z_{ij})$  and blockholders observe  $(s_j, z_{bj})$ . The shared component  $s_j$  induces correlation in posterior beliefs across shareholders.

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<sup>11</sup>Incorporating  $S_j$  into shareholders' information sets would replace Gaussian updating with a truncated-normal posterior for dispersed shareholders, since  $\eta_{Dj}$  does not render  $S_j$  redundant; for blockholders, who observe  $s_j$  itself, the binary recommendation carries no additional information. Our assumption that shareholders rely on their own assessment of public information rather than the headline recommendation avoids this complication. Even if shareholders are aware of the binary recommendation, its marginal information content conditional on their detailed assessment of public disclosures is likely small. Additionally, because blockholders observe the advisor's report directly, its signal precision  $\sigma_{u_l}^2$  is separately identified: while marginal support rates alone do not distinguish it from blockholders' private-signal precision, the co-movement of individual blockholder votes with dispersed support beyond what the shared report explains does. The dispersed composite  $\sigma_{u_D}^2$  is separately identified from the distribution of dispersed support, and, given  $\sigma_{u_l}^2$ , the decomposition  $\sigma_{u_D}^2 = \sigma_{u_l}^2 + \sigma_{v_D}^2$  is likewise recoverable. We return to this point in the estimation section.

### 2.3. Voting Strategy

Given the information environment described above, each shareholder observes a continuous public signal  $\eta_{ij}$ , equal to the group assessment  $\eta_{Dj}$  for dispersed shareholders and to the advisor's report  $s_j$  for blockholders, as well as her private signal  $z_{ij}$ . Conditional on these signals, shareholder  $i$  forms a posterior belief about the latent state  $x_j$  using standard Gaussian updating. Shareholder  $i$  votes in favor of the proposal if and only if her posterior expectation of proposal quality exceeds a cutoff  $k_i$ :

$$V_{ij} = 1 \iff \mathbb{E}[x_j \mid \eta_{ij}, z_{ij}] > k_i. \quad (9)$$

We can think of  $k_i$  as the shareholder's decision threshold: shareholders with lower  $k_i$  are more likely to support proposals, whereas those with higher  $k_i$  require higher proposal quality to vote in favor. Importantly,  $k_i$  and  $\delta_i$  need not move in unison, as we show below.

Because both the continuous public signal  $\eta_{ij}$  and the private signal  $z_{ij}$  are normally distributed around  $x_j$ , the posterior distribution of  $x_j$  given  $(\eta_{ij}, z_{ij})$  is normal with mean  $m_{ij}$  and variance  $\sigma_{x|\eta,z}^2$ . Specifically,

$$x_j \mid (\eta_{ij}, z_{ij}) \sim N(m_{ij}, \sigma_{x|\eta,z}^2),$$

where the posterior mean for shareholder  $i$  is

$$m_{ij} \equiv \mathbb{E}[x_j \mid \eta_{ij}, z_{ij}] = \frac{\frac{\eta_{ij}}{\sigma_{u_i}^2} + \frac{z_{ij}}{\sigma_{\varepsilon_i}^2}}{\Lambda_i}, \quad \Lambda_i \equiv 1 + \frac{1}{\sigma_{u_i}^2} + \frac{1}{\sigma_{\varepsilon_i}^2} \quad (10)$$

Here  $\sigma_{u_i}^2$  is the variance of the public signal noise relevant for shareholder  $i$  ( $\sigma_{u_D}^2$  for dispersed shareholders and  $\sigma_{u_I}^2$  for blockholders), and  $\sigma_{\varepsilon_i}^2$  is the variance of her private signal noise. Conditional on the true proposal quality  $x_j$  and the public signal  $\eta_{ij}$ , the only source of randomness is the idiosyncratic noise  $\varepsilon_{ij}$  in the private signal. Substituting  $z_{ij} = x_j + \varepsilon_{ij}$  and

noting that  $\varepsilon_{ij} \sim N(0, \sigma_{\varepsilon_i}^2)$  gives:

$$m_{ij} \mid (\eta_{ij}, x_j) \sim N \left( \frac{\frac{\eta_{ij}}{\sigma_{u_i}^2} + \frac{x_j}{\sigma_{\varepsilon_i}^2}}{\Lambda_i}, \frac{1}{\sigma_{\varepsilon_i}^2 \Lambda_i^2} \right).$$

The probability that shareholder  $i$  supports the proposal, conditional on  $(x_j, \eta_{ij})$ , is

$$\Pr(V_{ij} = 1 \mid x_j, \eta_{ij}) = \Pr(m_{ij} > k_i \mid x_j, \eta_{ij}) = \Phi \left( \sigma_{\varepsilon_i} \left[ \frac{\eta_{ij}}{\sigma_{u_i}^2} + \frac{x_j}{\sigma_{\varepsilon_i}^2} - k_i \Lambda_i \right] \right), \quad (11)$$

where  $\Phi(\cdot)$  denotes the standard normal cumulative distribution function. Equation (11) shows that a shareholder is more likely to vote in favor when her public signal  $\eta_{ij}$  is high, when proposal quality  $x_j$  is high, or when her cutoff  $k_i$  is low. The terms inside the brackets reflect the information-based component of the voting rule and each signal is weighted by its precision. The final term,  $k_i \Lambda_i$ , captures differences in voting thresholds and thus differences in baseline support rates. Heterogeneity in public signal precisions ( $\sigma_{u_i}^2$ ), private signal precisions ( $\sigma_{\varepsilon_i}^2$ ), and thresholds  $k_i$  generates cross-sectional variation in both the level and the responsiveness of voting behavior. This variation is central for identification in the empirical estimation.

## 2.4. Equilibrium

In this section, we lay out the components that determine the equilibrium and then define the equilibrium.

### 2.4.1. Equilibrium components

**Pivotality.** Although a shareholder does not know ex ante whether she will be pivotal, she chooses her vote as if at the pivotal margin and focuses on states in which the overall outcome is close (Bond and Eraslan, 2010).

Let the total support rate be defined by the function

$$\lambda(v_i, V_{B_j}^{-i}, \tau_j) = \psi_i v_i + \Psi_{\text{for}}(V_{B_j}^{-i}) + \Psi_D \tau_j,$$

where  $v_i \in \{0, 1\}$  is shareholder  $i$ 's vote,  $\psi_i$  is her voting weight,  $V_{B_j}^{-i}$  collects blockholders' votes

(excluding  $i$  if  $i$  is a blockholder),  $\Psi_{\text{for}}(V_{Bj}^{-i}) \equiv \sum_{\ell \neq i} \psi_{\ell} V_{\ell j}$ , and  $\tau_j$  is the fraction of dispersed shareholders supporting the proposal. The proposal passes if and only if  $\lambda_j(\cdot) \geq \lambda^*$ .

Shareholder  $i$  is pivotal if her vote flips the outcome:

$$\text{piv}_{ij} \equiv \{\lambda(1, V_{Bj}^{-i}, \tau_j) \geq \lambda^*\} \cap \{\lambda(0, V_{Bj}^{-i}, \tau_j) < \lambda^*\}.$$

For a blockholder  $b$  with weight  $\psi_b > 0$ , conditional on how other blockholders vote, pivotality occurs when dispersed support makes it such that  $b$ 's vote would flip the outcome:

$$\text{piv}_{bj} = \left\{ \tau_j \in \left[ \frac{\lambda^* - \psi_b - \Psi_{\text{for}}(V_{Bj}^{-b})}{\Psi_D}, \frac{\lambda^* - \Psi_{\text{for}}(V_{Bj}^{-b})}{\Psi_D} \right) \right\},$$

where  $\Psi_{\text{for}}(V_{Bj}^{-b})$  is the aggregate support rate of all blockholders excluding  $b$ . For a dispersed shareholder  $i$  with ownership weight  $\psi_D$ , pivotality means that, holding fixed all other votes,  $i$ 's vote flips the outcome. Let  $\tau_{-i,j}$  denote the fraction of dispersed shareholders other than  $i$  who vote in favor. Then  $i$  is pivotal iff

$$\begin{aligned} \Psi_{\text{for}}(V_{Bj}) + \Psi_D \tau_{-i,j} < \lambda^* \leq \Psi_{\text{for}}(V_{Bj}) + \Psi_D \tau_{-i,j} + \psi_D & \iff \\ \tau_{-i,j} \in \left[ \frac{\lambda^* - \Psi_{\text{for}}(V_{Bj}) - \psi_D}{\Psi_D}, \frac{\lambda^* - \Psi_{\text{for}}(V_{Bj})}{\Psi_D} \right). \end{aligned}$$

Pivotality is investor-specific and depends on the realized voting environment. Hence, the conditioning event relevant for an investor's best response is itself endogenous to her voting weight, along with her beliefs about the information and preferences of other shareholders. Voting decisions are therefore interdependent even conditional on observables: each investor's optimal action depends on her own information and on her beliefs about how others map information and preferences into votes.

**Best responses.** When deciding how to vote, each shareholder compares the expected payoff from supporting the proposal to that from opposing it, recognizing that her vote only affects the outcome in states where she is pivotal. Conditional on being pivotal and observing a posterior mean exactly equal to her cutoff,  $m_{ij} = k_i$ , each shareholder is indifferent between voting "For" and "Against," which motivates the following indifference condition at the pivotal

margin:

$$E[x_j \mid \eta_{ij}, m_{ij} = k_i, \text{piv}_{ij}] = -\delta_i, \quad (12)$$

where  $\delta_i$  is her innate preference towards the proposal passing. Equivalently, expressing the indifference condition in terms of the private signal, we may write

$$E[x_j \mid \eta_{ij}, z_{ij} = z_{ij}^*(\eta_{ij}), \text{piv}_{ij}] = -\delta_i, \quad (13)$$

where the cutoff private signal realization  $z_{ij}^*(\eta_{ij})$  solves  $m_{ij} = k_i$  and is given by

$$z_{ij}^*(\eta_{ij}) = \sigma_{\varepsilon_i}^2 \left( \Lambda_i k_i - \frac{\eta_{ij}}{\sigma_{u_i}^2} \right), \quad \Lambda_i = 1 + \frac{1}{\sigma_{u_i}^2} + \frac{1}{\sigma_{\varepsilon_i}^2}.$$

At the pivotal margin, the shareholder is willing to vote “For” only if the expected quality of the proposal, conditional on observing exactly the cutoff signal and on being pivotal, offsets her preference  $\delta_i$ . Equation (13) therefore characterizes, for each realization of the public signal, the pivotal margin at which shareholder  $i$  is just indifferent when her vote is decisive; the equilibrium cutoff  $k_i$  aggregates this margin across signal realizations, as we formalize in Section 2.4.3.

**Signal and strategic effects.** Expanding the expected payoff conditional on being pivotal yields

$$E[x_j \mid \eta_{ij}, z_{ij}, \text{piv}_{ij}] = \int_x x_j f(x_j \mid \eta_{ij}, z_{ij}, \text{piv}_{ij}) dx,$$

where the posterior density of proposal quality can be decomposed into a signal component and a strategic component:

$$f(x_j \mid \eta_{ij}, z_{ij}, \text{piv}_{ij}) \propto \underbrace{f(x_j)}_{\text{public signal effect}} \underbrace{f(\eta_{ij} \mid x_j)}_{\text{private signal effect}} \underbrace{\Pr(\text{piv}_{ij} \mid x_j, \eta_{ij})}_{\text{strategic effect}}. \quad (14)$$

The first two braced terms form the signal effect: they summarize what the shareholder

learns about proposal quality from her own signals,  $(\eta_{ij}, z_{ij})$ . Because dispersed shareholders observe  $\eta_{Dj}$  and all blockholders observe the advisor's report  $s_j$ , the public signal component is group-specific.

The final term,  $\Pr(\text{piv}_{ij} \mid x_j, \eta_{ij})$ , is the strategic effect. It captures the additional information contained in the event of being pivotal. This probability depends on how other shareholders vote, and therefore on their equilibrium strategies, their private information  $(\sigma_{-i}, \delta_{-i})$ , and on the public signal they observe. Since shareholder  $i$  does not observe the other group's public signal (e.g., a dispersed shareholder does not observe the report  $s_j$ ), the strategic effect implicitly integrates over the unobserved public signal of the other investor group. Conditioning on pivotality therefore shifts beliefs toward states of the world in which the aggregate vote is close, providing information about  $x_j$  beyond what is contained in  $(\eta_{ij}, z_{ij})$ .

#### 2.4.2. Posterior beliefs about proposal quality

Determining equilibrium voting strategies requires evaluating the posterior in (14) for each shareholder. This, in turn, requires computing each shareholder's probability of being pivotal for each possible value of proposal quality  $x_j$  and her observed public signal:  $\eta_{Dj}$  for dispersed shareholders and the report  $s_j$  for blockholders. Following Myatt (2015) and Zachariadis et al. (2020), we derive the limit of the game as  $N_D$  grows large. The formal expressions are given in Lemma B.1 and Lemma B.2 in the appendix; here we describe the key intuition for each investor type.

**Dispersed shareholders.** In the large- $N_D$  limit, the dispersed support rate is a deterministic function of  $(x_j, \eta_{Dj})$ . A dispersed shareholder is therefore pivotal only at knife-edge values of  $x_j$  for which the implied support rate exactly equals the threshold needed for passage, given each possible blockholder vote profile  $V_{Bj}$ . The posterior in (14) concentrates on these knife-edge states, each weighted by the conditional prior  $f(x_j \mid \eta_{Dj})$ , the private signal likelihood  $f(z_{Dj} \mid x_j)$ , and the probability of the blockholder vote profile that makes the state pivotal, integrated over the unobserved report  $s_j$  conditional on both  $x_j$  and  $\eta_{Dj}$ .

**Blockholders.** For a blockholder  $b$  with voting weight  $\psi_b$ , pivotality occurs when dispersed support falls in an interval  $[\tau_L^{V_{B,-b,j}}, \tau_H^{V_{B,-b,j}}]$ , not at a single point. Pivotality therefore has positive probability conditional on  $x_j$ . The blockholder's posterior in (14) combines the prior shaped by the report  $f(x_j | s_j)$ , the private signal likelihood  $f(z_{bj} | x_j)$ , the pivotality probability  $\Pi^{V_{B,-b,j}}(x_j, s_j)$  integrated over the unobserved dispersed public signal  $\eta_{Dj}$  conditional on both  $x_j$  and  $s_j$ , and the strategic likelihood of the other blockholders' vote profile  $\Pr(V_{B,-b,j} | x_j, s_j)$ . The conditioning on  $s_j$  in the pivotality probability reflects that the report is informative about the dispersed public signal beyond  $x_j$ : having seen the report herself, the blockholder is uncertain about dispersed shareholders' public assessment only through the noise with which they process it. Conditioning on pivotality shifts the blockholder's beliefs toward states in which dispersed support is close to the passage threshold, providing information about  $x_j$  beyond what is contained in  $(s_j, z_{bj})$ . The equilibrium cutoff  $k_b$  is then pinned down by the indifference condition in Definition 1, evaluated under this posterior.

### 2.4.3. Equilibrium Definition

Each dispersed shareholder observes  $(\eta_{Dj}, z_{Dj})$ , while blockholder  $b$  observes  $(s_j, z_{bj})$ , and shareholders vote according to cutoff rules in the posterior mean  $m_{ij}$  from (10): shareholder  $i$  votes "For" if and only if  $m_{ij} \geq k_i$ , where the cutoff  $k_i$  does not vary across proposals. Proposal-invariant cutoffs reflect how institutional voting operates in practice: investors map their assessment of a proposal into a vote through standing voting policies rather than proposal-by-proposal recalibration. The equilibrium concept is pure-strategy Bayesian-Nash within this class of cutoff strategies (Feddersen and Pesendorfer, 1997; Athey, 2001), defined directly on the limit economy in which the dispersed shareholder base is atomistic ( $N_D \rightarrow \infty$ ); the pivotal posteriors that discipline the cutoffs are derived in Appendix B.

**Definition 1:** Cutoff voting equilibrium

*Given the information environment and preferences  $\Delta$ , a cutoff voting equilibrium of the limit economy is a cutoff profile  $\mathbf{k} = \{k_D, \{k_b\}_{b=1}^{N_B}\}$  such that, when every shareholder votes according*

to  $V_{ij} = \mathbb{1} [m_{ij} \geq k_i]$ , each cutoff satisfies the indifference condition

$$\mathbb{E}[x_j \mid m_{Dj} = k_D, \text{piv}_{Dj}] = -\delta_D, \quad (15)$$

$$\mathbb{E}[x_j \mid m_{bj} = k_b, \text{piv}_{bj}] = -\delta_b, \quad \forall b \in \{1, \dots, N_B\}, \quad (16)$$

where each expectation is taken under the limiting posterior of Lemma B.1 or Lemma B.2, averaged over the signal realizations consistent with  $m_{ij} = k_i$  and the pivotal event.

Conditions (15)–(16) are the first-order conditions for optimal proposal-invariant cutoffs: at  $m_{ij} = k_i$  the shareholder is exactly indifferent between voting “For” and “Against” conditional on her vote being decisive, given the strategies of the other shareholders. The effect of pivotality is captured entirely by the equilibrium cutoffs:  $k_i$  embeds shareholder  $i$ ’s strategic inference from the event that her vote is decisive, which depends on the aggregate support implied by others’ strategies and information. In particular, preferences  $\delta_i$  and cutoffs  $k_i$  need not move together. Lemma B.3 in Appendix B shows that a cutoff voting equilibrium exists.

**Equilibrium Support Rates.** Given an equilibrium cutoff profile  $\mathbf{k} = \{k_D, \{k_b\}_{b=1}^B\}$ , the (prior) probability that shareholder  $i$  votes “For”, i.e., her equilibrium support rate, is

$$\Pr(V_{ij} = 1) = \Pr(m_{ij} \geq k_i) = \iint \mathbb{1}\{m_{ij}(\eta, z) \geq k_i\} f_i(\eta) f_i(z \mid \eta) d\eta dz, \quad (17)$$

where  $f_i(\eta)$  and  $f_i(z \mid \eta)$  denote the public and private signal densities implied by  $(\sigma_{u_i}^2, \sigma_{\varepsilon_i}^2)$  in the information environment.<sup>12</sup> Thus, equilibrium support rates are determined by the distribution of each shareholder’s posterior mean relative to her cutoff, with the cutoffs themselves pinned down by the pivotality-adjusted indifference conditions.

### 3. Model Analysis

We use comparative statics to show how preferences, information, and strategic behavior jointly shape observed support rates. Throughout, we consider a single proposal (and drop the subscript  $j$ ) with one blockholder holding 20% of the ownership and the remainder held by

<sup>12</sup>For dispersed shareholders,  $(\sigma_{u_i}^2, \sigma_{\varepsilon_i}^2) = (\sigma_{u_D}^2, \sigma_{\varepsilon_D}^2)$  and  $\eta = \eta_{Dj}$ ; for blockholder  $b$ ,  $(\sigma_{u_i}^2, \sigma_{\varepsilon_i}^2) = (\sigma_{u_b}^2, \sigma_{\varepsilon_b}^2)$  and  $\eta = s_j$ .

dispersed shareholders; expanding beyond one blockholder is simple. We also set  $\sigma_{vD} = 0$ , so that both investor groups observe the advisor's report itself, and we hold the report's precision  $1/\sigma_{u_I}^2$  fixed at a noisy value: the comparative statics below vary only the precision of the blockholder's private information.<sup>13</sup>

### 3.1. Decomposing the Observed Blockholder Support Rate

We first isolate how the blockholder's information precision and strategic voting considerations impact her observed voting behavior, what we refer to as the *signal* and *strategic* effects in the model.<sup>14</sup> This allows us to study how changes in observed voting behavior can reflect improvements in the blockholder's information quality or shifts in her strategic incentives from conditioning on being pivotal, two channels that may be confounded empirically.

To separate these effects, consider two objects. The first is the blockholder's equilibrium support rate,

$$p_b^S = \Pr(m_b \geq k_b),$$

where  $m_b$  is the blockholder's posterior mean (as in (10)), and  $k_b$  is her equilibrium voting threshold. This embeds both the signal and strategic effect. The second is the non-strategic support rate,

$$p_b^{NS} = \Pr(m_b \geq -\delta_b),$$

which is the support rate of the blockholder if she did not condition on pivotality. The difference between these two objects isolates the impact of strategic voting on the blockholder's equilibrium decision. As comparison, we also consider the blockholder's preference-implied support rate,

$$\Phi(\delta_b) = \Pr(x \geq -\delta_b),$$

which is the support rate if the blockholder voted purely by her private value (see (3)).

The signal effect is summarized by the gap between the non-strategic rate and the preference-

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<sup>13</sup>Noisy public information is where the confusion between private information and preferences is most severe, since a precise public signal would dominate votes; as we show in Section 4, marginal support rates cannot separate the two in any case.

<sup>14</sup>The signal effect is simply how the quality of information received (holding strategic effects constant) influences a shareholder's posterior beliefs about proposal quality. The strategic effect arises from how conditioning on being pivotal alters these beliefs in equilibrium. See equation 14.

implied benchmark, which admits a closed form:  $p_b^{NS} = \Phi\left(\delta_b \sqrt{\frac{\Lambda_b}{\Lambda_b - 1}}\right)$ , where  $\Lambda_b$  is the blockholder's total posterior precision from (10). Since  $\sqrt{\Lambda_b/(\Lambda_b - 1)} > 1$  for finite  $\Lambda_b$ , imperfect information magnifies the effect of preferences, pushing the non-strategic support rate away from  $\Phi(\delta_b)$ , with convergence to  $\Phi(\delta_b)$  as information becomes precise. The strategic effect is the remaining wedge between  $p_b^S$  and  $p_b^{NS}$ , and it is governed by the informational content of pivotality: for the blockholder to be decisive, dispersed support must fall near the passage threshold, and whether that event is good or bad news about proposal quality depends on her own information and on the voting behavior of the other shareholders. Observed blockholder voting therefore reflects preferences and information quality jointly, with strategic effects operating through the inference the blockholder draws from being pivotal. The next subsection shows how this joint dependence limits what observed support rates alone can reveal.

### 3.2. Information and Observational Equivalence

Given that support rates are determined jointly by preferences, information, and strategic behavior, this subsection illustrates a central implication of the model: the same observed support rate can be rationalized by different underlying information and preference environments. We hold the blockholder's observed support rate fixed and vary the precision of her private signal, recovering at each precision level the preference parameter needed to sustain the same voting outcome in equilibrium, with and without strategic voting.

In the exercise, we fix the public and dispersed environments ( $\sigma_{u_I} = 2$ ,  $\sigma_{\varepsilon_D} = 3$ ) and set the passing threshold to a simple majority. Both groups are calibrated to a common baseline: dispersed shareholders support 75% of proposals unconditionally, and the blockholder's observed support rate is held at 75% throughout. As the blockholder's private-signal noise  $\sigma_{\varepsilon_b}$  varies, her cutoff  $k_b$  is set to reproduce the observed support rate, and we recover the preference that rationalizes that cutoff: the strategic  $\delta_b$  solves the indifference condition in Definition 1, while the non-strategic benchmark  $\delta_b^{NS}$  solves  $p_b^{NS} = 75\%$ .

Figure 1 plots the preference-implied support rates  $\Phi(\delta_b)$  and  $\Phi(\delta_b^{NS})$  against the share of the blockholder's posterior precision contributed by her private signal. The dashed horizontal line marks the observed support rate, so the vertical distance between a curve and that line

measures how much of observed support is attributed to something other than preference: information under non-strategic voting, and information together with pivotal inference under strategic voting.

The non-strategic curve is monotone: noise amplifies the effect of any given preference on votes, so as the blockholder’s private signal improves, a stronger preference is required to sustain the same observed support rate. The strategic curve is not, and the wedge between it and the observed rate changes sign: the recovered preference-implied support ranges from roughly 67% to roughly 79% around the same observed 75%, because the news content of pivotality depends on the blockholder’s own information mix, good news about quality where her information is poor and bad news where it is strong.

Taken together, the figure shows that the same observed support rate can be rationalized by very different economics: a preference-implied support rate anywhere from about 67% to above the observed rate itself, depending on the blockholder’s information. Because the wedge between the strategic and non-strategic curves can change sign, strategic voting can make an investor appear either more or less biased than she is. The observed support rate provides one moment while the environment leaves two parameters free,  $\delta_b$  and  $\sigma_{\varepsilon_b}$ , so preferences are not point identified from support rates alone. We formalize this non-identification in Section 4, where the co-movement of blockholder votes with dispersed support, beyond what the shared report explains, restores identification. We return to the empirical counterpart of this wedge when we compare naive and strategic preference estimates in Section 5.

## 4. Identification and Estimation

We now describe the identification and estimation of the model from Section 2.<sup>15</sup> The data used for estimation are described in detail in Section 4.4. We suppose that we observe a dataset of proposals indexed by  $j$ , containing proposal outcomes and shareholder votes. Specifically, the data include proxy advisor recommendations  $S_j$ , realized dispersed shareholder support  $\tau_j$ , and blockholder-level information on ownership stakes and voting decisions. As we will show, this is sufficient to fully identify the model.

<sup>15</sup>We also return from the simplification of Section 3, where both investor groups observed the report itself, to the general information environment of Section 2.

## 4.1. Identification

For each proposal  $j$ , the econometrician observes the proxy advisor's binary recommendation  $S_j$ , the dispersed support rate  $\tau_j$ , and blockholder votes and ownership shares  $\{(V_{bj}, \psi_b)\}_{b=1}^{N_B}$  (and hence aggregate blockholder support  $s_{Bj}$ ). By contrast, proposal quality  $x_j$ , the advisor's report  $s_j$ , and the dispersed public signal  $\eta_{Dj}$  are unobserved. We use the joint cross-sectional distribution of  $(S_j, \tau_j, \{V_{bj}\}, \{\psi_b\})$  to identify the information environment and preferences  $\Delta$ .

Identification builds on three maintained features of the model. First, the cutoff profile  $\mathbf{k} = \{k_D, \{k_b\}_{b=1}^{N_B}\}$  arises from a cutoff voting equilibrium and satisfies the indifference conditions of Definition 1. Second, the proxy advisor's binary recommendation is monotonic in the underlying report,  $S_j = \mathbf{1} [s_j > \xi]$ , with a threshold that is constant across proposals. Third, conditional on the recommendation, the remaining variation in voting is generated by the latent quality  $x_j$  and the public and private signal shocks of the information environment in Section 2.

The argument has a simple architecture. The joint distribution of  $(\tau_j, S_j)$  and, for each blockholder, the joint distribution of  $(V_{bj}, S_j)$  deliver Gaussian reduced forms that restrict the structural parameters to a finite collection of one-dimensional branches indexed by the advisor noise  $\sigma_{u_l}$ . This remaining indeterminacy is the empirical counterpart of the non-identification result developed below. Joint behavior across shareholders then selects among these branches: vote–support covariances identify a scalar combination of advisor accuracy and dispersed private precision, while mean co-voting identifies  $\sigma_{u_l}$  itself. We develop each step in turn.

All technical detail is deferred to Appendix C: Section C.1 contains the formal lemma statements and their proofs, and Section C.3 the finite-sample implementation. The discussion here is entirely conceptual, referencing the corresponding identification lemmas where appropriate.

### 4.1.1. Dispersed and Proxy Advisor Parameters

The joint distribution of  $(\tau_j, S_j)$  identifies the recommendation threshold and the reduced form of dispersed voting. Under the model's atomistic dispersed base, the probit-transformed

support rate  $T_j = \Phi^{-1}(\tau_j)$  satisfies

$$T_j = \sigma_{\varepsilon_D} \left[ \frac{\eta_{Dj}}{\sigma_{u_D}^2} + \frac{x_j}{\sigma_{\varepsilon_D}^2} - k_D \Lambda_D \right],$$

so  $T_j$  is exactly normal, and  $(T_j, S_j)$  is a two-cell switching regression: writing  $s_j^* = s_j / \sqrt{1 + \sigma_{u_I}^2}$  for the standardized report and  $\xi^* = \xi / \sqrt{1 + \sigma_{u_I}^2}$  for the threshold in its units,

$$T_j = \mu_T + c s_j^* + \omega Z_j, \quad Z_j \perp s_j^*,$$

with  $\mu_T = -\sigma_{\varepsilon_D} k_D \Lambda_D$ ,  $c = \text{Cov}(T_j, s_j^*)$ ,  $Z_j$  standard normal and independent of  $s_j^*$ , and  $\omega^2 = \sigma_T^2 - c^2$  the variation in dispersed voting that the report cannot explain, where  $\sigma_T^2 = \text{Var}(T_j)$ . The recommendation frequency  $\Pr(S_j = 1) = 1 - \Phi(\xi^*)$  identifies  $\xi^*$ ; the two conditional means  $E[T_j \mid S_j]$  identify  $(\mu_T, c)$ , because the recommendation partitions the latent report and therefore shifts  $T_j$  through the truncated mean of  $s_j^*$ ; and, under Assumption C.1, the conditional variance  $\text{Var}(\tau_j \mid S_j = 0)$  identifies the residual scale  $\omega$ . Together these pin down  $\sigma_T$ , the correlation  $\rho_{Ts} = c/\sigma_T$  between dispersed voting and the report, and hence the entire joint distribution of  $(T_j, S_j)$  (Lemma C.1).

Intuitively, the recommendation cells reveal how dispersed support loads on the latent report: because  $S_j$  is a thresholded version of  $s_j^*$ , differences in support across recommendation cells identify the report channel, while residual variation within a cell identifies variation in dispersed support that the report does not explain. These reduced-form objects do not yet uniquely separate the dispersed-side primitives. Given advisor noise  $\sigma_{u_I}$ , they admit finitely many candidate combinations of  $(\sigma_{u_D}, \sigma_{\varepsilon_D}, k_D)$ , corresponding to different allocations of information between the public and private signals.

#### 4.1.2. Blockholder Parameters

Each blockholder's vote and the recommendation are two thresholded normal indices, so their joint distribution is summarized by two quantities: the blockholder's approval rate identifies her standardized cutoff  $\zeta_b = k_b/s_b$ , where  $s_b^2 = \text{Var}(m_b) = 1 - 1/\Lambda_b$ , and the rate at which her vote and the recommendation coincide identifies the correlation  $\rho_b$  between her posterior

mean and the standardized report (Lemma C.2). Because blockholders observe the report itself, these objects are connected by an exact restriction: the projection identity  $\text{Cov}(m_b, s_j) = \text{Var}(x_j) = 1$  forces

$$\rho_b \cdot \text{Corr}(m_b, x_j) = \frac{1}{\sqrt{1 + \sigma_{u_l}^2}},$$

so that, for a fixed observed correlation between a blockholder's vote and the recommendation, the blockholder can be well informed about proposal quality only if the advisor's report is itself precise. Given  $\sigma_{u_l}$ , each blockholder's private precision and cutoff then follow in closed form (Lemma C.3); the individual voting patterns confine the parameter to a finite union of one-dimensional curves indexed by  $\sigma_{u_l}$  (Corollary C.1), along which every blockholder's private noise rises with the advisor's.

Joint behavior across investors selects among these candidate curves. Conditional on the report, the covariance between a blockholder's vote and dispersed support varies through an advisor-orthogonal correlation, while the common-report component is already fixed by the individual reduced forms (Lemmas C.5 and C.6). The vote-support covariances therefore identify the scalar  $\varrho$ , a combination of advisor accuracy and dispersed private precision. This can leave at most two candidate parameter points with the same  $\varrho$ . Mean co-voting provides the final source of separation: conditional on the report, two blockholders remain correlated through residual uncertainty about proposal quality, and this correlation is strictly decreasing in  $\sigma_{u_l}$ . Mean co-voting therefore identifies advisor noise directly and eliminates the remaining conjugate ambiguity. Only one scalar direction from each joint-moment block is required for identification; the remaining moments provide overidentifying restrictions.

#### 4.1.3. Preferences

Finally, we identify the preference parameters

$$\Delta = \{ \delta_D, \{ \delta_b \}_{b=1}^{N_B} \}$$

from the indifference conditions of Definition 1 at the cutoffs. Once the information environment is fully pinned down, the conditional expectation  $E[x_j \mid m_{ij} = k_i, \text{piv}_{ij}]$  is a known

function of the information parameters through the pivotal posteriors of Appendix B, so each preference  $\delta_i$  is uniquely determined by the corresponding indifference condition.

#### 4.1.4. Formal Identification

We formalize the identification claim with the following proposition.

**Proposition 1:** Identification of model parameters

*Let the structural parameter vector be*

$$\theta \equiv \left( \xi^*, k_D, \sigma_{u_D}, \sigma_{\varepsilon_D}, \sigma_{u_I}, \{\sigma_{\varepsilon_b}, k_b\}_{b=1}^{N_B} \right) \in \Theta.$$

*Given the joint cross-sectional distribution of  $\{\tau_j, S_j, \{V_{bj}\}_{b=1}^{N_B}\}$  across proposals (together with the ownership weights  $\{\psi_b\}_{b=1}^{N_B}$ ), and under the maintained features above together with Assumption C.1, the parameter vector  $\theta$  is uniquely identified. Given  $\theta$ , the preference vector  $\Delta$  is in turn uniquely determined by the indifference conditions (15)–(16).*

*Proof.* See Appendix C.1. ■

## 4.2. Implications

Proposition 1 uses cross-investor dependence to separate the remaining components of the information structure: vote–support covariances identify the public–private information mix, while mean co-voting identifies advisor noise. A natural question is whether this joint behavior is actually necessary, or whether the individual voting patterns (that is, the joint distribution of dispersed support with the recommendation and, separately, each blockholder’s vote with the recommendation) already suffice. The following proposition shows that they do not.

**Proposition 2:** Non-identification from individual voting patterns

*Fix an interior data-generating parameter vector  $\theta_0 \in \Theta$  at which the dispersed-side solution is locally regular and can be continuously re-solved as the other information parameters vary. Then there exists a nondegenerate interval of advisor-noise values containing  $\sigma_{u_I}(\theta_0)$  and a continuous family of distinct parameter vectors  $\{\theta(\varsigma)\}$  that generate exactly the same joint distribution of  $(\tau, S)$  and, for every blockholder  $b$ , the same joint distribution of  $(V_b, S)$ . Along this family, the*

*information parameters, equilibrium cutoffs, and preferences vary, while the observable individual voting patterns remain unchanged; preferences are re-solved from the equilibrium indifference conditions so that each parameterization constitutes a cutoff voting equilibrium. Individual voting patterns therefore do not identify either the information structure or preferences.*

*Proof.* See Appendix C.2. ■

Intuitively, Proposition 2 shows that even full individual voting patterns need not separately identify information from preferences. This confounding arises even in the simplest case with only common public information: an investor's voting cutoff reflects both her preference and the precision of the public signal. Advisor noise can vary while blockholder private information, dispersed information, and preferences adjust so that the entire joint distribution of  $(\tau, S)$  and every joint distribution  $(V_b, S)$  remain unchanged. Strategic voting reinforces this confounding once investors have heterogeneous private information, because changing the information environment also changes what an investor learns from being pivotal, and hence the preference required to rationalize her equilibrium voting rule.

What breaks this observational equivalence is dependence across investors. Conditional on the recommendation, vote–support covariances identify the remaining public–private information mix, while co-voting across blockholders identifies advisor noise. Thus, identification comes from joint behavior across agents that is absent from their individual relationships with the recommendation. The next two examples illustrate the implications for common empirical approaches to voting data.

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#### 4.2.1. Ranking investors by observed support

Proposition 2 implies, a fortiori, that an empirical strategy relying only on mean support rates by investor type cannot separately identify information and preferences. This is not a limitation of using means or of a particular functional form: the proposition grants the econometrician the entire joint distribution of dispersed support with the recommendation and, for each blockholder, the entire joint distribution of her vote with the recommendation, and still obtains non-identification. A regression that controls flexibly for the ISS recommendation therefore cannot resolve the problem, because the missing identifying information lies in dependence across investors rather than in an investor's individual relationship with ISS. For example, consider a standard reduced-form regression estimated using a panel of blockholders and proposals across firms:

$$\text{Vote}_{ijft} = \mu_i + \mu_f + \mu_t + \beta \cdot \text{ISS}_{jft} + \gamma' X_{ijft} + \epsilon_{ijft}.$$

where  $ijft$  indexes investor, proposal, firm, and time. This specification summarizes each investor's voting behavior through conditional means. The investor fixed effect  $\mu_i$  therefore need not measure preferences alone: a high  $\mu_i$  may indicate a pro-management preference, or an unbiased investor whose information environment makes supporting management more likely when pivotal. Conversely, interpreting  $\mu_i$  as information quality requires assumptions about preferences. Controlling for  $\text{ISS}_{jft}$  absorbs variation associated with the observed recommendation, but does not separate common information, private information, and preferences; indeed, non-identification persists even when the econometrician observes the full joint distribution of each investor's vote with the recommendation.

#### 4.2.2. Interpreting joint voting behavior

A recent literature uses voting matrices to recover low-dimensional representations of investor behavior.<sup>16</sup> Bubb and Catan (2022) exploit cross-investor covariance through principal-component methods, while Bolton et al. (2020) use the W-NOMINATE algorithm to recover a

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<sup>16</sup>By voting matrices, we mean arrays of investors' votes across proposals.

spatial representation of voting behavior. These approaches use dependence across investors that is absent from simple rankings or conditional-mean regressions. The difficulty is that this dependence need not reflect preference similarity alone.

Our identification results make this point particularly transparent for covariance-based approaches. Holding fixed each blockholder’s individual relationship with the recommendation, the advisor-orthogonal correlation between the latent voting indices of blockholders  $b$  and  $b'$  is

$$\gamma_{bb'} = \frac{\sqrt{(1 - \rho_b^2)(1 - \rho_{b'}^2)}}{\rho_b \rho_{b'}} \frac{1}{\sigma_{u_l}^2},$$

where  $\rho_b$  measures how blockholder  $b$ ’s posterior belief correlates with the latent advisor report. Thus, two information structures can generate exactly the same individual voting patterns while implying different cross-investor covariance. A principal-component representation of the voting matrix can therefore change with the information environment even when preferences are held fixed. More generally, proximity in a low-dimensional voting representation can reflect shared information and equilibrium responses to pivotality as well as preference similarity. Our structural model separates these channels by imposing restrictions on how information and strategic behavior enter the joint distribution of votes.

The observational equivalence in Proposition 2 is established within our Gaussian cutoff environment, but the underlying confounding between common information, private information, and preferences may arise more broadly, in other voting models and beyond. Characterizing when individual behavior fails to separate these objects, and when cross-agent dependence restores identification, is an interesting direction for future work.

### 4.3. Estimation Routine

We stack the moments implied by the identification argument into a single sample moment vector. At the proposal level, we match the recommendation frequency and the conditional means  $E[T_j | S_j]$  and variances  $\text{Var}(\tau_j | S_j)$  for  $S_j \in 0, 1$ . At the blockholder level, we match vote rates by recommendation cell, leave-out vote–support covariances, the dispersion of aggregate blockholder support, and average co-voting in the against-recommendation cell. This yields  $7 + 5N_B$  moments for  $N_\Theta = 5 + 2N_B$  parameters, or 37 moments and 17 parameters in our

application. We estimate the model by GMM using an efficient weighting matrix computed from the sample moment covariance, with inference clustered at the proposal level. Preferences are then recovered from the equilibrium indifference conditions. Appendix C.3 provides the full moment definitions, weighting and inference details, and preference recovery.

## 4.4. Data

To estimate the model, we focus on executive compensation proposals (1‘Say-on-Pay’), in which shareholders cast advisory votes on management’s disclosed compensation program. Because these are management-sponsored proposals, a ‘1For’ vote is naturally interpreted as support for management. We focus on Say-on-Pay rather than more routine ballot items, such as director elections, because it exhibits substantially more cross-proposal variation in both shareholder support and proxy-advisor recommendations. This variation is useful for identification, which relies on how blockholder votes and dispersed support co-move with the recommendation across proposals.

Because Say-on-Pay is advisory, there is no statutory voting threshold that compels boards to revise compensation. ISS nevertheless treats 70% support as an important benchmark: support below 70% is considered a low-support outcome that triggers heightened scrutiny of the firm’s response and may affect subsequent recommendations on Say-on-Pay proposals and directors (ISS, 2022, Section 5, “Compensation”).<sup>17</sup> We therefore use 70% to define passage in the empirical analysis. The exact cutoff is not essential for identification of the information structure; it primarily determines the scale of the recovered preference parameters.

### 4.4.1. Sample Construction

Following Bubb and Catan (2022) and Bolton et al. (2020), we restrict the sample to proposals receiving less than 95% support. We define proposal turnout as the number of shares counted under the applicable voting base divided by shares outstanding, and drop proposals with turnout below 50%.

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<sup>17</sup>Consistent with this, institutional investor engagement changes sharply around 70% support (Dey et al., 2024). Low Say-on-Pay support is also associated with subsequent engagement and compensation changes (Ertimur et al., 2013), while Barry (2026) identifies 70% as an important threshold for compensation policy.

For each proposal, we collect mutual-fund votes from ISS and aggregate them to the fund-family level, classifying a family as voting for the proposal when over 90% of its funds vote for.<sup>18</sup> We merge institutional ownership from Thomson Reuters 13F using the quarter preceding the meeting and compute each manager’s ownership as shares held divided by shares outstanding. We then rescale ownership by proposal turnout so that it is expressed relative to shares participating in the vote, and classify managers with adjusted ownership of at least five percent as blockholders. We match 13F managers to ISS fund-families to recover each blockholder’s vote. Finally, given total support  $\lambda_j$ , we impute dispersed-shareholder support as

$$\tau_j = \frac{\lambda_j - V_j^{B\top} \psi_{Bj}}{\Psi_{Dj}},$$

where  $\Psi_{Dj}$  is the dispersed shareholders’ turnout-adjusted ownership share. The resulting voting outcomes  $\tau_j$ ,  $V_j^B$  and ownership structures  $\Psi_j$  are the inputs to the estimation procedure in Section 4.

#### 4.4.2. Sample summary

We summarize our sample of 7,851 Say-on-Pay votes in Table 1. The average firm has 2.68 blockholders, with combined ownership of 28.14%. Average total support is 84.16%. Support is lower among dispersed shareholders, with an average dispersed support rate of 81.44%, while blockholders are more supportive on average: conditional on being a blockholder, the mean blockholder support rate is 89.56%. Using the standard convention that votes with less than 70% support are considered failures, 86.24% of proposals pass, and 16.09% are close in the sense of total support between 60% and 80%.

Panel B summarizes ownership and voting for the largest blockholders. Vanguard is the most frequent blockholder, appearing in 7,422 votes, while BlackRock appears in 7,088. State Street appears in 2,676 votes, consistent with its smaller average stake. The Big Three hold economically large positions: average ownership is 11.28% for Vanguard, 11.89% for BlackRock, and 6.80% for State Street. All three are more supportive than dispersed shareholders

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<sup>18</sup>In practice, this is a slack requirement, as the funds within the fund families of the asset managers we study vote in unison almost always.

on average: Vanguard supports 92.70% of proposals, BlackRock supports 92.96%, and State Street supports 90.10%. Dimensional stands apart, supporting only 58.10% of the proposals on which it appears as a blockholder. Pivot probabilities vary meaningfully across investors, reflecting both differences in stake sizes and voting behavior: the average pivot probability is 12.29% for Vanguard and 14.60% for BlackRock, compared to 4.48% for State Street.

## 5. Results

### 5.1. Model fit

Table 2 summarizes model fit on economically important moments. At the proposal level (Panel A), the model captures average dispersed and total support across recommendation cells, passing and close-vote rates, the frequency of the advisor’s recommendation, and its marginal effect on dispersed support. Panel B reports each blockholder’s voting probability by recommendation cell, estimated pivot probability, and co-movement with dispersed support. Panel C provides an untargeted external validation: the model-implied effect of flipping the advisor’s recommendation is similar in magnitude to the regression-discontinuity estimate in Malenko and Shen (2016). Table A.2 reports the full set of targeted moments, model counterparts, and standardized differences.

The model is rejected by the overidentification test, with the remaining discrepancies concentrated in a few features of the joint distribution. First, the model overstates the dispersion of support on proposals the advisor endorses. In the data, support in this cell is unusually concentrated; the model reproduces its location but not its full peakedness, as Figure 2 shows. Second, the model systematically overpredicts co-voting among blockholders on proposals the advisor opposes: institutional votes in the data are closer to conditionally independent than the estimated shared-report channel implies. Other targeted moments exhibit smaller discrepancies in both directions.

We therefore view the estimated information structure as a parsimonious approximation rather than a literal description of every source of dependence in votes. The principal blockholder-side miss implies too much common variation in institutional voting, so the precise decomposition of public and private information should be interpreted with caution. Im-

portantly, however, the model’s main conclusions do not rely on co-voting alone: individual vote–recommendation patterns, dispersed support, vote–support co-movement, and cross-blockholder dependence jointly discipline the information environment, while preferences are recovered from the equilibrium conditions. The robustness exercises below further assess the two channels most relevant for this interpretation: strategic conditioning on pivotality and common preference variation across blockholders.

## 5.2. Parameter Estimates

Table 3 reports the estimated parameters. The advisor’s report is informative:  $\sigma_{u_I} = 1.161$  implies that the report’s correlation with underlying proposal quality is 0.653, and its implied correlation with the dispersed voting index is 0.642. The recommendation is therefore not orthogonal to what the broader investor base believes, but rather a noisy public summary of the same underlying component of proposal quality: shifts in the recommendation are informative partly because they move in tandem with dispersed sentiment.

Dispersed shareholders process this public information with substantial additional noise: their composite public signal has  $\sigma_{u_D} = 6.232$ , of which the advisor’s own noise accounts for only a small part (the implied correlation between the two groups’ public-signal errors is 0.186). The asymmetry shows up directly in the variance decomposition of beliefs (Panel B): the shared report accounts for between 25.31% and 36.94% of the variance in blockholders’ posterior beliefs, against 1.98% for the dispersed base, for whom the prior dominates. Turning to private information, dispersed shareholders have  $\sigma_{\varepsilon_D} = 1.916$ , while most blockholders’ private signals are more precise: Vanguard’s is the most precise at 0.916 and Fidelity’s the least at 1.934. The precisions of Fidelity and T. Rowe are the least precisely estimated coordinates.

Finally, the estimated preference parameters  $\delta_i$  shift a shareholder’s ideal point toward passage.  $\Phi(\delta_i)$  summarizes this on a probability scale: it is the share of proposals that shareholder  $i$  would ideally like to see pass, given the prior distribution of proposal quality and absent any information or strategic considerations. Because  $\Phi(\delta_i)$  depends on the assumed state distribution, its level should be interpreted with caution; however, cross-sectional comparisons across shareholders are informative about relative preferences.<sup>19</sup> Dispersed sharehold-

<sup>19</sup>This quantity is a preference index and should not be compared to the 70% support threshold used to classify

ers have  $\Phi(\delta_D) = 79.50\%$ . Most large blockholders are more pro-passage: Vanguard (84.54%), BlackRock (83.48%), State Street (84.59%), and T. Rowe (83.73%), with Fidelity (79.57%) essentially at the dispersed level. Dimensional is a clear outlier at 72.84%, the only blockholder less pro-passage than the dispersed base.

Importantly, these preference indices are not the same object as raw voting frequencies: Table 1 shows that vote-for rates are substantially higher for several investors (e.g., Vanguard 92.7% and BlackRock 93.0%) than their corresponding  $\Phi(\delta_i)$  values, underscoring that equilibrium support need not move one-for-one with underlying preferences.

### 5.3. Naive versus Strategic Inference of Preferences

A common way to gauge investor preferences is to read them from voting records, treating an investor that supports management more often as more favorable to management. Our estimates imply that this inference is systematically biased: equilibrium support reflects not only preference but also the rational inference a shareholder draws from being pivotal, the strategic voting for which [Maug and Rydqvist \(2009\)](#) provide evidence. The gap between support rates and preferences distorts what votes reveal about preferences.

Table 4 quantifies this in two ways. Panel A compares, for each blockholder, the gap between her support rate and that of the dispersed base with the gap between the corresponding preference-implied support rates. Differences in voting are systematically larger than the differences in underlying preferences: BlackRock supports proposals 13.4 percentage points more often than dispersed shareholders, yet its preference-implied support differs by only 4.0 points; Dimensional supports 21.8 points *less* often, against a preference gap of just 6.7 points. The difference-in-differences in column (3) is significant for every blockholder. Reading the strength of preferences off the size of voting gaps therefore overstates preference heterogeneity several-fold, in both directions.

Panel B asks what a researcher would infer about each blockholder's preference from her support rate alone, using the estimated information environment but ignoring the strategic content of pivotality. This naive recovery overstates pro-management preferences for four of the six blockholders because part of their support reflects rational inference from being

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Say-on-Pay outcomes.

pivotal rather than preference. It also changes the ranking: BlackRock moves from first under the naive measure to fourth under the strategic model, while State Street moves from fourth to first. Dimensional is misread most sharply. Its low support rate implies near-indifference under the naive recovery,  $\Phi(\delta^{\text{naive}}) = 52.9\%$ , but the strategic model places it clearly pro-passage,  $\Phi(\hat{\delta}) = 72.8\%$ . For Dimensional, being pivotal is bad news about proposal quality, so its opposition partially reflects strategic inference rather than hostility to management.

#### 5.4. Information and Preference Heterogeneity in Shareholder Voting

A central question in the governance literature is whether blockholders vote differently from other shareholders because of differences in preferences or in information quality (Hu et al., 2024; Matsusaka and Shu, 2022; Bubb and Catan, 2022; Bolton et al., 2020). We implement counterfactuals that separately equalize information and preferences across investor types by assigning blockholders the same public and private information precision as dispersed shareholders, and separately the same preferences, re-solving for the equilibrium under each counterfactual. Table 5 reports counterfactual voting outcomes when blockholders are assigned dispersed preferences (column 2), dispersed information (column 3), or both (column 4).

Equalizing preferences pulls dispersed and blockholder support toward a common level: dispersed support rises from 81.46% to 84.37% and blockholder support falls from 90.17% to 84.64%, while total support and the passing rate barely move. The close-vote rate declines from 13.39% to 10.85%, so the electorate’s ability to separate proposals is largely preserved.

Equalizing information has larger and qualitatively different effects. Blockholder support rises to 94.89%: stripped of their information advantage, blockholders fall back on the prior and their pro-passage preferences, and vote for almost everything. The cross-proposal variance of total support collapses from 2.38% to 1.32%, the close-vote rate jumps from 13.39% to 18.00%, and the passing rate rises by more than three percentage points. This aggregate rise in close votes comes almost entirely from contested proposals: among those the advisor opposes, the close-vote rate shoots up from 39.42% to 54.34%, whereas among endorsed proposals it barely moves, from 6.11% to 7.84% (Table 5, Panel B).

The close-vote rate and the variance of total support tell the same story. Blockholders’

precise signals make their vote shares track proposal quality, pushing both bad and good proposals away from the threshold. Removing that state-contingency makes voting outcomes cluster near the threshold regardless of the value of  $x_j$ . Equalizing preferences, on the other hand, leaves the state-contingency intact and has a small impact on aggregate outcomes.

While our results suggest that blockholders are somewhat biased toward management relative to dispersed shareholders, they vote in favor because their precise information tells them a proposal is good or bad, even when it is marginally close to the threshold. This has important implications for the governance literature and policy. Policies targeted at better representation of preferences (e.g., pass-through voting) risk distorting the informational advantage of blockholders.

## 5.5. Robustness of the Information and Preference Estimates

We conclude with two robustness tests that provide additional evidence on important aspects of the information environment on which the estimates rest. The first asks whether blockholders actually condition on the event that their vote is decisive, using a relationship the estimation does not target; the second asks whether the common component of institutional voting attributed to shared public information could instead be shared preferences.

### 5.5.1. Untargeted Evidence on Pivotal Conditioning

The voting equilibrium embeds the assumption that blockholders condition on the event that their vote is decisive; a natural concern is that this strategic content is imposed by the equilibrium structure rather than borne out by observed voting behavior. The concern matters because the mapping from observed votes to preferences depends on the pivotality adjustment, so the interpretation of the preference estimates relies on blockholders conditioning on decisiveness.

For every blockholder–proposal pair we compute the model-implied probability that the blockholder’s vote is decisive,  $\widehat{\text{piv}}_{bj}$ , based on the proposal’s ISS recommendation and ownership configuration. The predictor is constructed out of sample, with parameters estimated on data that exclude the proposal’s year, and the relationship between votes and decisiveness is not targeted in estimation. We ask whether votes respond to predicted decisiveness, in the

data and in model-simulated votes under the identical specification; Appendix D.1 details the construction, specification, and simulation underlying the test.

Table 6 reports the comparison: in the data, a ten percentage point increase in predicted decisiveness is associated with a 1.45 percentage point increase in support; the corresponding model-implied response is 1.71 percentage points.<sup>20</sup> Excluding the two near-unanimous blockholder  $\times$  recommendation cells, where votes have little room to move, the response is 4.39 (7.26) percentage points in the data (model).<sup>21</sup>

The full-sample comparison provides untargeted evidence consistent with pivotal conditioning: votes move with the model-implied probability of decisiveness, and the response in the data is similar in magnitude to that implied by the model for a relationship not targeted in estimation. In the restricted sample, the model predicts a larger response than appears in the data, suggesting that it may overstate the quantitative strength of pivotal conditioning. Because pivotal inference contributes to the mapping from observed support to recovered preferences, the exercise provides additional support for that interpretation of the preference estimates, while indicating that its magnitude should be interpreted with some caution.

### 5.5.2. Common Proposal-Level Preference Shocks

A second concern is that the common component of blockholder voting attributed to public information could instead reflect proposal characteristics that make all institutions more or less inclined to support the proposal. We allow this leading alternative to compete directly with the information channel by augmenting each blockholder’s voting index with a proposal-specific common preference component,

$$V_{bj} = \mathbf{1} \left[ m_{bj} + v_j \geq k_b \right], \quad v_j \sim N(0, \sigma_v^2),$$

where  $v_j$  is common to the blockholders, absent for dispersed shareholders, and independent of proposal quality, the advisor report, and all private signals. The extension adds one

<sup>20</sup>The positive relationship is an equilibrium implication rather than a mechanical feature of the predictor: in the relevant configurations, being decisive indicates that support from the other shareholders is strong enough to bring the proposal near passage, which is favorable news about quality.

<sup>21</sup>The excluded cells are Vanguard’s and BlackRock’s votes on proposals the advisor endorses, where both institutions’ For rates exceed 99%.

parameter and reduces exactly to the baseline model when  $\sigma_v = 0$ .

The two channels have distinct implications for the estimation moments. Both shared information and  $v_j$  can generate institutional co-voting. A common preference component that is orthogonal to quality, however, does not generate the corresponding relationship between blockholder votes and dispersed support. The estimation therefore allows the common preference component to absorb the co-voting otherwise attributed to public information, while the vote–support moments discipline how much of that substitution is consistent with the data. We re-estimate all parameters using the same moments and weighting matrix, both profiling over  $\sigma_v$  and estimating it jointly with the baseline parameters.

The common preference channel absorbs essentially none of the estimated co-movement. The criterion is minimized at  $\hat{\sigma}_v = 0.048$ , improving on the baseline criterion by only 0.07, and the profile places a 95% upper bound of 0.152 in cutoff units. At the unrestricted estimate, the channel accounts for less than one percent of predicted blockholder co-voting. More importantly, allowing it to compete with shared information leaves the estimated public- and private-information parameters essentially unchanged throughout the admissible range. The information decomposition is therefore not an artifact of excluding a common, quality-orthogonal institutional preference component. The exercise does not distinguish information from preference variation that is itself correlated with proposal quality. Details are in [Appendix D.2](#).

## 6. Conclusion

Institutional investors are central participants in shareholder voting, yet observed vote records may not map into underlying preferences when proposals are evaluated under incomplete information and voters act strategically. This paper develops and estimates a structural model of management-sponsored proposals in which shareholders differ in ownership stakes, information precision, and intrinsic preferences for passage. In equilibrium, voting follows cutoff strategies that reflect not only investors’ own signals, but also strategic inference from the voting environment itself, particularly the information embedded in being pivotal.

Estimating the model using Say-on-Pay votes and mutual fund voting records, we recover

institution-level information and preference parameters and show that preference-implied support differs from realized support. This divergence is not merely informational: a preference that nets out information effects but ignores the inference shareholders draw from being pivotal still differs sharply from the unconditional preference, and reorders blockholders' preference ranking. Reading preferences from votes thus requires accounting for strategic inference, not information alone. Because large institutions hold more precise information than dispersed shareholders, higher observed support need not indicate weaker monitoring or a stronger preference for passage.

The counterfactuals show that information, rather than preferences, is the more important margin for aggregate outcomes, with these effects concentrated in votes where the outcome is ex ante more uncertain, namely, when ISS recommends against the proposal. More broadly, the results imply that interpreting shareholder voice requires disentangling information from preferences and that policies equalizing influence across investors may discard the information embedded in blockholder votes.

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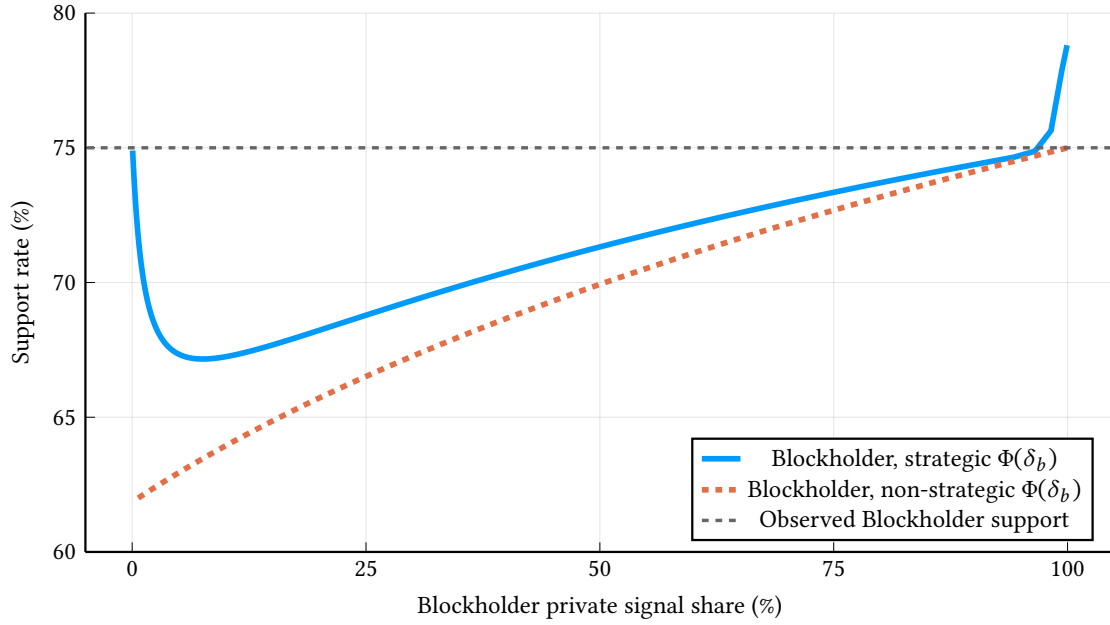
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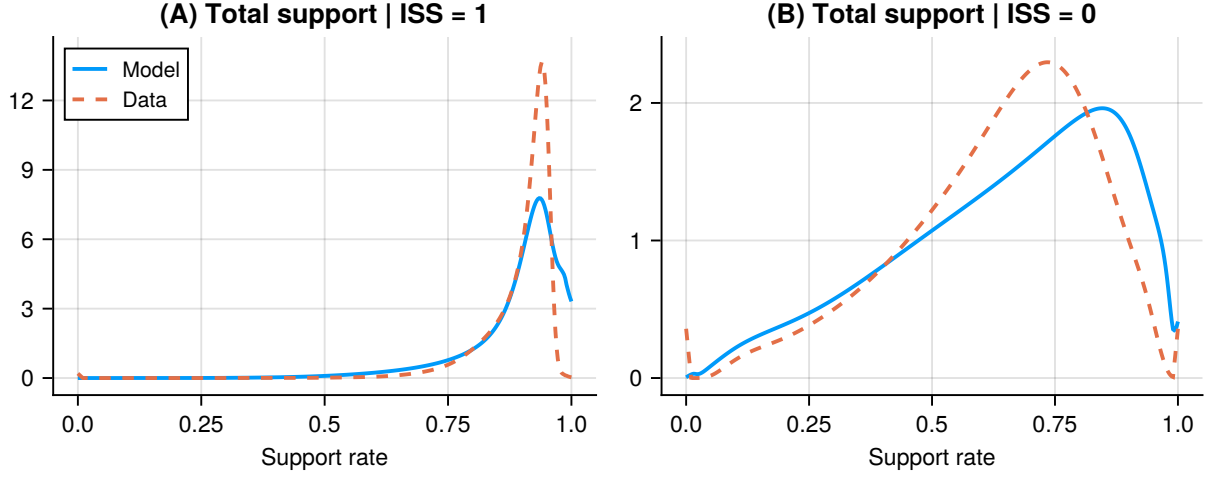
**Figure 1.** Comparative static exercise: Observationally equivalent blockholder support rates under different information and preference parameters

This figure presents the comparative static exercise from Section 3.2. One blockholder owns 20% of the firm, with the remainder held by dispersed shareholders. Both groups observe the advisor's report ( $\sigma_{vD} = 0$ ,  $\sigma_{uI} = 2$ ), dispersed private-signal noise is  $\sigma_{\varepsilon D} = 3$ , and the passing threshold is a simple majority. Dispersed shareholders are calibrated to an unconditional support rate of 75%, and the blockholder's observed support rate is held at 75% throughout (grey dashed line). As the blockholder's private-signal noise  $\sigma_{\varepsilon b}$  varies, her cutoff  $k_b$  is set to reproduce the observed support rate, and the preference that rationalizes the cutoff is recovered with and without strategic voting. The solid curve plots the preference-implied support rate  $\Phi(\delta_b)$  under strategic voting, where  $\delta_b$  solves the indifference condition in Definition 1; the dashed curve plots the non-strategic counterpart, recovered from  $p_b^{NS} = \Pr(m_b \geq -\delta_b)$ . The horizontal axis is the share of the blockholder's posterior precision contributed by her private signal,  $\frac{1/\sigma_{\varepsilon b}^2}{1+1/\sigma_{uI}^2+1/\sigma_{\varepsilon b}^2}$ .



**Figure 2.** Model fit: Distribution of support

This figure compares the empirical distribution of support rates to the distribution implied by simulations of the estimated model. The solid lines plot kernel density estimates of the simulated distributions and the dashed lines plot the same from the data. To construct the simulated distributions, we hold each proposal's blockholder ownership structure fixed at its empirical values (the set of blockholders, their ownership shares  $\{\psi_{bj}\}_b$ , and associated blockholder counts), and draw the latent state and shocks from the estimated model. Given simulated dispersed support and ISS recommendation  $(\tau_j, S_j)$ , we generate blockholder support using the blockholder-level model-implied voting probabilities; total support is then  $\tau_j + s_{Bj}$ .



**Table 1.** Summary statistics

This table summarizes the sample of Say-on-Pay proposals we use to estimate the model. In Panel A, we provide statistics at the proposal-level. Number of blockholders is the count of blockholders that own the firm and whom we can match a vote to; we define a blockholder as a shareholder who owns more than five percent of the firm’s shares on a turnout-adjusted basis. Total support is the number of shares voted in support of the proposal divided by the number of votes cast. Dispersed and blockholder support are the percent shareholders supporting the proposal, conditional on type, imputed using the method described in the text. Passing vote is a dummy variable equal to one if the proposal’s support rate exceeds the 70% passing threshold. Close vote is a dummy variable equal to one if the proposal’s total support is between 60% and 80%. In Panel B, we provide statistics at the blockholder-level. Number of votes lists the number of proposals in the sample that the blockholder appears as a block shareholder. Average ownership is the blockholder’s average ownership across all proposals. Support rate is the percent of proposals supported by the blockholder. Pivot probability is the percent of proposals where had the blockholder changed its vote, the proposal would have passed (failed) if it actually failed (passed).

| Panel A. Proposal-level |      |        |        |         |         |         |
|-------------------------|------|--------|--------|---------|---------|---------|
|                         | (1)  | (2)    | (3)    | (4)     | (5)     | (6)     |
|                         | N    | Mean   | SD     | 25th    | 50th    | 75th    |
| Number of blockholders  | 7851 | 2.68   | 0.88   | 2       | 3       | 3       |
| Blockholder ownership   | 7851 | 28.14% | 11.57% | 20.85%  | 28.36%  | 35.41%  |
| Total support           | 7851 | 84.16% | 14.81% | 80.59%  | 90.46%  | 93.62%  |
| Blockholder support     | 7780 | 89.56% | 24.67% | 100.00% | 100.00% | 100.00% |
| Dispersed support       | 7851 | 81.44% | 15.00% | 77.63%  | 87.45%  | 91.09%  |
| Passing vote            | 7851 | 86.24% |        |         |         |         |
| Close vote              | 7851 | 16.09% |        |         |         |         |

| Panel B. Blockholder-level |          |           |              |             |          |         |
|----------------------------|----------|-----------|--------------|-------------|----------|---------|
|                            | (1)      | (2)       | (3)          | (4)         | (5)      | (6)     |
|                            | Vanguard | BlackRock | State Street | Dimensional | Fidelity | T. Rowe |
| Number of votes            | 7422     | 7088      | 2676         | 1568        | 1253     | 996     |
| Average ownership          | 11.28%   | 11.89%    | 6.80%        | 7.90%       | 9.99%    | 9.92%   |
| Support rate               | 92.70%   | 92.96%    | 90.10%       | 58.10%      | 86.03%   | 90.36%  |
| Pivot probability          | 12.29%   | 14.60%    | 4.48%        | 6.44%       | 12.61%   | 10.14%  |

**Table 2.** Model fit

This table compares data moments with their model-implied counterparts at the estimated parameters. Panel A reports proposal-level moments: means and variances of dispersed and total support by recommendation cell, the passing and close-vote rates, the recommendation frequency, and the average marginal effect of the recommendation on dispersed support. Panel B reports blockholder-level moments: each blockholder's voting probability by recommendation cell, its pivot probability (the share of proposals on which switching that blockholder's vote would change the outcome), and the marginal co-movement of its vote with dispersed support. Model columns are computed from simulations that hold each proposal's blockholder ownership structure fixed at its empirical value, draw states and signals from the estimated model, and record realized votes; simulated proposals are reweighted so that the joint distribution of dispersed-support quintiles and the recommendation matches the data. Panel C reports an untargeted external validation: the model-implied effect of flipping the advisor's recommendation on the probability of passage, alongside the regression-discontinuity estimate that a negative recommendation lowers say-on-pay voting support by 26.6 percentage points in the specification with full controls (Malenko and Shen, 2016, Table 3, column 5); the sample and estimand differ (passage probability versus voting support), so the comparison speaks to magnitude consistency only.

| <b>Panel A. Proposal-level</b>                             |        |        |
|------------------------------------------------------------|--------|--------|
|                                                            | (1)    | (2)    |
|                                                            | Data   | Model  |
| $E[\text{Dispersed support} \mid \text{ISS} = 0]$          | 62.41% | 64.62% |
| $\text{Var}(\text{Dispersed support} \mid \text{ISS} = 0)$ | 3.53%  | 3.17%  |
| $E[\text{Dispersed support} \mid \text{ISS} = 1]$          | 86.76% | 83.81% |
| $\text{Var}(\text{Dispersed support} \mid \text{ISS} = 1)$ | 0.60%  | 1.68%  |
| $E[\text{Total support} \mid \text{ISS} = 0]$              | 63.64% | 64.37% |
| $\text{Var}(\text{Total support} \mid \text{ISS} = 0)$     | 3.15%  | 4.36%  |
| $E[\text{Total support} \mid \text{ISS} = 1]$              | 89.91% | 89.07% |
| $\text{Var}(\text{Total support} \mid \text{ISS} = 1)$     | 0.43%  | 0.86%  |
| Passing vote                                               | 86.24% | 84.42% |
| Close vote                                                 | 16.09% | 16.22% |
| $\text{Pr}(\text{ISS} = 1)$                                | 78.16% | 78.37% |
| ISS-Dispersed support AME                                  | 1.48%  | 1.49%  |

**Panel B.** Blockholder-level

|                                    | (1)      | (2)    | (3)       | (4)    | (5)          | (6)    | (7)         | (8)    | (9)      | (10)   | (11)    | (12)   |
|------------------------------------|----------|--------|-----------|--------|--------------|--------|-------------|--------|----------|--------|---------|--------|
|                                    | Vanguard |        | BlackRock |        | State Street |        | Dimensional |        | Fidelity |        | T. Rowe |        |
|                                    | Data     | Model  | Data      | Model  | Data         | Model  | Data        | Model  | Data     | Model  | Data    | Model  |
| $\Pr(V_b = 1 \mid \text{ISS} = 0)$ | 67.22%   | 67.90% | 69.23%    | 68.47% | 47.75%       | 44.49% | 3.85%       | 5.29%  | 51.51%   | 48.13% | 66.06%  | 64.65% |
| $\Pr(V_b = 1 \mid \text{ISS} = 1)$ | 99.49%   | 99.52% | 99.30%    | 99.60% | 97.54%       | 99.01% | 71.58%      | 70.91% | 98.48%   | 98.81% | 97.29%  | 99.63% |
| Pivot probability                  | 12.29%   | 13.43% | 14.60%    | 15.34% | 4.48%        | 5.94%  | 6.44%       | 7.45%  | 12.61%   | 10.44% | 10.14%  | 9.81%  |
| $V_b$ -Dispersed support AME       | 0.45%    | 0.43%  | 0.41%     | 0.41%  | 0.62%        | 0.60%  | 2.10%       | 2.15%  | 0.66%    | 0.63%  | 0.46%   | 0.41%  |

**Panel C.** External validation

|                                                       | (1)      | (2)                                                              |
|-------------------------------------------------------|----------|------------------------------------------------------------------|
|                                                       | Model    | External benchmark<br>( <a href="#">Malenko and Shen, 2016</a> ) |
| ISS recommendation-flip effect on passage probability |          |                                                                  |
| All proposals                                         | 13.43 pp | –                                                                |
| Negative-recommendation proposals                     | 25.64 pp | 26.6 pp (RD, voting support)                                     |

**Table 3.** Estimated parameters

This table reports the estimated parameters of the information structure and voting behavior. Panel A displays the public-information parameters: the recommendation threshold  $\xi$  (in units of the standardized report), the advisor's signal noise  $\sigma_{u_I}$ , the dispersed composite public noise  $\sigma_{u_D}$ , and the implied correlation between the two groups' public-signal errors,  $\text{Corr}(u_D, u_I) = \sigma_{u_I} / \sigma_{u_D}$ . Panel B displays parameters for each shareholder type  $i \in \{D, \{b\}_1^{N_b}\}$ : the private-signal noise  $\sigma_i$ , the equilibrium voting cutoff  $k_i$ , and the preference  $\delta_i$ . Analytic standard errors, clustered at the proposal level, are reported in parentheses, and 95% percentile confidence intervals from a recentered proposal-cluster bootstrap (400 draws) in brackets. See Appendix C.3 for details. Panel C reports each type's preference-implied support rate  $\Phi(\delta_i)$  and the decomposition of posterior-belief variance into prior, common-signal (the advisor's report), and private-signal shares; standard errors in parentheses are from the same recentered proposal-cluster bootstrap.

| Panel A. Public Information Parameters |                |                |                         |
|----------------------------------------|----------------|----------------|-------------------------|
| (1)                                    | (2)            | (3)            | (4)                     |
| $\xi$                                  | $\sigma_{u_I}$ | $\sigma_{u_D}$ | $\text{Corr}(u_D, u_I)$ |
| -0.79                                  | 1.16           | 6.23           | 0.19                    |
| (0.02)                                 | (0.03)         | (0.39)         | (0.01)                  |
| [-0.82,-0.75]                          | [1.08,1.28]    | [5.76,10.51]   | [0.12,0.21]             |

**Panel B.** Dispersed and Blockholder Parameters

|            | (1)                              | (2)                              | (3)                              | (4)                              | (5)                              | (6)                              | (7)                              |
|------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|
|            | Dispersed                        | Blockholders                     |                                  |                                  |                                  |                                  |                                  |
| Parameter  | Dispersed                        | Vanguard                         | BlackRock                        | State Street                     | Dimensional                      | Fidelity                         | T. Rowe                          |
| $\sigma_i$ | 1.92<br>(0.09)<br>[1.61,2.09]    | 0.92<br>(0.14)<br>[0.73,1.23]    | 1.02<br>(0.18)<br>[0.78,1.43]    | 1.42<br>(0.38)<br>[0.94,2.55]    | 1.05<br>(0.12)<br>[0.81,1.37]    | 1.93<br>(1.25)<br>[1.29,4.54]    | 1.21<br>(1.54)<br>[0.80,2.74]    |
| $k_i$      | -0.40<br>(0.01)<br>[-0.44,-0.38] | -1.21<br>(0.04)<br>[-1.27,-1.12] | -1.21<br>(0.05)<br>[-1.29,-1.11] | -0.94<br>(0.04)<br>[-1.03,-0.84] | -0.07<br>(0.02)<br>[-0.10,-0.03] | -0.86<br>(0.03)<br>[-0.94,-0.79] | -1.15<br>(0.10)<br>[-1.30,-0.99] |
| $\delta_i$ | 0.82<br>(0.04)<br>[0.74,0.94]    | 1.02<br>(0.06)<br>[0.85,1.10]    | 0.97<br>(0.07)<br>[0.83,1.08]    | 1.02<br>(0.04)<br>[0.92,1.08]    | 0.61<br>(0.06)<br>[0.49,0.81]    | 0.83<br>(0.04)<br>[0.75,0.92]    | 0.98<br>(0.14)<br>[0.68,1.11]    |

**Panel C. Parameter interpretations**

|                                         | (1)               | (2)               | (3)               | (4)               | (5)               | (6)               | (7)                |
|-----------------------------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|--------------------|
|                                         | Blockholders      |                   |                   |                   |                   |                   |                    |
| Parameter                               | Dispersed         | Vanguard          | BlackRock         | State Street      | Dimensional       | Fidelity          | T. Rowe            |
| <b>Preference-implied support rates</b> |                   |                   |                   |                   |                   |                   |                    |
| $\Phi(\delta_i)$                        | 79.50%<br>(0.89%) | 84.54%<br>(0.88%) | 83.49%<br>(0.92%) | 84.59%<br>(0.68%) | 72.84%<br>(1.56%) | 79.57%<br>(0.98%) | 83.73%<br>(1.68%)  |
| <b>Variance shares</b>                  |                   |                   |                   |                   |                   |                   |                    |
| Prior                                   | 77.03%<br>(1.84%) | 34.09%<br>(4.06%) | 36.99%<br>(4.40%) | 44.65%<br>(5.10%) | 37.73%<br>(4.13%) | 49.76%<br>(4.87%) | 41.31%<br>(8.06%)  |
| Common signal                           | 1.98%<br>(0.41%)  | 25.31%<br>(2.39%) | 27.47%<br>(2.81%) | 33.16%<br>(3.55%) | 28.01%<br>(2.27%) | 36.94%<br>(3.33%) | 30.67%<br>(5.65%)  |
| Private signal                          | 20.99%<br>(2.22%) | 40.59%<br>(5.88%) | 35.54%<br>(6.62%) | 22.19%<br>(7.97%) | 34.26%<br>(5.77%) | 13.30%<br>(7.26%) | 28.02%<br>(13.31%) |

**Table 4.** Naive vs. strategic inference of shareholder preferences

Panel A compares, for each blockholder, the gap between her support rate and that of the dispersed base with the gap between the corresponding preference-implied support rates. Column (1) is the difference in model-implied support rates,  $\hat{p}_D - \hat{p}_b$ ; column (2) the difference in preference-implied support rates,  $\Phi(\hat{\delta}_D) - \Phi(\hat{\delta}_b)$ , preference alone translated into probability units with no information or strategic structure; column (3) is their difference-in-differences. Standard errors, from a proposal-clustered bootstrap of the joint distribution of the estimates, are reported in parentheses; the bootstrap respects the correlation of sampling errors across quantities recovered from the same  $\hat{\theta}$ . Panel B compares, for each of the six blockholders, the raw support rate  $\hat{p}_b$ , the preference a researcher would infer from it under the counterfactual assumption that shareholder  $b$  votes sincerely, using the naive cutoff  $-\delta_b$  rather than the equilibrium (pivotality-adjusted) cutoff while holding the estimated information environment fixed and matching  $b$ 's observed level of support, and the preference implied by the estimated strategic equilibrium; preferences are expressed as preference-implied support rates  $\Phi(\delta)$ . Standard errors in parentheses are from the same proposal-clustered bootstrap as in Panel A. Entities are ranked from most to least pro-management separately under each assumption. Panel A entries are differences in percentage points; Panel B entries are in percent.

| <b>Panel A.</b> Dispersed vs. each blockholder (percentage points) |                                                  |                                                                      |                        |
|--------------------------------------------------------------------|--------------------------------------------------|----------------------------------------------------------------------|------------------------|
|                                                                    | (1)                                              | (2)                                                                  | (3)                    |
|                                                                    | $\Delta$ support rate<br>$\hat{p}_D - \hat{p}_b$ | $\Delta$ preference<br>$\Phi(\hat{\delta}_D) - \Phi(\hat{\delta}_b)$ | Diff-Diff<br>(1) – (2) |
| BlackRock                                                          | -13.37%<br>(0.37)                                | -3.98%<br>(2.76)                                                     | -9.39%<br>(2.72)       |
| Vanguard                                                           | -13.21%<br>(0.34)                                | -5.03%<br>(2.71)                                                     | -8.18%<br>(2.66)       |
| T. Rowe                                                            | -12.21%<br>(0.87)                                | -4.23%<br>(3.82)                                                     | -7.98%<br>(3.90)       |
| State Street                                                       | -11.20%<br>(0.51)                                | -5.09%<br>(1.55)                                                     | -6.11%<br>(1.57)       |
| Fidelity                                                           | -5.72%<br>(0.93)                                 | -0.07%<br>(1.94)                                                     | -5.65%<br>(2.02)       |
| Dimensional                                                        | 21.80%<br>(1.01)                                 | 6.67%<br>(1.32)                                                      | 15.14%<br>(1.44)       |

**Panel B.** Naive vs. strategic ranking (percent)

|              | (1)              | (2)                             | (3)                                     | (4)                    | (5)                            |
|--------------|------------------|---------------------------------|-----------------------------------------|------------------------|--------------------------------|
|              | $\hat{p}_b$      | $\Phi(\delta_b^{\text{naive}})$ | Rank<br>$\Phi(\delta_b^{\text{naive}})$ | $\Phi(\hat{\delta}_b)$ | Rank<br>$\Phi(\hat{\delta}_b)$ |
| BlackRock    | 93.03%<br>(0.29) | 88.49%<br>(0.84)                | 1                                       | 83.49%<br>(1.65)       | 4                              |
| Vanguard     | 92.87%<br>(0.25) | 88.38%<br>(0.76)                | 2                                       | 84.54%<br>(1.50)       | 2                              |
| T. Rowe      | 91.87%<br>(0.84) | 85.78%<br>(1.68)                | 3                                       | 83.73%<br>(3.25)       | 3                              |
| State Street | 90.86%<br>(0.47) | 81.43%<br>(1.19)                | 4                                       | 84.59%<br>(0.99)       | 1                              |
| Fidelity     | 85.38%<br>(0.89) | 81.09%<br>(1.10)                | 5                                       | 79.57%<br>(1.19)       | 5                              |
| Dimensional  | 57.85%<br>(0.99) | 52.86%<br>(0.74)                | 6                                       | 72.84%<br>(2.45)       | 6                              |

**Table 5.** The impact of information and preference heterogeneity on shareholder voting outcomes

This table displays the impact of equalizing preferences and information across shareholders. In particular, we first set all blockholders to have the same preference as dispersed shareholders (i.e.,  $\delta_b = \delta_D$  for all  $b$ ). Then, we set all blockholders to have the same information quality as dispersed shareholders (i.e.,  $\sigma_{\varepsilon_b} = \sigma_{\varepsilon_D}$  for all  $b$ , with each blockholder observing a public signal with noise  $\sigma_{u_D}$  in place of the report). To estimate each counterfactual, we solve the model under the counterfactual parameter vector, and then use the moment-generating conditions to build counterfactual outcomes. In Panel A, in column (1), for consistency, we also solve the model under the estimated parameters, so the displayed moments are not perfectly consistent with the GMM-based moments (though very close). In column 2, we display results from the equal preferences counterfactual, and in column 3 we display results from the equal information counterfactual. Column 4 displays results from a counterfactual in which both preferences and information are equalized. Panel B displays analogous results, split by ISS recommendation.

| <b>Panel A. All proposals</b> |            |                      |                      |        |
|-------------------------------|------------|----------------------|----------------------|--------|
|                               | (1)        | (2)                  | (3)                  | (4)    |
|                               | Full model | Equalize preferences | Equalize information | Both   |
| Dispersed support             | 81.46%     | 84.37%               | 80.78%               | 80.56% |
| Blockholder support           | 90.17%     | 84.64%               | 94.89%               | 96.06% |
| Total support                 | 84.02%     | 84.71%               | 84.92%               | 84.85% |
| Var(Total support)            | 2.38%      | 2.72%                | 1.32%                | 1.37%  |
| Passing rate                  | 85.43%     | 84.88%               | 88.75%               | 88.49% |
| Close rate                    | 13.39%     | 10.85%               | 18.00%               | 16.85% |

**Panel B.** By ISS recommendation

|                     | (1)        | (2)    | (3)                  | (4)    | (5)                  | (6)    | (7)    | (8)    |
|---------------------|------------|--------|----------------------|--------|----------------------|--------|--------|--------|
|                     | Full model |        | Equalize preferences |        | Equalize information |        | Both   |        |
|                     | ISS=0      | ISS=1  | ISS=0                | ISS=1  | ISS=0                | ISS=1  | ISS=0  | ISS=1  |
| Dispersed support   | 62.43%     | 86.78% | 66.76%               | 89.30% | 61.47%               | 86.18% | 61.16% | 85.98% |
| Blockholder support | 63.19%     | 97.67% | 42.73%               | 96.30% | 92.99%               | 95.42% | 92.41% | 97.08% |
| Total support       | 62.59%     | 90.01% | 60.82%               | 91.38% | 70.33%               | 89.01% | 69.60% | 89.11% |
| Var(Total support)  | 3.72%      | 0.36%  | 3.95%                | 0.34%  | 1.95%                | 0.38%  | 2.09%  | 0.34%  |
| Passing rate        | 37.90%     | 98.71% | 34.64%               | 98.92% | 53.88%               | 98.50% | 52.13% | 98.65% |
| Close rate          | 39.42%     | 6.11%  | 34.23%               | 4.32%  | 54.34%               | 7.84%  | 52.42% | 6.91%  |

**Table 6.** Untargeted validation of pivotal conditioning

Each entry is the coefficient  $\beta$  on  $\widehat{\text{piv}}_{bj}$ , the model-implied ex-ante probability that blockholder  $b$ 's vote is decisive on proposal  $j$ , computed from the proposal's observed ownership configuration and ISS recommendation at parameters estimated excluding the proposal's year (equation (D.37)), from the linear probability specification:

$$V_{bj} = \alpha_{b \times S_j} + \beta \widehat{\text{piv}}_{bj} + \gamma' w_{bj} + \varepsilon_{bj},$$

where  $\alpha_{b \times S_j}$  are blockholder  $\times$  recommendation fixed effects and  $w_{bj}$  collects the ownership controls (own stake, other blockholders' total stake, and the number of blockholders present) and the realized dispersed support  $\tau_j$ . The Data specifications use actual votes, with standard errors clustered by proposal in parentheses. The Model specifications replace the outcome with the vote probability implied by re-solving the equilibrium indifference condition of Definition 1 at each proposal's ownership configuration; the standard errors are the dispersion of the coefficient across 100 Bernoulli-simulated vote panels. The predictor uses no realized votes or support and none of blockholder  $b$ 's own estimated parameters. The full sample has  $N = 20,007$  blockholder-proposal vote rows; the second column excludes the two near-unanimous blockholder $\times$ recommendation cells (Vanguard and BlackRock under an ISS For recommendation, For rates above 0.99), leaving  $N = 9,078$ . See Appendix D.1 for further details.

|                                                   | (1)              | (2)                   |
|---------------------------------------------------|------------------|-----------------------|
| Response of voting to $\widehat{\text{piv}}_{bj}$ | Full sample      | Excl. saturated cells |
| Data                                              | 0.145<br>(0.042) | 0.439<br>(0.135)      |
| Model                                             | 0.171<br>(0.038) | 0.726<br>(0.116)      |
| Observations                                      | 20,007           | 9,078                 |

## A. Appendix Figures and Tables

**Table A.1.** Definitions of empirical quantities

| Quantity                                       | Definition                                                                                                                                                                    |
|------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>Proposal-level variables</b>                |                                                                                                                                                                               |
| $S_j$                                          | ISS recommendation: $S_j = 1$ if ISS recommends voting <i>For</i> the proposal, $S_j = 0$ if <i>Against</i> . Tables label these cells ISS = 1 and ISS = 0.                   |
| $\lambda_j$                                    | Total support rate: shares voted <i>For</i> divided by total votes cast on the proposal.                                                                                      |
| $\tau_j$                                       | Dispersed support rate: support among dispersed shareholders, imputed from total support and blockholder votes, $\tau_j = (\lambda_j - V_j^{BT} \psi_{Bj}^X) / \Psi_{Dj}^X$ . |
| $s_{Bj}$                                       | Blockholder support: ownership-weighted share of blockholders voting <i>For</i> , $V_j^{BT} \psi_{Bj}^X / \Psi_{Bj}^X$ .                                                      |
| $T_j$                                          | Probit-transformed dispersed support, $T_j = \Phi^{-1}(\tau_j)$ ; the scale on which the dispersed reduced form is estimated.                                                 |
| $\chi_j$                                       | Turnout: shares voted divided by shares outstanding.                                                                                                                          |
| Passing vote                                   | Indicator $\mathbb{1}\{\lambda_j > 70\%\}$ : total support exceeds the 70% threshold used to classify Say-on-Pay outcomes.                                                    |
| Close vote                                     | Indicator $\mathbb{1}\{60\% \leq \lambda_j \leq 80\%\}$ : total support falls between 60% and 80%.                                                                            |
| <b>Proposal-level moments</b>                  |                                                                                                                                                                               |
| $\Pr(\text{ISS} = 1)$                          | Recommendation frequency: share of proposals ISS recommends <i>For</i> .                                                                                                      |
| $\mathbb{E}[\cdot \mid \text{ISS} = s]$        | Mean of dispersed or total support within recommendation cell $s \in \{0, 1\}$ ; on the probit scale, $\mathbb{E}[T_j \mid S_j = s]$ .                                        |
| $\text{Var}(\cdot \mid \text{ISS} = s)$        | Cross-proposal variance of dispersed or total support within recommendation cell $s$ .                                                                                        |
| ISS–Dispersed support AME                      | Average marginal effect of the recommendation on dispersed support: the mean change in $\tau_j$ associated with $S_j = 1$ versus $S_j = 0$ .                                  |
| <b>Blockholder-level variables and moments</b> |                                                                                                                                                                               |
| Blockholder                                    | A 13F manager whose turnout-adjusted ownership in the proposal is at least 5%.                                                                                                |
| $V_{bj}$                                       | Blockholder $b$ 's vote: $V_{bj} = 1$ if $b$ votes <i>For</i> proposal $j$ .                                                                                                  |
| $\psi_{bj}$                                    | Blockholder $b$ 's turnout-adjusted ownership share in proposal $j$ .                                                                                                         |

*Continued on next page*

Table A.1 (continued)

| Quantity                                          | Definition                                                                                                                                                                                          |
|---------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Support rate ( $\hat{p}_b$ )                      | Share of the proposals on which $b$ is a blockholder that $b$ votes For.                                                                                                                            |
| $\Pr(V_b = 1 \mid \text{ISS} = s)$                | Blockholder $b$ 's vote-For rate within recommendation cell $s$ .                                                                                                                                   |
| Pivot probability                                 | Share of proposals on which reversing $b$ 's vote would change the pass/fail outcome.                                                                                                               |
| $V_b$ -Dispersed support AME                      | Average co-movement of $b$ 's vote with dispersed support: the mean change in $\tau_j$ associated with $V_{bj} = 1$ .                                                                               |
| Number of votes                                   | Number of proposals on which $b$ appears as a blockholder.                                                                                                                                          |
| <b>Identifying moments and derived quantities</b> |                                                                                                                                                                                                     |
| Leave-out covariance                              | $\text{Cov}(V_{bj} - \bar{V}_{-b,j}, \tau_j \mid S_j = s)$ : covariance of $b$ 's vote, netted against the other blockholders' average $\bar{V}_{-b,j}$ , with dispersed support, within cell $s$ . |
| Mean co-voting                                    | $\text{Cov}(V_{bj}, \bar{V}_{-b,j} \mid S_j = 0)$ : average co-movement of $b$ 's vote with the other blockholders on proposals the advisor opposes.                                                |
| $\text{Var}(\bar{V}_j \mid \text{ISS} = s)$       | Cross-proposal variance of average blockholder support within recommendation cell $s$ .                                                                                                             |
| $\Phi(\delta_i)$                                  | Preference-implied support rate: the share of proposals type $i$ would ideally like to pass, absent any information or strategic considerations.                                                    |
| $\Phi(\delta_b^{\text{naive}})$                   | Naive preference-implied support: the preference a researcher would infer from $b$ 's raw support rate under sincere voting, holding the estimated information environment fixed.                   |

**Table A.2.** Targeted moments and model fit

This table reports the moments matched by the GMM estimator, grouped as in Appendix C.3: the first-stage block, blockholder vote rates by recommendation cell, the aggregate co-movement of blockholder support, the leave-out covariances with dispersed support, and mean co-voting in the against-recommendation cell. Data and Model are the sample moments and their model-implied counterparts at the estimated parameters; Diff is model minus data; the  $t$ -statistic standardizes Diff by its proposal-clustered standard error.  $V_1, \dots, V_6$  index Vanguard, BlackRock, State Street, Dimensional, Fidelity, and T. Rowe;  $BH_{agg}$  is average blockholder support.

| Notation                                       | Data  | Model | Diff   | $t$ -stat |
|------------------------------------------------|-------|-------|--------|-----------|
| <i>First-stage (dispersed, proposal-level)</i> |       |       |        |           |
| $\mathbb{E}[T \mid S=1]$                       | 1.165 | 1.144 | -0.020 | -5.051    |
| $\mathbb{E}[T \mid S=0]$                       | 0.369 | 0.424 | +0.055 | 3.785     |
| $\text{Var}(\tau \mid S=0)$                    | 0.035 | 0.032 | -0.004 | -2.996    |
| $\text{Var}(\tau \mid S=1)$                    | 0.006 | 0.017 | +0.011 | 12.296    |
| $\text{Pr}(S=1)$                               | 0.782 | 0.784 | +0.002 | 0.456     |
| <i>Blockholder vote rates</i>                  |       |       |        |           |
| $\text{Pr}(V_1=1 \mid S=0)$                    | 0.672 | 0.679 | +0.007 | 0.572     |
| $\text{Pr}(V_1=1 \mid S=1)$                    | 0.995 | 0.995 | +0.000 | 0.339     |
| $\text{Pr}(V_2=1 \mid S=0)$                    | 0.692 | 0.685 | -0.008 | -0.640    |
| $\text{Pr}(V_2=1 \mid S=1)$                    | 0.993 | 0.996 | +0.003 | 2.631     |
| $\text{Pr}(V_3=1 \mid S=0)$                    | 0.477 | 0.445 | -0.033 | -1.307    |
| $\text{Pr}(V_3=1 \mid S=1)$                    | 0.975 | 0.990 | +0.015 | 4.513     |
| $\text{Pr}(V_4=1 \mid S=0)$                    | 0.038 | 0.053 | +0.014 | 1.322     |
| $\text{Pr}(V_4=1 \mid S=1)$                    | 0.716 | 0.709 | -0.007 | -0.522    |
| $\text{Pr}(V_5=1 \mid S=0)$                    | 0.515 | 0.481 | -0.034 | -1.232    |
| $\text{Pr}(V_5=1 \mid S=1)$                    | 0.985 | 0.988 | +0.003 | 0.809     |
| $\text{Pr}(V_6=1 \mid S=0)$                    | 0.661 | 0.647 | -0.014 | -0.444    |
| $\text{Pr}(V_6=1 \mid S=1)$                    | 0.973 | 0.996 | +0.023 | 4.009     |
| <i>Aggregate co-movement</i>                   |       |       |        |           |
| $\text{Var}(BH_{agg} \mid S=0)$                | 0.136 | 0.143 | +0.007 | 2.471     |
| $\text{Var}(BH_{agg} \mid S=1)$                | 0.013 | 0.011 | -0.002 | -1.882    |

| Notation                                        | Data   | Model  | Diff   | <i>t</i> -stat |
|-------------------------------------------------|--------|--------|--------|----------------|
| <i>Leave-out covariances</i>                    |        |        |        |                |
| $\text{Cov}(V_1 - \bar{V}_{-1}, \tau \mid S=0)$ | 0.014  | 0.005  | -0.009 | -3.224         |
| $\text{Cov}(V_1 - \bar{V}_{-1}, \tau \mid S=1)$ | -0.001 | -0.001 | +0.000 | 0.377          |
| $\text{Cov}(V_2 - \bar{V}_{-2}, \tau \mid S=0)$ | -0.007 | 0.002  | +0.008 | 3.097          |
| $\text{Cov}(V_2 - \bar{V}_{-2}, \tau \mid S=1)$ | -0.001 | -0.001 | -0.000 | -2.085         |
| $\text{Cov}(V_3 - \bar{V}_{-3}, \tau \mid S=0)$ | -0.003 | -0.003 | +0.000 | 0.017          |
| $\text{Cov}(V_3 - \bar{V}_{-3}, \tau \mid S=1)$ | -0.001 | -0.000 | +0.001 | 1.823          |
| $\text{Cov}(V_4 - \bar{V}_{-4}, \tau \mid S=0)$ | -0.015 | -0.027 | -0.012 | -2.450         |
| $\text{Cov}(V_4 - \bar{V}_{-4}, \tau \mid S=1)$ | 0.009  | 0.010  | +0.001 | 1.251          |
| $\text{Cov}(V_5 - \bar{V}_{-5}, \tau \mid S=0)$ | -0.017 | -0.004 | +0.013 | 2.375          |
| $\text{Cov}(V_5 - \bar{V}_{-5}, \tau \mid S=1)$ | 0.001  | -0.000 | -0.001 | -1.221         |
| $\text{Cov}(V_6 - \bar{V}_{-6}, \tau \mid S=0)$ | -0.013 | -0.001 | +0.012 | 1.645          |
| $\text{Cov}(V_6 - \bar{V}_{-6}, \tau \mid S=1)$ | 0.000  | -0.000 | -0.000 | -0.881         |
| <i>Mean co-voting (ISS=0)</i>                   |        |        |        |                |
| $\overline{\text{Cov}}(V_1, V_{-1} \mid S=0)$   | 0.041  | 0.070  | +0.029 | 5.652          |
| $\overline{\text{Cov}}(V_2, V_{-2} \mid S=0)$   | 0.046  | 0.070  | +0.024 | 4.988          |
| $\overline{\text{Cov}}(V_3, V_{-3} \mid S=0)$   | 0.042  | 0.071  | +0.029 | 2.924          |
| $\overline{\text{Cov}}(V_4, V_{-4} \mid S=0)$   | -0.001 | 0.013  | +0.014 | 1.422          |
| $\overline{\text{Cov}}(V_5, V_{-5} \mid S=0)$   | 0.030  | 0.072  | +0.042 | 3.951          |
| $\overline{\text{Cov}}(V_6, V_{-6} \mid S=0)$   | 0.030  | 0.072  | +0.042 | 3.526          |

## B. Model Appendix

### B.1. Equilibrium Posterior Densities

This appendix derives the limiting posterior densities that enter the equilibrium conditions of Section 2.4.3. Each shareholder's cutoff is pinned down by an indifference condition evaluated under her posterior over proposal quality, conditional on her signals and on the event that her vote is decisive; Lemmas B.1 and B.2 characterize these posteriors in the limit as  $N_D \rightarrow \infty$  for dispersed shareholders and blockholders, respectively. Throughout, as in the model, blockholders observe the proxy advisor's report  $s_j = x_j + u_{Ij}$  directly, while dispersed shareholders observe the noisier group assessment  $\eta_{Dj} = s_j + v_{Dj} = x_j + u_{Dj}$ , so the report is the common component of the two groups' public information, with  $\text{Cov}(\eta_{Dj}, s_j | x_j) = \sigma_{u_I}^2$ . The two derivations differ in the nature of the pivotal event: in the limit, a dispersed shareholder is pivotal only at knife-edge states in which the dispersed support rate exactly equals the threshold implied by a blockholder vote profile, whereas a blockholder is pivotal whenever dispersed support falls in an interval, an event of positive probability.

**Common objects.** The following objects appear in both lemmas. We abbreviate the private signal noise parameters as  $\sigma_D \equiv \sigma_{\varepsilon_D}$  and  $\sigma_b \equiv \sigma_{\varepsilon_b}$ , write  $\phi$  and  $\Phi$  for the standard normal density and distribution function, and maintain throughout that all noise variances ( $\sigma_{u_I}^2$ ,  $\sigma_{v_D}^2$ ,  $\sigma_D^2$ ,  $\{\sigma_b^2\}$ ) are strictly positive. Conditional on  $(x_j, \eta_{Dj})$ , each dispersed shareholder votes "For" with probability

$$p_D(x_j, \eta_{Dj}) = \Phi \left( \sigma_D \left[ \frac{\eta_{Dj}}{\sigma_{u_D}^2} + \frac{x_j}{\sigma_D^2} - k_D \Lambda_D \right] \right), \quad \Lambda_D = 1 + \frac{1}{\sigma_{u_D}^2} + \frac{1}{\sigma_D^2},$$

and by the law of large numbers the dispersed support rate satisfies  $\tau_j = p_D(x_j, \eta_{Dj})$  almost surely in the limit as  $N_D \rightarrow \infty$ . Because the index inside  $\Phi$  is affine with strictly positive coefficients on both arguments,  $p_D$  is strictly increasing in  $x_j$  and in  $\eta_{Dj}$  and ranges over all of  $(0, 1)$  in each argument. Conditional on  $(x_j, s_j)$ , blockholder votes are independent across blockholders: by the exclusion restriction of Section 2.2.1, the report is the only information blockholders share, so only the mutually independent private signals  $\varepsilon_{b'j}$  remain random.

Blockholder  $b'$  votes “For” with probability  $\Phi(A_{b'}s_j + B_{b'}x_j - C_{b'})$ , where

$$A_{b'} = \frac{\sigma_{b'}}{\sigma_{u_I}^2}, \quad B_{b'} = \frac{1}{\sigma_{b'}}, \quad C_{b'} = \sigma_{b'}\Lambda_{b'}k_{b'}, \quad \Lambda_{b'} = 1 + \frac{1}{\sigma_{u_I}^2} + \frac{1}{\sigma_{b'}^2}.$$

The likelihood of a full vote profile  $V_{Bj} \in \{0, 1\}^{N_B}$  is therefore the product of probit terms

$$\Pr(V_{Bj} | x_j, s_j) = \prod_{b'=1}^{N_B} \left[ \Phi(A_{b'}s_j + B_{b'}x_j - C_{b'}) \right]^{V_{Bj}(b')} \left[ 1 - \Phi(A_{b'}s_j + B_{b'}x_j - C_{b'}) \right]^{1-V_{Bj}(b')}, \quad (\text{B.1})$$

and  $\Pr(V_{B,-b,j} | x_j, s_j)$ , the likelihood of the profile of all blockholders except  $b$ , is the same product taken over  $b' \neq b$ .

Finally, each group must integrate over the public signal it does not observe, and the joint normality of  $(x_j, s_j, \eta_{Dj})$  delivers the required conditional laws. For a dispersed shareholder, who observes  $\eta_{Dj}$  but not the report,

$$s_j | (x_j, \eta_{Dj}) \sim N\left(x_j + \frac{\sigma_{u_I}^2}{\sigma_{u_D}^2}(\eta_{Dj} - x_j), \frac{\sigma_{u_I}^2 \sigma_{vD}^2}{\sigma_{u_D}^2}\right); \quad (\text{B.2})$$

because  $\eta_{Dj}$  and  $s_j$  share the advisor’s error  $u_{Ij}$ , the dispersed signal remains informative about the report even conditional on  $x_j$ . For a blockholder, who observes the report but not  $\eta_{Dj}$ ,

$$\eta_{Dj} | (x_j, s_j) \sim N(s_j, \sigma_{vD}^2), \quad (\text{B.3})$$

which is free of  $x_j$ : since  $\eta_{Dj} = s_j + v_{Dj}$ , a blockholder who has seen the report is uncertain about the dispersed public assessment only through the dispersed processing noise  $v_{Dj}$ .

**Lemma B.1:** Dispersed shareholder posterior density

*We restrict attention to symmetric strategies among dispersed shareholders, so each dispersed shareholder’s best-response condition is the same and there is a single limit to derive. As  $N_D \rightarrow \infty$ , the posterior distribution of  $x_j$  converges weakly to a discrete distribution supported on the pivotal states defined below; written in density notation,*

$$\lim_{N_D \rightarrow \infty} f(x_j | z_{Dj}, \eta_{Dj}, \text{piv}_{Dj}) \propto$$

$$f(x_j | \eta_{Dj}) \sum_{V_{Bj}} \underbrace{f(z_{Dj} | x_j)}_{\text{signal effect}} \underbrace{\Pr(V_{Bj} | x_j, \eta_{Dj})}_{\text{strategic effect}} \underbrace{\text{dirac}(p_D(x_j, \eta_{Dj}) - \tau^{V_{Bj}})}_{\text{pivotal constraint}} = \quad (\text{B.4a})$$

$$\sum_{V_{Bj}} \underbrace{f(x_{\eta_{Dj}}^{V_{Bj}} | \eta_{Dj})}_{\text{prior (given } \eta_{Dj})} \underbrace{f(z_{Dj} | x_{\eta_{Dj}}^{V_{Bj}})}_{\text{signal effect}} \underbrace{\chi^{V_{Bj}}}_{\text{Jacobian}} \underbrace{\Pr(V_{Bj} | x_{\eta_{Dj}}^{V_{Bj}}, \eta_{Dj})}_{\text{strategic effect}} \text{dirac}(x_j - x_{\eta_{Dj}}^{V_{Bj}}). \quad (\text{B.4b})$$

The lemma uses the following objects:

- **Threshold dispersed share:** given the blockholder vote profile  $V_{Bj}$ ,

$$\tau^{V_{Bj}} = \frac{\lambda^* - \Psi_{\text{for}}(V_{Bj})}{\Psi_D}, \quad q^{V_{Bj}} \equiv \Phi^{-1}(\tau^{V_{Bj}}),$$

is the dispersed support rate at which the proposal exactly passes. Profiles for which the proposal passes or fails regardless of dispersed support ( $\tau^{V_{Bj}} \notin (0, 1)$ , so that  $\Phi^{-1}$  is undefined) admit no pivotal state; they have zero pivotality probability and drop out of the sums in (B.4a)–(B.4b).

- **Pivotal state:** the unique solution in  $x_j$  to  $p_D(x_j, \eta_{Dj}) = \tau^{V_{Bj}}$ ,

$$x_{\eta_{Dj}}^{V_{Bj}} = \sigma_D^2 \left( \Lambda_D k_D - \frac{\eta_{Dj}}{\sigma_{u_D}^2} + \frac{q^{V_{Bj}}}{\sigma_D} \right).$$

- **Jacobian correction term,** from the change of variables  $\text{dirac}(p_D(x_j, \eta_{Dj}) - \tau^{V_{Bj}}) = \chi^{V_{Bj}} \text{dirac}(x_j - x_{\eta_{Dj}}^{V_{Bj}})$ :

$$\chi^{V_{Bj}} = \frac{\sigma_D}{\phi(q^{V_{Bj}})}.$$

- **Strategic effect:** the blockholder vote-profile likelihood (B.1), integrated over the report, which the dispersed shareholder does not observe, using the conditional density (B.2):

$$\Pr(V_{Bj} | x_j, \eta_{Dj}) = \int \Pr(V_{Bj} | x_j, s) f(s | x_j, \eta_{Dj}) ds.$$

*Proof of Lemma B.1.* Fix a proposal  $j$ . By symmetry, all dispersed shareholders share the same information structure and strategy, so it suffices to derive the posterior for a representative dispersed shareholder. The proof proceeds in four steps: we factor the posterior by Bayes' rule, integrate the unobserved report out of the strategic term, take the large- $N_D$  limit of the pivotality event, and collapse the resulting knife-edge condition to an atomic posterior.

1. **Bayes' rule and separation of signal vs. pivotality.** Consider the posterior conditional on the dispersed shareholder's private signal  $z_{Dj}$ , the dispersed public signal  $\eta_{Dj}$ , and the event of pivotality  $\text{piv}_{Dj}$ . By Bayes' rule,

$$f(x_j | z_{Dj}, \eta_{Dj}, \text{piv}_{Dj}) \propto f(x_j | \eta_{Dj}) f(z_{Dj} | x_j) \Pr(\text{piv}_{Dj} | x_j, z_{Dj}, \eta_{Dj}). \quad (\text{B.5})$$

Conditional on  $x_j$ , the dispersed private signal  $z_{Dj}$  is independent of  $\eta_{Dj}$ , of the report, and of other shareholders' votes, so  $\Pr(\text{piv}_{Dj} | x_j, z_{Dj}, \eta_{Dj}) = \Pr(\text{piv}_{Dj} | x_j, \eta_{Dj})$ . Substituting into (B.5) yields

$$f(x_j | z_{Dj}, \eta_{Dj}, \text{piv}_{Dj}) \propto f(x_j | \eta_{Dj}) f(z_{Dj} | x_j) \Pr(\text{piv}_{Dj} | x_j, \eta_{Dj}). \quad (\text{B.6})$$

2. **Decomposition over blockholder vote profiles, integrating out the report.** Let  $V_{Bj} \in \{0, 1\}^{N_B}$  denote the blockholder vote profile. Conditioning on  $V_{Bj}$  and using the law of total probability,

$$\Pr(\text{piv}_{Dj} | x_j, \eta_{Dj}) = \sum_{V_{Bj}} \Pr(\text{piv}_{Dj} | x_j, \eta_{Dj}, V_{Bj}) \Pr(V_{Bj} | x_j, \eta_{Dj}). \quad (\text{B.7})$$

From the dispersed shareholder's perspective the report  $s_j$  is unobserved, and conditioning on  $x_j$  alone does not integrate it out correctly: because  $\eta_{Dj}$  and  $s_j$  share the advisor's error  $u_{Ij}$ , the dispersed signal remains informative about the report conditional on  $x_j$ , with the conditional law (B.2). Conditional on  $(x_j, s_j)$ , however, the blockholder votes depend only on the private signals  $\{\varepsilon_{b'j}\}_{b'=1}^{N_B}$ , which are independent of  $v_{Dj}$ ; hence  $\Pr(V_{Bj} | x_j, s_j, \eta_{Dj}) = \Pr(V_{Bj} | x_j, s_j)$ , the probit product (B.1), and

$$\Pr(V_{Bj} | x_j, \eta_{Dj}) = \int \Pr(V_{Bj} | x_j, s) f(s | x_j, \eta_{Dj}) ds, \quad (\text{B.8})$$

which is the strategic effect stated in the lemma.

3. **Large- $N_D$  limit and the pivotality constraint.** Fix  $(x_j, \eta_{Dj})$ . Given the symmetric dispersed strategy, dispersed votes are i.i.d. conditional on  $(x_j, \eta_{Dj})$ , independent of  $V_{Bj}$  (pri-

vate signals are independent across shareholders), and satisfy

$$\frac{1}{N_D} \sum_{i=1}^{N_D} \mathbf{1}\{V_{ij} = 1\} \xrightarrow[N_D \rightarrow \infty]{a.s.} p_D(x_j, \eta_{Dj}).$$

A dispersed shareholder is pivotal under profile  $V_{Bj}$  only when the number of other dispersed “For” votes equals the single integer count at which her vote flips the outcome, which grows as  $\tau^{V_{Bj}} N_D$ . At any fixed  $(x_j, \eta_{Dj})$  this probability vanishes, so the limit posterior must be obtained by normalizing before passing to the limit. By the local central limit theorem for the binomial count,

$$\Pr(\text{piv}_{Dj} \mid x_j, \eta_{Dj}, V_{Bj}) = \left(2\pi N_D \tau^{V_{Bj}} (1 - \tau^{V_{Bj}})\right)^{-1/2} \exp\left(-N_D \text{KL}(\tau^{V_{Bj}} \parallel p_D(x_j, \eta_{Dj}))\right) (1 + o(1)),$$

where  $\text{KL}(\tau \parallel p)$  denotes the Kullback–Leibler divergence between Bernoulli distributions: the pivot probability decays at the polynomial rate  $N_D^{-1/2}$  where  $p_D(x_j, \eta_{Dj}) = \tau^{V_{Bj}}$  and exponentially elsewhere. Scaling by  $N_D$  and integrating against a continuous function of  $x_j$ , a Laplace approximation around the root of  $p_D(x_j, \eta_{Dj}) = \tau^{V_{Bj}}$  contributes the Gaussian width  $\sqrt{2\pi \tau^{V_{Bj}} (1 - \tau^{V_{Bj}}) / N_D} / \partial_x p_D$ , so the  $\tau^{V_{Bj}} (1 - \tau^{V_{Bj}})$  factors cancel between the prefactor and the width, and

$$N_D \Pr(\text{piv}_{Dj} \mid x_j, \eta_{Dj}, V_{Bj}) \Rightarrow \text{dirac}(p_D(x_j, \eta_{Dj}) - \tau^{V_{Bj}})$$

weakly in  $x_j$ . The cancellation matters: it makes the scaling uniform across blockholder vote profiles, so the *relative* weights of the profiles in the limit posterior carry no residual  $\tau^{V_{Bj}} (1 - \tau^{V_{Bj}})$  factor. This argument follows the treatment of pivotal beliefs in large voting games in [Myatt \(2015\)](#) and [Zachariadis et al. \(2020\)](#). Because the  $N_D$  scaling is common to all profiles, it is absorbed by the proportionality sign; substituting the limit object and (B.8) into (B.6)–(B.7) yields

$$f(x_j \mid z_{Dj}, \eta_{Dj}, \text{piv}_{Dj}) \propto f(x_j \mid \eta_{Dj}) \sum_{V_{Bj}} f(z_{Dj} \mid x_j) \Pr(V_{Bj} \mid x_j, \eta_{Dj}) \text{dirac}(p_D(x_j, \eta_{Dj}) - \tau^{V_{Bj}}),$$

which is (B.4a).

4. **Collapse to an atomic posterior via the Dirac delta identity.** For fixed  $\eta_{Dj}$  and  $V_{Bj}$  with  $\tau^{V_{Bj}} \in (0, 1)$ , the mapping  $x_j \mapsto p_D(x_j, \eta_{Dj})$  is strictly increasing and ranges over all of  $(0, 1)$ , so the equation  $p_D(x_j, \eta_{Dj}) = \tau^{V_{Bj}}$  has the unique solution  $x_{\eta_{Dj}}^{V_{Bj}}$  given in the lemma. Let  $q^{V_{Bj}} = \Phi^{-1}(\tau^{V_{Bj}})$ . Then at the root,

$$q^{V_{Bj}} = \sigma_D \left[ \frac{\eta_{Dj}}{\sigma_{u_D}^2} + \frac{x_{\eta_{Dj}}^{V_{Bj}}}{\sigma_D^2} - k_D \Lambda_D \right].$$

Moreover,

$$\frac{\partial}{\partial x_j} p_D(x_j, \eta_{Dj}) = \phi \left( \sigma_D \left[ \frac{\eta_{Dj}}{\sigma_{u_D}^2} + \frac{x_j}{\sigma_D^2} - k_D \Lambda_D \right] \right) \cdot \sigma_D \cdot \frac{1}{\sigma_D^2} = \frac{1}{\sigma_D} \phi \left( \sigma_D \left[ \frac{\eta_{Dj}}{\sigma_{u_D}^2} + \frac{x_j}{\sigma_D^2} - k_D \Lambda_D \right] \right).$$

Evaluated at  $x_j = x_{\eta_{Dj}}^{V_{Bj}}$ , this derivative equals  $\phi(q^{V_{Bj}})/\sigma_D$ . Using the standard identity

$$\text{dirac}(g(x)) = \sum_{x^* : g(x^*)=0} \frac{\text{dirac}(x - x^*)}{|g'(x^*)|},$$

with  $g(x) = p_D(x, \eta_{Dj}) - \tau^{V_{Bj}}$ , we obtain

$$\text{dirac}(p_D(x_j, \eta_{Dj}) - \tau^{V_{Bj}}) = \frac{\sigma_D}{\phi(q^{V_{Bj}})} \text{dirac}(x_j - x_{\eta_{Dj}}^{V_{Bj}}) \equiv \chi^{V_{Bj}} \text{dirac}(x_j - x_{\eta_{Dj}}^{V_{Bj}}).$$

Substituting this into (B.4a) and evaluating each factor at  $x_j = x_{\eta_{Dj}}^{V_{Bj}}$  yields (B.4b). This completes the proof. ■

**Remark on Lemma B.1.** The Dirac delta function in (B.4a) enforces the pivotality condition for dispersed shareholders by restricting the posterior density to values of the latent proposal quality  $x_j$  that make a dispersed voter exactly pivotal: those for which the implied dispersed support rate  $p_D(x_j, \eta_{Dj})$  equals the threshold share  $\tau^{V_{Bj}}$  associated with a particular blockholder vote profile  $V_{Bj}$ . Intuitively, as  $N_D \rightarrow \infty$ , there is a unique draw of  $x_j$  (conditional on the dispersed public signal  $\eta_{Dj}$ ) for which a dispersed shareholder is pivotal, and the posterior density tilts strongly towards these knife-edge states.

Each such state corresponds to one blockholder vote profile and its associated quality  $x_{\eta_{Dj}}^{V_{Bj}}$ . Its contribution is weighted by the (conditional) prior density  $f(x_{\eta_{Dj}}^{V_{Bj}} | \eta_{Dj})$ , the likelihood of the dispersed private signal  $f(z_{Dj} | x_{\eta_{Dj}}^{V_{Bj}})$ , the Jacobian term  $\chi^{V_{Bj}}$ , and the strategic likelihood  $\Pr(V_{Bj} | x_{\eta_{Dj}}^{V_{Bj}}, \eta_{Dj})$ , which averages over the report conditional on both the pivotal state and the dispersed public signal: because the two groups' public signals share the advisor's error,  $\eta_{Dj}$  is informative about the report over and above  $x_j$ .

**Lemma B.2:** Blockholder posterior density

*Given differences in preferences and information, each blockholder  $b$  may have a separate posterior density over the state. As  $N_D \rightarrow \infty$ , the conditional  $b$ -posterior density for any  $x_j$  converges to*

$$\lim_{N_D \rightarrow \infty} f(x_j | z_{bj}, s_j, \text{piv}_{bj}) \propto \underbrace{f(x_j | s_j)}_{\text{signal effect}} \underbrace{f(z_{bj} | x_j)}_{\text{pivotality}} \underbrace{\sum_{V_{B,-b,j}} \Pi^{V_{B,-b,j}}(x_j, s_j) \Pr(V_{B,-b,j} | x_j, s_j)}_{\text{strategic effect}}, \quad (\text{B.9})$$

where  $f(x_j | s_j)$  is the normal posterior implied by the prior  $x_j \sim N(0, 1)$  and the report  $s_j$ , and  $\Pr(V_{B,-b,j} | x_j, s_j)$  is the probit product likelihood of the other blockholders' votes defined below (B.1). The remaining objects are:

- **Pivotal-bounding dispersed support rates given  $V_{B,-b,j}$ :**

$$\tau_L^{V_{B,-b,j}} = \frac{\lambda^* - \Psi_{\text{for}}(V_{B,-b,j}) - \psi_b}{\Psi_D}, \quad \tau_H^{V_{B,-b,j}} = \frac{\lambda^* - \Psi_{\text{for}}(V_{B,-b,j})}{\Psi_D},$$

with  $q_L^{V_{B,-b,j}} = \Phi^{-1}(\tau_L^{V_{B,-b,j}})$  and  $q_H^{V_{B,-b,j}} = \Phi^{-1}(\tau_H^{V_{B,-b,j}})$ . Blockholder  $b$  is pivotal when the dispersed support rate satisfies  $\tau_j \in [\tau_L^{V_{B,-b,j}}, \tau_H^{V_{B,-b,j}}]$ .

- **Pivotality probability for blockholder  $b$ :** in the large- $N_D$  limit,  $\tau_j = p_D(x_j, \eta_{Dj})$ , and  $p_D(x_j, \eta_{Dj})$  is strictly increasing in  $\eta_{Dj}$  for fixed  $x_j$ , so pivotality is equivalent to  $\eta_{Dj}$  lying in an interval  $[\eta_L^{V_{B,-b,j}}(x_j), \eta_H^{V_{B,-b,j}}(x_j)]$  with endpoints

$$\eta_r^{V_{B,-b,j}}(x_j) = \sigma_{u_D}^2 \left( \Lambda_D k_D - \frac{x_j}{\sigma_D^2} + \frac{q_r^{V_{B,-b,j}}}{\sigma_D} \right), \quad r \in \{L, H\}.$$

When a bound falls outside  $(0, 1)$  the corresponding constraint does not bind, and we extend the notation by  $\Phi^{-1}(t) = -\infty$  for  $t \leq 0$  and  $\Phi^{-1}(t) = +\infty$  for  $t \geq 1$ , so that profiles for which pivotality is one-sided or impossible are handled by the same formula. The blockholder does not observe  $\eta_{Dj}$ ; integrating its conditional density (B.3) over this interval gives

$$\Pi^{V_{B,-b,j}}(x_j, s_j) = \int_{\eta_L^{V_{B,-b,j}}(x_j)}^{\eta_H^{V_{B,-b,j}}(x_j)} f(\eta_{Dj} | x_j, s_j) d\eta_{Dj} = \Phi\left(\frac{\eta_H^{V_{B,-b,j}}(x_j) - s_j}{\sigma_{vD}}\right) - \Phi\left(\frac{\eta_L^{V_{B,-b,j}}(x_j) - s_j}{\sigma_{vD}}\right).$$

*Proof of Lemma B.2.* Fix a proposal  $j$  and a focal blockholder  $b$ . Unlike dispersed shareholders, blockholders may have heterogeneous preferences and private signal variances, so we derive the posterior for a given  $b$ . The proof proceeds in five steps: we factor the posterior by Bayes' rule, decompose the pivotality event over the other blockholders' vote profiles, characterize pivotality as an interval condition on dispersed support, express its probability as an integral over the unobserved dispersed public signal, and recombine.

1. **Bayes' rule.** By Bayes' rule,

$$f(x_j | z_{bj}, s_j, \text{piv}_{bj}) \propto f(x_j | s_j) f(z_{bj} | x_j) \Pr(\text{piv}_{bj} | x_j, z_{bj}, s_j). \quad (\text{B.10})$$

Conditional on  $(x_j, s_j)$ , the private signal  $z_{bj}$  is independent of the other shareholders' votes and of  $\eta_{Dj}$ , so  $\Pr(\text{piv}_{bj} | x_j, z_{bj}, s_j) = \Pr(\text{piv}_{bj} | x_j, s_j)$ . Hence

$$f(x_j | z_{bj}, s_j, \text{piv}_{bj}) \propto f(x_j | s_j) f(z_{bj} | x_j) \Pr(\text{piv}_{bj} | x_j, s_j). \quad (\text{B.11})$$

2. **Decompose pivotality over other-blockholder vote profiles.** Let  $V_{B,-b,j} \in \{0, 1\}^{N_B-1}$  denote the vote profile of all blockholders except  $b$ . By the law of total probability,

$$\Pr(\text{piv}_{bj} | x_j, s_j) = \sum_{V_{B,-b,j}} \Pr(\text{piv}_{bj} | x_j, s_j, V_{B,-b,j}) \Pr(V_{B,-b,j} | x_j, s_j). \quad (\text{B.12})$$

Conditional on  $(x_j, s_j)$ , the other blockholders' votes depend only on their private signals, so they are independent of each other and of  $\eta_{Dj}$ ; this delivers the probit product form for  $\Pr(V_{B,-b,j} | x_j, s_j)$  stated in the lemma.

3. **Characterize pivotality as an interval condition on dispersed support.** Fix  $(x_j, s_j, V_{B,-b,j})$ .

Blockholder  $b$  is pivotal when the total fraction of shares cast in favor by all shareholders other than  $b$  lies in the interval  $[\lambda^* - \psi_b, \lambda^*]$ , or equivalently when the dispersed support rate satisfies

$$\tau_j \in [\tau_L^{V_{B,-b,j}}, \tau_H^{V_{B,-b,j}}],$$

with the bounds defined in the lemma. As  $N_D \rightarrow \infty$ , the dispersed support rate satisfies  $\tau_j = p_D(x_j, \eta_{Dj})$  almost surely by the law of large numbers. The focal blockholder does not observe  $\eta_{Dj}$ , but she has seen the report, and conditional on  $(x_j, s_j)$  the dispersed public signal is distributed as in (B.3); because votes and  $\eta_{Dj}$  are independent given  $(x_j, s_j)$ , conditioning additionally on  $V_{B,-b,j}$  does not change this distribution. The distribution of  $\eta_{Dj}$  is atomless, so the boundary of the interval carries no probability and the finite- $N_D$  pivotal event converges to the stated interval event. Therefore

$$\Pr(\text{piv}_{bj} \mid x_j, s_j, V_{B,-b,j}) = \Pr\left(p_D(x_j, \eta_{Dj}) \in [\tau_L^{V_{B,-b,j}}, \tau_H^{V_{B,-b,j}}] \mid x_j, s_j\right) \equiv \Pi^{V_{B,-b,j}}(x_j, s_j). \quad (\text{B.13})$$

Because  $\eta_{Dj}$  and  $s_j$  are correlated conditional on  $x_j$  through the common advisor error  $u_{Ij}$ , the report shifts the conditional distribution of the dispersed signal one for one.

4. **Express  $\Pi^{V_{B,-b,j}}(x_j, s_j)$  as an integral over  $\eta_{Dj}$ .** For fixed  $x_j$ ,  $p_D(x_j, \eta_{Dj})$  is strictly increasing in  $\eta_{Dj}$  and ranges over all of  $(0, 1)$ . Hence, with the boundary conventions stated in the lemma, the event  $p_D(x_j, \eta_{Dj}) \in [\tau_L^{V_{B,-b,j}}, \tau_H^{V_{B,-b,j}}]$  is equivalent to  $\eta_{Dj} \in [\eta_L^{V_{B,-b,j}}(x_j), \eta_H^{V_{B,-b,j}}(x_j)]$ , where the endpoints are obtained by inverting  $p_D(x_j, \eta_{Dj}) = \tau_L^{V_{B,-b,j}}$  and  $p_D(x_j, \eta_{Dj}) = \tau_H^{V_{B,-b,j}}$ , yielding the expressions in the lemma. Therefore, using (B.3),

$$\Pi^{V_{B,-b,j}}(x_j, s_j) = \int_{\eta_L^{V_{B,-b,j}}(x_j)}^{\eta_H^{V_{B,-b,j}}(x_j)} f(\eta_{Dj} \mid x_j, s_j) d\eta_{Dj} = \Phi\left(\frac{\eta_H^{V_{B,-b,j}}(x_j) - s_j}{\sigma_{vD}}\right) - \Phi\left(\frac{\eta_L^{V_{B,-b,j}}(x_j) - s_j}{\sigma_{vD}}\right).$$

5. **Combine.** Substituting (B.13) into (B.12) gives

$$\Pr(\text{piv}_{bj} \mid x_j, s_j) = \sum_{V_{B,-b,j}} \Pi^{V_{B,-b,j}}(x_j, s_j) \Pr(V_{B,-b,j} \mid x_j, s_j).$$

Plugging this into (B.11) yields

$$f(x_j \mid z_{bj}, s_j, \text{piv}_{bj}) \propto f(x_j \mid s_j) f(z_{bj} \mid x_j) \sum_{V_{B,-b,j}} \Pi^{V_{B,-b,j}}(x_j, s_j) \Pr(V_{B,-b,j} \mid x_j, s_j),$$

which is exactly (B.9). This completes the proof. ■

**Remark on Lemma B.2.** Given the voting profile of the other blockholders  $V_{B,-b,j}$ , the fraction of shares cast in favor by all shareholders excluding  $b$  is  $\Psi_{\text{for}}(V_{B,-b,j}) + \tau_j \Psi_D$ . Blockholder  $b$  is pivotal when this lies in  $[\lambda^* - \psi_b, \lambda^*]$ , which is equivalent to the dispersed support rate falling in  $[\tau_L^{V_{B,-b,j}}, \tau_H^{V_{B,-b,j}}]$ .

In the large- $N_D$  limit, the dispersed support rate equals  $\tau_j = p_D(x_j, \eta_{Dj})$  for a given  $(x_j, \eta_{Dj})$ . The blockholder does not observe  $\eta_{Dj}$ , but having seen the report herself, she is uncertain about the dispersed public assessment only through the dispersed processing noise:  $\eta_{Dj} \mid (x_j, s_j) \sim N(s_j, \sigma_{vD}^2)$ . From her perspective, pivotality for a given profile  $V_{B,-b,j}$  therefore occurs with probability  $\Pi^{V_{B,-b,j}}(x_j, s_j)$ , in which the state  $x_j$  enters only through the interval of dispersed signals that would make her pivotal, while the report  $s_j$  centers the distribution of  $\eta_{Dj}$  over that interval.

The posterior in (B.9) therefore has three components: (i) a prior  $f(x_j \mid s_j)$  shaped by the report, (ii) a private signal likelihood  $f(z_{bj} \mid x_j)$ , and (iii) a strategic term combining the likelihood of the other blockholders' votes given  $(x_j, s_j)$  with the pivotality probability  $\Pi^{V_{B,-b,j}}(x_j, s_j)$ , which summarizes how dispersed public information affects the event that blockholder  $b$  is decisive.

**Lemma B.3:** Existence of a cutoff voting equilibrium

*A cutoff voting equilibrium of Definition 1 exists.*

*Proof.* Two observations deliver the result. First, best responses to cutoff strategies are cutoff strategies. Fix the other voters' cutoffs and condition on the public signals. For blockholder  $b$ , the interim gain from voting For is  $U_b(z_{bj}) = E[(x_j + \delta_b) \mathbf{1}[\text{piv}_{bj}] \mid s_j, z_{bj}]$ , and the pivotal event has positive probability conditional on every  $(x_j, s_j)$ , since dispersed support

has full support given the state. The function  $x_j \mapsto (x_j + \delta_b) \Pr(\text{piv}_{bj} \mid x_j, s_j)$  therefore changes sign exactly once, at  $x_j = -\delta_b$ ; and since the conditional density of  $x_j$  given  $(s_j, z_{bj})$  is Gaussian, hence strictly totally positive, the expectation  $U_b$  changes sign at most once in  $z_{bj}$ , from negative to positive, by the variation-diminishing property (Karlin, 1968). The best response is thus a cutoff in  $z_{bj}$ , equivalently in  $m_{bj}$ , with the threshold at the indifference point. The same argument applies to a dispersed shareholder under her limiting pivotal posterior of Lemma B.1. This is the single-crossing structure of Athey (2001).

Second, the indifference map on cutoffs has a fixed point; the argument follows the cutoff-vector fixed-point construction of Athey (2001), adapted to the limit economy and to the proposal-invariant cutoff class. For a cutoff profile  $\mathbf{k}$ , each conditional expectation  $t \mapsto E[x_j \mid m_{ij} = t, \text{piv}_{ij}]$ , with the pivotal event evaluated at  $\mathbf{k}$ , is continuous, strictly increasing, and divergent as  $t \rightarrow \pm\infty$ : the posterior of  $x_j$  given  $m_{ij} = t$  is Gaussian with mean linear in  $t$  and fixed variance, and reweighting it by the pivotal probability, bounded by one with tails governed by the signal variances alone, moves the conditional mean by at most a bounded amount. Each indifference condition (15)–(16) therefore has a unique solution given  $\mathbf{k}$ , continuous in  $\mathbf{k}$  by dominated convergence and uniformly bounded, so the map sends a sufficiently large compact box in  $\mathbb{R}^{1+N_B}$  into itself. Brouwer’s fixed-point theorem delivers a cutoff profile satisfying Definition 1, which by the first observation is a profile of mutual best responses. ■

## C. Estimation Appendix

### C.1. Identification

This section proves Proposition 1 for  $N_B$  blockholders. We begin with intuition. Hold the advisor’s noise  $\sigma_{u_l}$  fixed at a candidate value. Given that value, the data deliver every remaining parameter: the recommendation frequency pins the advisor’s threshold; the mean and dispersion of dispersed support across recommendation cells recover the dispersed-side parameters; and, because blockholders observe the report itself, each blockholder’s response to For/Against proposals yields her private precision and cutoff in closed form.

However, as our non-identification argument in Section 3 illustrates, one can find another  $\sigma_{u_l}$  and reproduce exactly the same individual voting patterns by varying the other parameters

in the model. For example, the same patterns can arise from a precise advisor whose report blockholders corroborate with precise private signals of their own, or from an advisor on whose report blockholders, having little private information, simply lean. This is the non-identification result of Proposition 2 proven below. Given a candidate  $\sigma_{u_I}$ , the dispersed data provide two moments—the dispersion of support and its co-movement with the report—to recover public and private signal noise. These moments need not uniquely determine the split. Support may co-move with the report because dispersed shareholders are informed about the same underlying quality or because their public assessment inherits the advisor’s error. Different combinations of public and private noise can therefore generate the same reduced form. The candidate solutions are roots of a cubic, so there are at most three for any  $\sigma_{u_I}$ , each tracing out a branch as  $\sigma_{u_I}$  varies. The individual voting patterns therefore restrict the structural parameters to finitely many one-dimensional branches rather than a unique point.

The covariances between blockholder votes and dispersed support provide the first source of separation across these branches. The individual patterns fix how blockholder votes and dispersed support each relate to the recommendation, but not how they relate to one another after conditioning on the report. This residual co-movement runs through information about the underlying quality that is shared across their private signals. Along the candidate branches, changes in advisor noise alter blockholder private precision, while the different dispersed-side roots alter how much of the variation in support orthogonal to the report reflects information about quality rather than dispersed-specific noise. Vote–support covariances therefore reveal how much of this residual variation is genuinely informational.

All of these vote–support covariances identify the same scalar combination  $\varrho$  of advisor accuracy and dispersed private precision. Matching  $\varrho$  collapses the finite collection of candidate branches to at most two points: the true parameter and an explicit conjugate.<sup>22</sup> Mean co-voting eliminates this final ambiguity. Conditional on the report, two blockholders share the residual uncertainty in the underlying state induced by the advisor’s error, so their co-

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<sup>22</sup>Once the vote–support covariance fixes  $\varrho$ , the dispersed-side restrictions imply that  $\sigma_{u_I}^2$  solves a quadratic equation. Hence at most two values of advisor noise can generate the same individual voting patterns and vote–support co-movement: the true value and one conjugate root.

voting is strictly monotone in  $\sigma_{u_I}$ . The mean co-voting moment therefore identifies advisor noise directly and separates a point from its conjugate. Only one scalar direction in the co-voting block is needed for this step; the remaining co-voting moments provide overidentifying restrictions.

Formally, the argument has three layers. First, the observables deliver exact Gaussian reduced forms for dispersed support and each blockholder's voting behavior (Lemmas C.1–C.2). Second, given a candidate  $\sigma_{u_I}$ , these reduced forms determine every remaining coordinate up to the finite number of dispersed-side roots described above, confining the parameter to a finite collection of one-dimensional branches (Lemmas C.3–C.4, Corollary C.1). Third, the vote–support covariances identify  $\varrho$ , and mean co-voting identifies  $\sigma_{u_I}$ , eliminating the conjugate and selecting a unique structural parameter (Lemmas C.5–C.6, Corollary C.2). Preferences are then recovered from the indifference conditions of Definition 1. Throughout, these are statements about exact population moments; the finite-sample implementation is described in Section C.3, and the numerical identification checks are reported in Section C.4.

**Setup and notation.** We retain the shorthand  $\sigma_D \equiv \sigma_{\varepsilon_D}$  and  $\sigma_b \equiv \sigma_{\varepsilon_b}$  of Appendix B, recall the posterior precisions  $\Lambda_D = 1 + \sigma_{u_D}^{-2} + \sigma_D^{-2}$  and  $\Lambda_b = 1 + \sigma_{u_I}^{-2} + \sigma_b^{-2}$  from (10), and suppress the proposal subscript  $j$  where no confusion arises. The structural parameter vector is

$$\begin{aligned} \theta &= (\xi^*, k_D, \sigma_{u_D}, \sigma_D, \sigma_{u_I}, \{\sigma_b, k_b\}_{b=1}^{N_B}) \in \Theta, \\ \Theta &= \left\{ \xi^*, k_D, k_b \in \mathbb{R}; \sigma_D, \sigma_{u_I}, \sigma_b > 0; \sigma_{u_D} \geq \sigma_{u_I} \right\}. \end{aligned} \quad (\text{C.1})$$

The inequality  $\sigma_{u_D} \geq \sigma_{u_I}$  is definitional:  $\sigma_{u_D}^2 = \sigma_{u_I}^2 + \sigma_{vD}^2$  with  $\sigma_{vD}^2 \geq 0$ ; equality is the case in which dispersed shareholders observe the report itself, as in Section 3, and the argument below nests it. We write  $N_\Theta \equiv 5 + 2N_B$  for the number of structural parameters. Here,

$$\xi^* \equiv \xi / \sqrt{1 + \sigma_{u_I}^2}$$

is the recommendation threshold expressed in units of the standardized report

$$s^* = \frac{s}{\sqrt{1 + \sigma_{u_I}^2}} = \frac{x + u_I}{\sqrt{1 + \sigma_{u_I}^2}} \sim N(0, 1), \quad S = \mathbf{1}[s^* > \xi^*], \quad (\text{C.2})$$

so that the raw threshold  $\xi$  of Section 2.2.1 is recovered as  $\xi = \xi^* \sqrt{1 + \sigma_{u_I}^2}$  once  $\sigma_{u_I}$  is identified. Preferences do not appear in (C.1): by Definition 1,  $\Delta$  is recovered from  $\theta$  through the equilibrium indifference conditions, a step we return to at the end of the proof.

We use the probit transform of dispersed support,  $T \equiv \Phi^{-1}(\tau)$ , and write  $\mu_T = E[T]$ ,  $\sigma_T^2 = \text{Var}(T)$ , and  $\rho_{Ts} = \text{Corr}(T, s^*)$ . For each blockholder,  $s_b^2 \equiv \text{Var}(m_b) = 1 - 1/\Lambda_b$  is the variance of the posterior mean,  $\zeta_b \equiv k_b/s_b$  is the standardized cutoff, and  $\rho_b \equiv \text{Corr}(m_b, s^*)$  is the correlation between the blockholder's index and the standardized report. It is also useful to record the loading decomposition of the posterior mean,

$$m_b = a_b x + b_b u_I + c_b \varepsilon_b, \quad a_b = \frac{\sigma_{u_I}^{-2} + \sigma_b^{-2}}{\Lambda_b}, \quad b_b = \frac{\sigma_{u_I}^{-2}}{\Lambda_b}, \quad c_b = \frac{\sigma_b^{-2}}{\Lambda_b}, \quad (\text{C.3})$$

with  $\Lambda_b = 1 + \sigma_{u_I}^{-2} + \sigma_b^{-2}$ , which satisfies the identity  $a_b + b_b \sigma_{u_I}^2 = 1$ . Finally,  $\rho_{xs}(\zeta) \equiv 1/\sqrt{1 + \zeta^2}$  denotes the accuracy of the advisor's standardized report,  $\text{Corr}(x, s^*)$ , when  $\sigma_{u_I} = \zeta$ ; we reserve  $\zeta$  for candidate values of  $\sigma_{u_I}$ .

The population moment map  $g : \Theta \rightarrow \mathbb{R}^{7+4N_B}$  collects, in order: the first-stage block ( $E[T \mid S=1]$ ,  $E[T \mid S=0]$ ,  $\text{Var}(\tau \mid S=0)$ ,  $\text{Var}(\tau \mid S=1)$ ,  $\text{Pr}(S=1)$ ); the vote-rate block  $E[V_b \mid S=s]$  for each blockholder and each cell; the vote-support covariances

$$g_b^{V\tau}(s) = \text{Cov}(V_b, \tau \mid S=s); \quad (\text{C.4})$$

and the aggregate co-movement block,  $\text{Var}(\bar{V} \mid S=s)$  for  $\bar{V} = N_B^{-1} \sum_b V_b$ . The proof of Proposition 1 uses only the first three blocks; the aggregate block is overidentifying, as are the co-voting moments added in estimation. In estimation the vote-support covariances themselves enter as the leave-out contrasts

$$g_b^{LO}(s) = \text{Cov}(V_b - \bar{V}_{-b}, \tau \mid S=s), \quad \bar{V}_{-b} = \frac{1}{N_B - 1} \sum_{\ell \neq b} V_\ell, \quad (\text{C.5})$$

which difference out co-movement common to all blockholders (Section C.3).

**Maintained assumptions.** For self-containedness, we restate the maintained assumptions of Section 4: (i) the cutoff profile  $\mathbf{k} = \{k_D, \{k_b\}_{b=1}^{N_B}\}$  arises from a cutoff voting equilibrium and satisfies the indifference conditions of Definition 1; (ii) the advisor's binary recommendation is monotonic in the underlying report,  $S = \mathbb{1}[s > \xi]$ , with a threshold constant across proposals; and (iii) conditional on the recommendation, the remaining variation in dispersed and blockholder voting is generated by the latent quality  $x$  and the public and private signal shocks of Section 2. Conditions (i)–(iii) restate the model itself.

**Identifying assumptions.** Beyond the maintained structure of the model, the proof requires one regularity condition: monotonicity of the first-stage cell variance in the residual scale  $\omega$  (Assumption C.1). This condition is specific to our choice of raw-support variance as the identifying moment; alternative moments based on probit-transformed support recover  $\omega$  directly. We state the condition where it arises, and Section C.4 assesses it directly at the estimated parameters.

**Lemma C.1:** Dispersed-side reduced form is an exact switching regression

For every  $\theta \in \Theta$ :

- (i) *The recommendation frequency identifies the threshold:  $\Pr(S = 1) = 1 - \Phi(\xi^*)$ , which is strictly decreasing in  $\xi^*$  and free of every other parameter.*
- (ii) *The probit-transformed support rate is exactly linear in the state and the dispersed shareholders' public noise,*

$$T = \mu_T + \alpha x + \beta u_D, \quad \alpha = \sigma_D \left( \frac{1}{\sigma_{u_D}^2} + \frac{1}{\sigma_D^2} \right), \quad \beta = \frac{\sigma_D}{\sigma_{u_D}^2}, \quad \mu_T = -\sigma_D k_D \Lambda_D, \quad (\text{C.6})$$

and  $(T, s^*)$  is bivariate normal. Equivalently,

$$T = \mu_T + c s^* + \omega Z, \quad c = \text{Cov}(T, s^*) = \frac{\alpha + \beta \sigma_{u_I}^2}{\sqrt{1 + \sigma_{u_I}^2}}, \quad Z \sim N(0, 1), Z \perp s^*, \quad (\text{C.7})$$

where  $\omega^2 = \sigma_T^2 - c^2 > 0$  on all of  $\Theta$ , by the identity

$$\sigma_T^2 (1 + \sigma_{u_I}^2) - (\alpha + \beta \sigma_{u_I}^2)^2 = \frac{\sigma_{u_I}^2}{\sigma_D^2} + \beta^2 (1 + \sigma_{u_I}^2) (\sigma_{u_D}^2 - \sigma_{u_I}^2), \quad (\text{C.8})$$

whose right side is strictly positive on  $\Theta$ .

(iii) The two cell means identify  $(\mu_T, c)$ : writing  $M_1(\xi^*) = \phi(\xi^*)/(1 - \Phi(\xi^*))$  and  $M_0(\xi^*) = \phi(\xi^*)/\Phi(\xi^*)$  for the inverse Mills ratios,

$$c = \frac{E[T | S=1] - E[T | S=0]}{M_1(\xi^*) + M_0(\xi^*)}, \quad \mu_T = \frac{M_0 E[T | S=1] + M_1 E[T | S=0]}{M_0 + M_1}. \quad (\text{C.9})$$

(iv) Conditional on the recommendation cell,  $T \stackrel{d}{=} \mu_T + c W_s + \omega Z$ , where  $W_s$  is  $s^*$  truncated to the cell (a law fixed by  $\xi^*$  alone), so that

$$\text{Var}(\tau | S=s) = V_s(\omega) \equiv \text{Var}(\Phi(\mu_T + c W_s + \omega Z)) \quad (\text{C.10})$$

is a function of  $\omega$  alone once  $(\mu_T, c, \xi^*)$  are fixed.

Under Assumption C.1 below,  $\text{Var}(\tau | S=0)$  identifies  $\omega$ . Together with the identified  $(\mu_T, c, \xi^*)$ , this uniquely determines the representation (C.7), and hence the joint distribution of  $(T, S)$ . Equivalently,  $\sigma_T = \sqrt{c^2 + \omega^2}$  and  $\rho_{Ts} = c/\sigma_T$ . The  $S=1$  cell variance is overidentifying.

*Proof.* For (i),  $s^*$  is standard normal for every  $\theta$  by (C.2), so  $\Pr(S = 1) = 1 - \Phi(\xi^*)$  regardless of the remaining coordinates.

For (ii), by the law of large numbers (Appendix B),  $\tau = p_D(x, \eta_D)$ , so  $T = \Phi^{-1}(\tau)$  equals the probit index of  $p_D$ :

$$T = \sigma_D \left[ \frac{\eta_D}{\sigma_{u_D}^2} + \frac{x}{\sigma_D^2} - k_D \Lambda_D \right].$$

Substituting  $\eta_D = x + u_D$  gives (C.6). Joint normality of  $(x, u_D, u_I)$  implies that  $(T, s^*)$  is bivariate normal, with

$$\text{Cov}(T, s^*) = \frac{\alpha \text{Cov}(x, x) + \beta \text{Cov}(u_D, u_I)}{\sqrt{1 + \sigma_{u_I}^2}}.$$

Since  $\text{Cov}(u_D, u_I) = \sigma_{u_I}^2$ , this delivers  $c$  in (C.7). The orthogonal decomposition of  $T$  with respect to  $s^*$  then defines  $Z$  and

$$\omega^2 = \sigma_T^2 - c^2, \quad \sigma_T^2 = \alpha^2 + \beta^2 \sigma_{u_D}^2.$$

Using  $\alpha - \beta = 1/\sigma_D$ , straightforward expansion gives

$$\omega^2 = \frac{\sigma_{u_I}^2}{\sigma_D^2(1 + \sigma_{u_I}^2)} + \beta^2 (\sigma_{u_D}^2 - \sigma_{u_I}^2) > 0.$$

The first term is strictly positive since  $\sigma_{u_I}, \sigma_D \in (0, \infty)$ , while the second is nonnegative since  $\sigma_{u_D} \geq \sigma_{u_I}$  on  $\Theta$ . Hence  $|\rho_{Ts}| < 1$  and  $\omega > 0$ . The two terms are, respectively, the private-signal channel and the dispersed-specific public-noise channel: the two sources of variation in dispersed support that the report cannot explain. In particular, the private channel alone keeps  $\omega > 0$  in the boundary case  $\sigma_{u_D} = \sigma_{u_I}$ , in which dispersed shareholders observe the report itself.

For (iii), taking conditional expectations of (C.7) within the two recommendation cells gives

$$\mathbb{E}[T \mid S=1] = \mu_T + cM_1(\xi^*), \quad \mathbb{E}[T \mid S=0] = \mu_T - cM_0(\xi^*).$$

Since  $M_0, M_1 > 0$ , subtracting the two equations identifies

$$c = \frac{\mathbb{E}[T \mid S=1] - \mathbb{E}[T \mid S=0]}{M_1(\xi^*) + M_0(\xi^*)},$$

after which either cell mean identifies  $\mu_T$ , giving (C.9). The sign of  $c$ , and hence of  $\rho_{Ts}$ , is therefore determined by the ordering of the two cell means.

For (iv), conditioning on  $S = s$  restricts  $s^*$  to the corresponding recommendation cell but does not affect  $Z$ , since  $Z \perp s^*$  and  $S$  is a function of  $s^*$  alone. Thus, letting  $W_s$  denote a standard normal variable truncated to the cell  $S = s$ ,

$$T \mid S = s \stackrel{d}{=} \mu_T + cW_s + \omega Z, \quad Z \sim N(0, 1), \quad Z \perp W_s.$$

Since  $\tau = \Phi(T)$ , this immediately gives (C.10).

Under Assumption C.1, (C.10) identifies  $\omega$ ; together with the previously identified  $(\mu_T, c, \xi^*)$ , this uniquely determines the joint distribution of  $(T, S)$ . The  $S=1$  cell variance is overidentifying. ■

**Assumption C.1:** First-stage regularity

*At the identified reduced-form values  $(\mu_T, c, \xi^*)$ , the map  $\omega \mapsto V_0(\omega)$  of (C.10), the conditional variance of dispersed support in the against-recommendation cell as a function of the advisor-orthogonal residual scale, is strictly monotone on  $(0, \infty)$ .*

**Remark on Assumption C.1.** The recommendation cells identify the location and report-loading of dispersed support directly, while our baseline second moment identifies the residual scale  $\omega$  through the conditional variance of raw support. Assumption C.1 ensures that this moment is one-to-one in  $\omega$ , ruling out the knife-edge case in which two different residual scales generate the same cell variance. This regularity condition is specific to the choice of raw-support variance as the identifying moment. At the population level, one could instead use the conditional variance of probit-transformed support, since

$$\text{Var}(T \mid S = s) = c^2 \text{Var}(W_s) + \omega^2,$$

which recovers  $\omega^2$  directly once  $(c, \xi^*)$  are identified. In other words, this assumption is imposed for convenience in the moment we choose to target, rather than as a fundamental identification requirement.

**Lemma C.2:** Exact inversion of the blockholder reduced forms

*For every  $\theta \in \Theta$  and every  $b$ , the pair  $(V_b, S)$  arises from thresholding a standard bivariate normal pair:  $(\tilde{m}_b, s^*)$  is standard bivariate normal with correlation  $\rho_b$ , where  $\tilde{m}_b = m_b/s_b$ , and  $V_b = \mathbf{1}[\tilde{m}_b > \zeta_b]$ ,  $S = \mathbf{1}[s^* > \xi^*]$ . Given  $\xi^*$ :*

- (i)  $\Pr(V_b = 1) = 1 - \Phi(\zeta_b)$  identifies  $\zeta_b$  globally;
- (ii)  $\Pr(V_b = 1, S = 1) = \bar{\Phi}_2(\zeta_b, \xi^*; \rho_b)$ , the standard bivariate normal upper-orthant probability, is strictly increasing in  $\rho_b$  and identifies  $\rho_b$  globally.

The  $2N_B$  vote-rate moments therefore identify  $\{(\rho_b, \zeta_b)\}_{b=1}^{N_B}$ .

*Proof.* Joint normality of  $(x, u_I, \varepsilon_b)$  makes  $(m_b, s^*)$  bivariate normal with mean zero, and standardizing gives the stated representation. For (i),  $1 - \Phi(\zeta_b)$  is strictly decreasing in  $\zeta_b$ , so the marginal vote rate uniquely identifies  $\zeta_b$ . For (ii), Plackett's identity,

$$\frac{\partial \Phi_2(h, k; \rho)}{\partial \rho} = \phi_2(h, k; \rho) > 0,$$

implies that the upper-orthant probability is strictly increasing in  $\rho_b$  (Plackett, 1954). Since the observed joint rate is generated by some  $\rho_b \in (-1, 1)$ , strict monotonicity pins down that  $\rho_b$  uniquely. ■

**Remark on Lemmas C.1–C.2.** These results recover the reduced forms contained in dispersed support and the individual blockholder–recommendation tables: the joint law of  $(\tau, S)$  and, for each blockholder separately, the joint law of  $(V_b, S)$ . The next two lemmas show that these reduced forms determine every structural coordinate as an explicit function of one remaining scalar, the advisor noise  $\sigma_{u_I}$ .

**Lemma C.3:** Blockholder parameters given advisor noise follow from a projection identity  
Fix  $\theta \in \Theta$  and write  $\varsigma = \sigma_{u_I}$ .

(i) Because blockholders observe the report itself,  $s$  belongs to the conditioning set of  $m_b = E[x \mid s, z_b]$ , so

$$\text{Cov}(m_b, s) = \text{Cov}(x, s) = 1. \quad (\text{C.11})$$

(ii) The posterior-mean variance satisfies  $s_b^2 = 1 - 1/\Lambda_b$ , and  $\text{Corr}(m_b, x) = s_b$ . Dividing (C.11) by the standard deviations of  $m_b$  and  $s$  therefore gives

$$\rho_b = \frac{1}{s_b \sqrt{1 + \varsigma^2}} \iff \rho_b \text{Corr}(m_b, x) = \rho_{xs}(\varsigma). \quad (\text{C.12})$$

(iii) Given  $\varsigma$  and the reduced-form correlation  $\rho_b$ , (C.12) directly identifies

$$s_b = \frac{1}{\rho_b \sqrt{1 + \varsigma^2}}.$$

Combining this with  $s_b^2 = 1 - 1/\Lambda_b$  uniquely determines  $\sigma_b$ , while  $k_b = \zeta_b s_b$ . In closed form,

$$\frac{1}{\sigma_b^2} = \frac{\zeta^{-2}(1 + \zeta^{-2})(1 - \rho_b^2)}{\rho_b^2(1 + \zeta^{-2}) - \zeta^{-2}}, \quad k_b = \frac{\zeta_b}{\rho_b \sqrt{1 + \zeta^2}}. \quad (\text{C.13})$$

The inversion is admissible if and only if

$$\rho_b > \rho_{xs}(\zeta) \quad \Longleftrightarrow \quad \zeta > \frac{\sqrt{1 - \rho_b^2}}{\rho_b}. \quad (\text{C.14})$$

For fixed  $\zeta$ , the map  $\sigma_b \mapsto \rho_b$  is strictly increasing with range  $(\rho_{xs}(\zeta), 1)$ .

Consequently, a candidate  $\zeta$  is consistent with all blockholder reduced forms only if

$$\zeta > \zeta_{lo} \equiv \max_b \frac{\sqrt{1 - \rho_b^2}}{\rho_b}, \quad (\text{C.15})$$

and for every such  $\zeta$  the blockholder coordinates  $\{\sigma_b(\zeta), k_b(\zeta)\}_{b=1}^{N_B}$  are uniquely determined by (C.13).

*Proof.* For (i), the projection error  $x - m_b$  is orthogonal to the conditioning variables, so  $\text{Cov}(m_b, s) = \text{Cov}(x, s) = 1$ . For (ii), the law of total variance gives  $s_b^2 = 1 - 1/\Lambda_b$ , while the same projection orthogonality gives  $\text{Cov}(m_b, x) = \text{Var}(m_b) = s_b^2$ , and hence  $\text{Corr}(m_b, x) = s_b$ . Dividing (C.11) by  $s_b \sqrt{1 + \zeta^2}$  gives (C.12).

For (iii), (C.12) gives  $s_b = 1/[\rho_b \sqrt{1 + \zeta^2}]$ . Writing  $A = \zeta^{-2}$  and  $r = \sigma_b^{-2}$ ,

$$s_b^2 = \frac{A + r}{1 + A + r} = \frac{A}{\rho_b^2(1 + A)}.$$

Solving for  $r$  gives (C.13). Its denominator is positive if and only if  $\rho_b^2 > 1/(1 + \zeta^2) = \rho_{xs}(\zeta)^2$ , which gives (C.14);  $k_b = \zeta_b s_b$  by definition. Finally, as  $\sigma_b$  increases from 0 to  $\infty$ ,  $s_b$  falls from 1 to  $\rho_{xs}(\zeta)$ , so (C.12) implies that  $\rho_b$  increases strictly from  $\rho_{xs}(\zeta)$  to 1.  $\blacksquare$

**Lemma C.4:** Dispersed-side parameters given the advisor noise solve a cubic

Fix the identified  $(\mu_T, \sigma_T, \rho_{Ts})$  and a candidate  $\zeta > 0$ . Write  $p = \sigma_{u_D}^{-2}$ ,  $q = \sigma_D^{-2}$ ,  $w = \sqrt{q}$ , and

$$\kappa(\zeta) \equiv \rho_{Ts} \sigma_T \sqrt{1 + \zeta^2} = \text{Cov}(T, s) = \alpha + \beta \zeta^2 > 0. \quad (\text{C.16})$$

In precision coordinates, the dispersed-side reduced form satisfies

$$\sigma_T^2 = \frac{(p+q)^2 + p}{q}, \quad \kappa = \frac{p(1+\zeta^2) + q}{\sqrt{q}}, \quad k_D = \frac{-\mu_T \sqrt{q}}{1+p+q}. \quad (\text{C.17})$$

For fixed  $\zeta$ , the second equation uniquely gives  $p$  as a function of  $w$ ,

$$p(w) = \frac{\kappa w - w^2}{1 + \zeta^2},$$

which is positive exactly for  $w \in (0, \kappa)$ . Substituting  $p(w)$  and  $q = w^2$  into the variance equation shows that admissible dispersed-side parameters correspond exactly to roots on  $(0, \kappa)$  of

$$G_\zeta(w) = \zeta^4 w^3 + 2\kappa \zeta^2 w^2 + \left[ \kappa^2 - (1 + \zeta^2) - \sigma_T^2 (1 + \zeta^2)^2 \right] w + \kappa(1 + \zeta^2) = 0, \quad (\text{C.18})$$

subject also to the definitional restriction  $\sigma_{u_D}(w) = p(w)^{-1/2} \geq \zeta$ . At the endpoints,

$$G_\zeta(0) = \kappa(1 + \zeta^2) > 0, \quad G_\zeta(\kappa) = \kappa(1 + \zeta^2)^2(\kappa^2 - \sigma_T^2). \quad (\text{C.19})$$

Moreover,  $\kappa(\zeta) \leq \sigma_T$  according as  $\zeta \leq \zeta_{hi} \equiv \sqrt{1 - \rho_{Ts}^2}/\rho_{Ts}$ . Hence, for  $\zeta < \zeta_{hi}$ ,  $G_\zeta$  has an odd number of roots in  $(0, \kappa)$ , counted with multiplicity, and therefore at least one; for  $\zeta > \zeta_{hi}$  it has an even number, hence zero or two. Since  $G_\zeta$  is cubic, there are at most three candidate roots, and every admissible root uniquely determines  $(\sigma_{u_D}, \sigma_D, k_D)$  through  $p(w)$ ,  $q = w^2$ , and (C.17).

*Proof.* From  $\alpha = (p+q)/\sqrt{q}$  and  $\beta = p/\sqrt{q}$ , substituting into  $\sigma_T^2 = \alpha^2 + \beta^2/p$  and  $\kappa = \alpha + \beta\zeta^2$  gives (C.17); the expression for  $k_D$  follows from  $\mu_T = -\sigma_D k_D \Lambda_D$ . Writing  $q = w^2$ , the  $\kappa$  equation gives  $p(w) = (\kappa w - w^2)/(1 + \zeta^2)$ , with  $p(w) > 0$  exactly when  $w \in (0, \kappa)$ . Substitution into the variance equation and clearing denominators gives (C.18). The endpoint values in (C.19) follow by direct evaluation. Finally,

$$\kappa < \sigma_T \iff \rho_{Ts} \sqrt{1 + \zeta^2} < 1 \iff \zeta < \frac{\sqrt{1 - \rho_{Ts}^2}}{\rho_{Ts}} = \zeta_{hi}.$$

Thus  $G_\zeta$  has opposite signs at the endpoints when  $\zeta < \zeta_{hi}$  and the same sign when  $\zeta > \zeta_{hi}$ , yielding the stated root counts by continuity and the fact that  $G_\zeta$  is cubic. ■

**Remark on Lemma C.4.** To see why matching the dispersed-side moments leads to a cubic, note that, given  $\varsigma$ , the reduced form supplies two magnitudes, the dispersion of dispersed support  $\sigma_T$  and its co-movement with the report  $\kappa$ , to determine the two precisions  $(p, q)$ . The co-movement equation is linear in the public precision  $p$  once the private scale  $w$  is fixed, while the dispersion equation is quadratic in the combined precision  $p + q$ . Eliminating  $p$  therefore leaves a single polynomial equation in  $w$ , with degree three. The possibility of multiple roots also has a natural interpretation: at a given advisor noise, there can be more than one allocation of public and private information precision that generates the same observed dispersion and co-movement. These alternative allocations generate the additional branches characterized in Corollary C.1; the joint vote–support and mean co-voting moments subsequently distinguish among them.

**Corollary C.1:** The identified set after matching individual voting patterns

*Fix the reduced forms  $(\xi^*, \mu_T, \sigma_T, \rho_{Ts}, \{\rho_b, \zeta_b\})$  generated by some  $\theta_0 \in \Theta$ . Under Assumption C.1, the set of parameters in  $\Theta$  reproducing the first-stage and vote-rate blocks,*

$$\mathcal{I} = \{ \theta \in \Theta : \text{first-stage and vote-rate blocks of } g(\theta) \text{ equal those of } g(\theta_0) \},$$

*is contained in the one-dimensional root set indexed by  $\varsigma = \sigma_{u_l}$ : for each  $\varsigma$ , the blockholder coordinates are given by (C.13), while the dispersed-side coordinates correspond to an admissible root of the cubic (C.18), of which there are at most three. Every point of  $\mathcal{I}$  satisfies  $\varsigma > \varsigma_{lo}$ . On the region  $\varsigma \in (\varsigma_{lo}, \varsigma_{hi})$ , at least one root of the cubic exists in  $(0, \kappa(\varsigma))$  for every  $\varsigma$ , though not necessarily an admissible one, and*

$$\rho_{Ts} < \rho_{xs}(\sigma_{u_l}) < \min_b \rho_b. \quad (\text{C.20})$$

*The interval  $(\varsigma_{lo}, \varsigma_{hi})$  is nonempty if and only if  $\rho_{Ts} < \min_b \rho_b$ . This ordering is therefore necessary for the sandwich region to exist, but is not itself implied by the model. At the true parameter, the full sandwich (C.20) holds if and only if  $\sigma_{u_l} < \varsigma_{hi}$ .*

*Proof.* Any  $\theta \in \mathcal{I}$  reproduces  $\{\rho_b, \zeta_b\}$ , so Lemma C.3 forces  $\varsigma > \varsigma_{lo}$  and uniquely determines

$\{\sigma_b, k_b\}$  given  $\varsigma$ . It also reproduces  $(\mu_T, \sigma_T, \rho_{Ts})$ , so Lemma C.4 requires its dispersed-side coordinates to correspond to an admissible root of  $G_\varsigma$ , of which there are at most three for each  $\varsigma$ . For  $\varsigma \in (\varsigma_{lo}, \varsigma_{hi})$ , Lemma C.4 guarantees at least one root in  $(0, \kappa(\varsigma))$ , while the definitions of  $\varsigma_{lo}$  and  $\varsigma_{hi}$  give the two inequalities in (C.20). ■

**Remark on Corollary C.1.** This is the precise sense in which individual voting patterns cannot identify the model: they confine  $\theta$  to explicitly parametrized curves along which advisor noise trades off against every blockholder's private-signal precision, but they contain no information about the location along those curves. The final ingredient is the moment block that varies along the curves.

**Lemma C.5:** Leave-out covariances give an exact common-private decomposition

For  $u \in \mathbb{R}$ , define the conditional-mean profiles

$$\pi_b(u) = \mathbb{E}[V_b \mid s^* = u] = \Phi\left(\frac{\rho_b u - \zeta_b}{\sqrt{1 - \rho_b^2}}\right), \quad \mathcal{T}(u) = \mathbb{E}[\tau \mid s^* = u] = \Phi\left(\frac{\mu_T + cu}{\sqrt{1 + \omega^2}}\right). \quad (\text{C.21})$$

Define also the advisor-orthogonal partial correlation

$$\gamma_b \equiv \text{Corr}(\tilde{m}_b, T \mid s^*) = \frac{\rho_{bT} - \rho_b \rho_{Ts}}{\sqrt{(1 - \rho_b^2)(1 - \rho_{Ts}^2)}}, \quad \rho_{bT} = \frac{\alpha a_b + \beta b_b \sigma_{u_l}^2}{s_b \sigma_T}. \quad (\text{C.22})$$

This conditional correlation is constant in the realization of  $s^*$ . Then, for each recommendation cell  $s \in \{0, 1\}$ ,

$$\text{Cov}(V_b, \tau \mid S = s) = \underbrace{\text{Cov}_{u \sim TN_s}(\pi_b(u), \mathcal{T}(u))}_{c_{b,s} : \text{common-report channel}} + \underbrace{\mathbb{E}_{u \sim TN_s}[h_b(u; \gamma_b)]}_{\mathcal{L}_{b,s}(\gamma_b) : \text{advisor-orthogonal channel}}, \quad (\text{C.23})$$

where  $TN_s$  denotes the law of  $s^*$  truncated to cell  $s$ ,

$$h_b(u; \gamma) = \text{Cov}(\mathbf{1}[X > x_b(u)], \Phi(\mu_T + cu + \omega Y)), \quad x_b(u) = \frac{\zeta_b - \rho_b u}{\sqrt{1 - \rho_b^2}},$$

and  $(X, Y)$  is standard bivariate normal with correlation  $\gamma$ . Moreover,

$$h_b(u; 0) = 0, \quad \frac{\partial h_b(u; \gamma)}{\partial \gamma} = \int \omega \phi(\mu_T + cu + \omega y) \phi_2(x_b(u), y; \gamma) dy > 0. \quad (\text{C.24})$$

Hence  $\mathcal{L}_{b,s}(\cdot)$  is strictly increasing with  $\mathcal{L}_{b,s}(0) = 0$ . Both  $C_{b,s}$  and the function  $\mathcal{L}_{b,s}(\cdot)$  depend only on  $(\rho_b, \zeta_b, \mu_T, c, \omega, \xi^*)$ , which are fixed by Lemmas C.1–C.2. Consequently, along any curve of Corollary C.1,

$$g_b^{LO}(s) = \left[ C_{b,s} - \frac{1}{N_B - 1} \sum_{\ell \neq b} C_{\ell,s} \right] + \left[ \mathcal{L}_{b,s}(\gamma_b) - \frac{1}{N_B - 1} \sum_{\ell \neq b} \mathcal{L}_{\ell,s}(\gamma_\ell) \right] \quad (\text{C.25})$$

varies only through  $(\gamma_1(\varsigma), \dots, \gamma_{N_B}(\varsigma))$ .

*Proof.* Conditional on  $s^* = u$ , the pair  $(\tilde{m}_b, T)$  is bivariate normal with means  $(\rho_b u, \mu_T + cu)$ , standard deviations  $(\sqrt{1 - \rho_b^2}, \omega)$ , and correlation  $\gamma_b$ , all independent of  $u$ . The expression for  $\gamma_b$  in (C.22) is the standard partial-correlation formula, with  $\rho_{bT}$  obtained from (C.6) and (C.3) using  $\text{Cov}(u_D, u_I) = \sigma_{u_I}^2$ . The conditional-mean profiles in (C.21) then follow directly from Gaussian thresholding and the identity  $E[\Phi(a + bZ)] = \Phi(a/\sqrt{1 + b^2})$ .

Applying the law of total covariance over  $s^* = u$  within recommendation cell  $s$  gives (C.23):  $C_{b,s}$  is the covariance of the two conditional-mean profiles, while  $\mathcal{L}_{b,s}(\gamma_b)$  is the average conditional covariance remaining after conditioning on the report.

To establish (C.24), write  $\psi(y) = \Phi(\mu_T + cu + \omega y)$ . Hoeffding's covariance identity gives

$$h_b(u; \gamma) = \int \psi'(y) \left[ \bar{\Phi}_2(x_b(u), y; \gamma) - \bar{\Phi}(x_b(u)) \bar{\Phi}(y) \right] dy.$$

Since  $\psi'(y) = \omega \phi(\mu_T + cu + \omega y) > 0$ , differentiating under the integral and applying Plackett's identity yields

$$\frac{\partial h_b(u; \gamma)}{\partial \gamma} = \int \omega \phi(\mu_T + cu + \omega y) \phi_2(x_b(u), y; \gamma) dy > 0.$$

The interchange is justified by local Gaussian domination for  $\gamma \in (-1, 1)$ . At  $\gamma = 0$ ,  $X$  and  $Y$  are independent, so  $h_b(u; 0) = 0$ . Hence  $\mathcal{L}_{b,s}(\gamma)$  is strictly increasing with  $\mathcal{L}_{b,s}(0) = 0$ .

Finally, along any curve of Corollary C.1,  $(\rho_b, \zeta_b, \mu_T, c, \omega, \xi^*)$  are fixed at their reduced-form values. Thus  $C_{b,s}$  and the function  $\mathcal{L}_{b,s}(\cdot)$  are fixed, and the leave-out covariance (C.25) varies only through  $(\gamma_1(\zeta), \dots, \gamma_{N_B}(\zeta))$ . ■

**Remark on Lemma C.5.** The leave-out design does not difference out the common-report channel by cancellation of loadings; rather,  $C_{b,s}$  is frozen because it is a functional of reduced-form objects alone. Raising advisor noise reduces every blockholder's fundamental tracking through the informativeness identity (C.12), thereby changing the advisor-orthogonal co-movement between blockholder votes and dispersed support. The leave-out contrasts isolate this variation because the common-report component remains fixed along the identified curves. Within each cell the  $N_B$  contrasts sum to zero by construction, so the block carries  $2(N_B - 1)$  free moments.

**Lemma C.6:** The joint moments depend on two scalars

Define  $\varrho \equiv \rho_{xs}(\sigma_{u_I})/\sigma_D$ , and write  $\gamma_{bb'} \equiv \text{Corr}(m_b, m_{b'} \mid s^*)$  for the pairwise correlation conditional on the report,  $b \neq b'$ .

(i) For every  $\theta \in \Theta$ , the advisor-orthogonal correlations of Lemma C.5 and their pairwise counterparts satisfy

$$\gamma_b = \frac{\sqrt{1 - \rho_b^2}}{\rho_b \omega} \varrho, \quad \gamma_{bb'} = \frac{\sqrt{(1 - \rho_b^2)(1 - \rho_{b'}^2)}}{\rho_b \rho_{b'}} \frac{1}{\sigma_{u_I}^2}. \quad (\text{C.26})$$

(ii) On the identified set of Corollary C.1, the coefficients in (C.26) are fixed at their reduced-form values. Hence each  $\text{Cov}(V_b, \tau \mid S = s)$  is strictly increasing in  $\varrho$ , while each mean co-voting moment  $\text{Cov}(V_b, V_{-b} \mid S = s)$  and the aggregate variance  $\text{Var}(\bar{V} \mid S = s)$  is strictly decreasing in  $\sigma_{u_I}$ . Thus the vote-support covariances identify  $\varrho$  on the identified set, while any single co-voting or aggregate moment identifies  $\sigma_{u_I}$ .

(iii) On the identified set,

$$\sigma_{u_D}^{-2} = \varrho(c - \varrho), \quad (\text{C.27})$$

and  $y = \sigma_{u_I}^2$  solves

$$\varrho^2 y^2 + (2c\varrho - \sigma_T^2)y + \left(c^2 + \frac{c}{\varrho} - 1 - \sigma_T^2\right) = 0. \quad (\text{C.28})$$

At most two points of the identified set therefore share a value of  $\varrho$ : a point itself and its conjugate, obtained by replacing  $\sigma_{u_I}^2$  with the second root

$$\mathfrak{y} = \frac{\sigma_T^2 - 2c\varrho}{\varrho^2} - \sigma_{u_I}^2. \quad (\text{C.29})$$

The conjugate lies on the identified set if and only if  $\mathfrak{y} \in (\varsigma_{I_0}^2, \sigma_{u_D}^2]$ , with  $\sigma_{u_D}$  common to the point and its conjugate.

*Proof.* For (i), condition on  $s^*$ . Substituting  $u_I = \sqrt{1 + \sigma_{u_I}^2} s^* - x$  into (C.3) and (C.6) shows that, conditional on  $s^*$ ,  $m_b$  and  $T$  load on  $x$  with coefficients  $a_b - b_b = \sigma_b^{-2}/\Lambda_b$  and  $\alpha - \beta = 1/\sigma_D$ , respectively. Since the private noises are mutually independent, their conditional covariance runs only through the residual variation in  $x$ . Hence

$$\begin{aligned} \gamma_b &= \frac{(a_b - b_b)\sigma_D^{-1} \text{Var}(x | s^*)}{s_b \sqrt{1 - \rho_b^2} \omega}, \\ \gamma_{bb'} &= \frac{(a_b - b_b)(a_{b'} - b_{b'}) \text{Var}(x | s^*)}{s_b \sqrt{1 - \rho_b^2} s_{b'} \sqrt{1 - \rho_{b'}^2}}, \\ \text{Var}(x | s^*) &= \frac{\sigma_{u_I}^2}{1 + \sigma_{u_I}^2}. \end{aligned}$$

Using  $\rho_b s_b \sqrt{1 + \sigma_{u_I}^2} = 1$  from (C.12) and  $\Lambda_b - \sigma_b^{-2} = 1 + \sigma_{u_I}^2$  reduces these expressions to (C.26).

For (ii), the reduced forms fix  $(\rho_b, \zeta_b, \omega)$ , and (C.12) implies  $\rho_b > 0$ . Thus (C.26) makes each  $\gamma_b$  strictly increasing in  $\varrho$  and each  $\gamma_{bb'}$  strictly decreasing in  $\sigma_{u_I}$ . By Lemma C.5,  $C_{b,s}$  is fixed and  $\mathcal{L}_{b,s}$  is strictly increasing, so  $\text{Cov}(V_b, \tau | S = s)$  is strictly increasing in  $\varrho$ .

For the co-voting moments, conditional on  $s^* = u$  the standardized blockholder indices are bivariate normal with correlation  $\gamma_{bb'}$ , so

$$\mathbb{E}[V_b V_{b'} | S = s] = \mathbb{E}_{u \sim TN_s} \left[ \bar{\Phi}_2(x_b(u), x_{b'}(u); \gamma_{bb'}) \right].$$

Plackett's identity makes this expression strictly increasing in  $\gamma_{bb'}$ . Since the vote-rate block fixes the marginal vote probabilities, the pairwise covariances are therefore strictly decreasing in  $\sigma_{u_I}$ , as are their averages and  $\text{Var}(\bar{V} \mid S = s)$ .

For (iii), let  $y = \sigma_{u_I}^2$ . By definition of  $\varrho$ ,

$$q = \sigma_D^{-2} = \varrho^2(1 + y), \quad \kappa = c\sqrt{1 + y}.$$

Substituting these identities into the co-movement equation in (C.17) gives  $c = (p + \varrho^2)/\varrho$ , and hence  $p = \varrho(c - \varrho)$ . Substituting  $p$  and  $q$  into the variance equation in (C.17) and simplifying gives (C.28).

Thus two points sharing  $\varrho$  also share  $p$ , and hence  $\sigma_{u_D}$ , while their values of  $\sigma_{u_I}^2$  are the two roots of the same quadratic. The sum of those roots gives (C.29). The conjugate is admissible exactly when  $\mathfrak{y} > \varsigma_{lo}^2$ , which ensures blockholder consistency, and  $\mathfrak{y} \leq \sigma_{u_D}^2$ , which enforces  $\sigma_{u_D} \geq \sigma_{u_I}$ . Finally, its associated cubic root is  $w = \varrho\sqrt{1 + \mathfrak{y}}$  and lies in  $(0, \kappa)$  automatically because  $p = \varrho(c - \varrho) > 0$  implies  $\varrho \in (0, c)$ . ■

**Remark on Lemma C.6.** Conditional on the report, a pair of blockholders remains linked through the uncertainty in the advisor's signal, so their correlation reads the advisor noise  $\sigma_{u_I}$  directly. A blockholder and dispersed support, by contrast, share only residual variation in the state, so their correlation reads the composite scalar  $\varrho$ . These are the two dials that the joint moments add to the individual voting patterns.

**Corollary C.2:** Joint moments eliminate the conjugate

*On the identified set of Corollary C.1, the vote–support covariance block identifies  $\varrho$ , and the mean co-voting block identifies  $\sigma_{u_I}$ . Hence the first-stage, vote-rate, vote–support, and mean co-voting blocks jointly identify  $\theta$ .*

*Proof.* By Lemma C.6(ii), the vote–support covariances are strictly increasing in  $\varrho$  on the identified set, so equality of that block implies equality of  $\varrho$ . The same lemma shows that each mean co-voting moment  $\text{Cov}(V_b, V_{-b} \mid S = s)$  is strictly decreasing in  $\sigma_{u_I}$ , so equality of the co-voting block implies equality of  $\sigma_{u_I}$ . Given  $(\varrho, \sigma_{u_I})$ , Lemma C.6(iii) uniquely determines  $\sigma_{u_D}$  and  $\sigma_D$ , after which  $k_D$  follows from (C.17); Lemma C.3 uniquely determines the blockholder

coordinates. Hence  $\theta$  is uniquely determined. ■

**Remark on Corollary C.2.** The role of mean co-voting is particularly transparent from the conjugate characterization in Lemma C.6(iii). The vote–support covariances identify  $\varrho$  but can leave one observationally equivalent conjugate with the same value of  $\varrho$ . Mean co-voting varies strictly with  $\sigma_{u_i}$  and therefore separates these two points directly. Thus no no-conjugate restriction is required when, as in our moment specification, mean co-voting is included in the identifying moment set. Only one scalar direction in the co-voting block is needed for identification; the remaining co-voting moments provide overidentifying restrictions.

*Proof of Proposition 1.* Let  $\theta, \theta_0 \in \Theta$  satisfy  $g(\theta) = g(\theta_0)$ , where  $g$  collects the first-stage, vote-rate, vote–support covariance, and mean co-voting blocks. By Lemma C.1 and Assumption C.1, the two parameters share  $\xi^*$  and  $(\mu_T, c, \omega)$ , hence  $(\sigma_T, \rho_{Ts})$  and the entire joint law of  $(T, S)$ . By Lemma C.2, they also share every  $(\rho_b, \zeta_b)$ . Lemmas C.3–C.4 therefore place both parameters on the identified set of Corollary C.1 generated by these common reduced forms.

Their vote–support covariance and mean co-voting blocks also agree. Corollary C.2 therefore implies  $\theta = \theta_0$ .

Finally, given  $\theta$ , Definition 1 determines preferences  $\Delta$  uniquely. The indifference conditions (15)–(16) imply

$$\delta_i = -E[x \mid m_i = k_i, \text{piv}_i],$$

and the right-hand side is an explicit functional of  $\theta$  through the limiting pivotal posteriors of Lemmas B.1 and B.2. Hence  $(\theta, \Delta)$  is identified. ■

**Remark on local identification.** At any  $\theta_0$  where the Jacobian  $D = \partial g / \partial \theta'$  has full column rank  $N_\Theta$ , the parameter is also locally identified in the sense of Rothenberg (1971), and the local GMM criterion has nonsingular curvature  $D' \widehat{W} D$ . The block structure makes the source of this rank transparent: the first-stage and vote-rate blocks identify the reduced-form coordinates, the vote–support covariances supply variation in the scalar  $\varrho$  through (C.24) and (C.26), and mean co-voting supplies variation in  $\sigma_{u_i}$  through the pairwise correlation in (C.26). A direct numerical rank check is outlined in Section C.4.

**Remark on overidentification.** The identification argument uses only a small number of independent directions in the joint-moment blocks. By Lemma C.6, the vote–support covariances all identify the same scalar  $\varrho$ , while any one mean co-voting moment identifies  $\sigma_{u_l}$ . Consequently, additional vote–support covariances, the remaining mean co-voting moments, the aggregate co-movement block, and the  $S=1$  cell variance provide overidentifying restrictions. These moments enter the estimation criterion and are therefore reflected in the Hansen  $J$  statistic, while also providing additional finite-sample curvature and model-fit discipline.

## C.2. Non-Identification from Individual Voting Patterns

*Proof of Proposition 2.* Fix  $\theta_0 \in \Theta$ , write  $\varsigma_0 = \sigma_{u_l}(\theta_0)$ , and let  $(\xi^*, \mu_T, \sigma_T, \rho_{Ts}, \{\rho_b, \zeta_b\})$  denote its reduced forms. We construct a family of structural parameters indexed by a candidate advisor noise  $\varsigma$  that preserves all of these objects.

For the blockholder side, Lemma C.3 uniquely determines  $\{\sigma_b(\varsigma), k_b(\varsigma)\}$  from  $(\rho_b, \zeta_b)$  for every  $\varsigma > \varsigma_{lo}$ , and Lemma C.3(iv) implies  $\varsigma_0 > \varsigma_{lo}$ . For the dispersed side, let  $w_0 = 1/\sigma_D(\theta_0)$ . By Lemma C.4,  $w_0$  is an admissible root of  $G_{\varsigma_0}$ . Because this root is simple, the implicit function theorem gives a neighborhood  $\mathcal{N}$  of  $\varsigma_0$  and a continuously differentiable root branch  $w(\varsigma)$  satisfying  $w(\varsigma_0) = w_0$ . Since  $\theta_0$  is interior, shrinking  $\mathcal{N}$  if necessary preserves  $w(\varsigma) \in (0, \kappa(\varsigma))$  and  $\sigma_{u_D}(\varsigma) > \varsigma$ . For each  $\varsigma \in \mathcal{N}$ , define  $\theta(\varsigma)$  by combining  $\xi^*$ , the blockholder coordinates from Lemma C.3, and the dispersed-side coordinates implied by  $w(\varsigma)$  through (C.17). Then  $\theta(\varsigma) \in \Theta$  and  $\theta(\varsigma_0) = \theta_0$ .

By construction, every  $\theta(\varsigma)$  preserves the dispersed reduced form  $(\xi^*, \mu_T, \sigma_T, \rho_{Ts})$ , and therefore the entire joint law of  $(\tau, S)$  by Lemma C.1. It also preserves every  $(\rho_b, \zeta_b)$ , and therefore every joint law of  $(V_b, S)$  by Lemma C.2. Thus all individual voting patterns are identical along the family even though the underlying information parameters vary. In particular, as  $\varsigma$  rises, Lemma C.3 requires each blockholder’s private noise  $\sigma_b(\varsigma)$  to rise as well in order to preserve her observed relationship with the report.

Finally, for each  $\varsigma$ , re-solve the preference vector  $\Delta(\varsigma)$  from the indifference conditions of Definition 1 evaluated at  $\theta(\varsigma)$ . The cutoff profile associated with each  $\theta(\varsigma)$  therefore satisfies the equilibrium indifference conditions. Hence a continuum of distinct information structures

and associated preferences generates exactly the same individual voting patterns, proving non-identification. ■

**Remark on Proposition 2.** The non-identification result is strong in terms of what the econometrician observes. It does not arise from restricting attention to conditional means or a small set of moments: the econometrician observes the entire joint distribution of  $(\tau, S)$  and, for every blockholder  $b$ , the entire joint distribution of  $(V_b, S)$ . Even this collection of individual voting patterns leaves a continuum of observationally equivalent information structures and preferences. What breaks the equivalence is joint behavior across shareholders. Along the family above, the vote–support covariances vary through the scalar  $\varrho$  of Lemma C.6; matching these moments reduces the continuum to at most the two conjugate points characterized there. Mean co-voting then identifies  $\sigma_{u_i}$  directly and separates those remaining points. Thus the identifying information comes specifically from dependence across agents that is absent from their individual relationships with the recommendation.

### C.3. Estimation Strategy

Estimation stacks the population moments of Section C.1, augmented by the co-voting block, into a single GMM criterion. This subsection records the moment vector, the model-implied moment functions, the weighting and inference conventions, and the recovery of preferences.

**Moment vector.** The estimator matches  $7 + 5N_B$  moments (37 for  $N_B = 6$ ): the five first-stage moments  $(E[T | S=1], E[T | S=0], \text{Var}(\tau | S=0), \text{Var}(\tau | S=1), \text{Pr}(S=1))$ ; the  $2N_B$  vote rates  $E[V_b | S=s]$ ; the  $2N_B$  leave-out covariances  $g_b^{LO}(s)$  of (C.5); the aggregate co-movement pair  $\text{Var}(\bar{V} | S=s)$ ; and the  $N_B$  mean co-voting moments

$$g_b^{CV} = \text{Cov}(V_b, \bar{V}_{-b} | S=0), \quad (\text{C.30})$$

each blockholder’s average pairwise co-voting with the remaining blockholders in the  $S=0$  cell. With  $N_\Theta = 17$  free parameters, the criterion carries 20 overidentifying restrictions. Sample counterparts are computed at the proposal level; blockholder cells use the votes present for that blockholder, and the leave-out and aggregate averages are taken over the blockholders

present on each proposal.

**Conditional state distribution.** The blockholder moment functions condition on the observed pair  $(\tau_j, S_j)$ . The required distribution is that of the state and the advisor's error given dispersed support and the recommendation.

**Lemma C.7:** Joint conditional law of the state and the advisor error

Fix  $\theta \in \Theta$  and condition on  $T = \Phi^{-1}(\tau)$ . The triple  $(x, s^*, T)$  is jointly Gaussian, with

$$\rho_{xT} = \frac{\alpha}{\sigma_T}, \quad \text{Var}(x | T) = 1 - \rho_{xT}^2, \quad \text{Var}(s^* | T) = 1 - \rho_{Ts}^2, \quad \text{Cov}(x, s^* | T) = \rho_{xs} - \rho_{xT} \rho_{Ts},$$

and conditional means  $E[x | T=t] = (\alpha/\sigma_T^2)(t - \mu_T)$ ,  $E[s^* | T=t] = (\rho_{Ts}/\sigma_T)(t - \mu_T)$ . Conditioning additionally on the recommendation truncates  $s^* | T$  to a half-line at  $\xi^*$ , so the exact first and second moments of  $(x, s^*) | (T, S)$  follow from the univariate truncated-normal formulas (Tallis, 1961): with  $a = (\xi^* - E[s^* | T]) / \text{sd}(s^* | T)$  and  $M(a)$  the corresponding Mills ratio, the truncation shifts the mean of  $s^* | T$  by  $\pm M(a) \text{sd}(s^* | T)$  and rescales its variance, and  $x$  updates through  $\text{Cov}(x, s^* | T)$ . The advisor error then follows from the exact identity

$$u_I = \sqrt{1 + \sigma_{u_I}^2} s^* - x, \tag{C.31}$$

so the mean, variance, and covariance with  $x$  of  $u_I | (T, S)$  are linear-quadratic combinations of the truncated moments of  $(x, s^*) | (T, S)$ .

*Proof.* Joint normality and the stated correlations follow from (C.6) and (C.2);  $\text{Cov}(x, T) = \alpha$  and  $\text{Cov}(T, s^*) = c = \rho_{Ts}\sigma_T$ . Given  $T$ , the event  $S = 1$  is  $\{s^* > \xi^*\}$ , a one-sided truncation of the Gaussian  $s^* | T$ ; the moment formulas are standard. Identity (C.31) restates  $s^* = (x + u_I) / \sqrt{1 + \sigma_{u_I}^2}$ . ■

**Blockholder moment functions.** Conditional on  $(x, u_I)$ , blockholder  $b$ 's posterior mean is Gaussian with mean  $a_b x + b_b u_I$  and standard deviation  $c_b \sigma_b = 1/(\sigma_b \Lambda_b)$ , so

$$\Pr(V_b = 1 | x, u_I) = \Phi\left(\sigma_b \Lambda_b (a_b x + b_b u_I - k_b)\right). \tag{C.32}$$

To integrate (C.32) over the conditional law of Lemma C.7, we replace the truncated distribution of  $(x, u_I) \mid (\tau_j, S_j)$  by the Gaussian distribution with the same (exact) first and second moments. Under this moment-matched approximation the conditional vote probability has the closed probit form

$$\Pr(V_b = 1 \mid \tau_j, S_j) = \Phi(Q_{bj}), \quad Q_{bj} = \frac{\sigma_b \Lambda_b (a_b \mu_{x,j} + b_b \mu_{u,j} - k_b)}{\sqrt{1 + (\sigma_b \Lambda_b)^2 \mathcal{V}_{bj}}}, \quad \mathcal{V}_{bj} = a_b^2 v_{x,j} + 2 a_b b_b v_{xu,j} + b_b^2 v_{u,j}, \quad (\text{C.33})$$

where  $(\mu_{x,j}, \mu_{u,j}, v_{x,j}, v_{u,j}, v_{xu,j})$  are the conditional moments of Lemma C.7 at  $(\tau_j, S_j)$ , and the pairwise co-voting probability is the bivariate probit

$$\Pr(V_b = 1, V_{b'} = 1 \mid \tau_j, S_j) = \Phi_2(Q_{bj}, Q_{b'j}; r_{bb',j}), \quad r_{bb',j} = \frac{(\sigma_b \Lambda_b)(\sigma_{b'} \Lambda_{b'}) \mathcal{V}_{bb',j}}{\sqrt{1 + (\sigma_b \Lambda_b)^2 \mathcal{V}_{bj}} \sqrt{1 + (\sigma_{b'} \Lambda_{b'})^2 \mathcal{V}_{b'j}}}, \quad (\text{C.34})$$

with  $\mathcal{V}_{bb',j} = a_b a_{b'} v_{x,j} + (a_b b_{b'} + a_{b'} b_b) v_{xu,j} + b_b b_{b'} v_{u,j}$  the implied index covariance, driven by the common loadings on  $(x, u_I)$ ; conditional on  $(x, u_I)$ , votes are independent across blockholders, as in Appendix B. The approximation affects only the evaluation of these conditional moment functions; the identification argument of Section C.1 uses exact population moments throughout. Model counterparts of the vote-rate moments average (C.33) over the sample distribution of  $(\tau_j, S_j)$  within each recommendation cell, and the leave-out, aggregate, and co-voting moments are built from (C.33)–(C.34) against the observed  $\tau_j$  in the same way. The first-stage moments have the exact closed forms of Lemma C.1, with the cell variances (C.10) evaluated by one-dimensional quadrature.

**Criterion, weighting, and inference.** Let  $\hat{g}(\theta)$  stack the differences between model and sample moments. The estimator is efficiently weighted GMM (Hansen, 1982). Because each moment is a sample statistic minus its model prediction, the efficient weighting matrix does not depend on  $\theta$ : we form  $\hat{S}$ , the moment covariance built from influence functions clustered at the proposal level so that all votes cast on the same proposal contribute jointly, and take  $\widehat{W}$  to be its generalized (Moore–Penrose) inverse. The generalized inverse handles the singularity that the leave-out contrasts build into  $\hat{S}$  by construction. The criterion  $\hat{g}' \widehat{W} \hat{g}$  is minimized numerically, with a preliminary pass under the diagonal weighting  $\text{diag}(\hat{S})^{-1}$  as a warm start.

Volatility parameters are optimized in precision coordinates within wide box bounds, with a mild quadratic penalty on log-volatilities below zero stabilizing the search (the penalty is negligible at the reported estimates and is excluded from reported criterion values), and the criterion is minimized by derivative-free local search from multiple starting values, followed by iterated restarts until the criterion improvement is negligible. The definitional restriction  $\sigma_{u_D} \geq \sigma_{u_I}$  is not imposed in the search and is verified to hold at the estimates. Overidentification is priced by the Hansen  $J$  statistic on 20 degrees of freedom. Analytic standard errors use the sandwich form  $(G' \widehat{W} G)^{-1}$  with  $G$  the numerical Jacobian of the kept moments. As a complement that is robust to misspecification of the moment covariance, we compute a recentered proposal-cluster bootstrap (Hall and Horowitz, 1996): proposals are resampled with replacement carrying all of their votes, each draw's moments are recentered at the original-sample fit so that the bootstrap is centered on the estimator rather than on the rejected overidentifying restrictions, and the criterion is re-minimized from a warm start. Percentile intervals from 400 draws are the intervals of record; for coordinates along which the criterion is locally flat, we instead invert the profiled criterion to obtain confidence sets, since percentile intervals are unreliable there.

**Preference recovery.** Given  $\hat{\theta}$ , preferences are recovered from Definition 1:  $\hat{\delta}_i = -E[x \mid m_i = \hat{k}_i, \text{piv}_i]$ , with the conditional expectation evaluated by quadrature under the limiting pivotal posteriors of Lemmas B.1 and B.2 at  $\hat{\theta}$ , holding each proposal's observed ownership structure fixed. Standard errors for  $\hat{\Delta}$  follow by the delta method from the joint distribution of  $\hat{\theta}$ .

## C.4. Numerical Assessment of Identification

The regularity condition and rank statements used in Section C.1 concern a small number of explicitly defined functions and can be assessed directly at the estimated reduced forms. We outline four complementary checks; all objects involved are available in closed form from Lemmas C.1–C.6.

First, Assumption C.1 concerns the univariate map  $\omega \mapsto V_0(\omega)$  in (C.10). Its monotonicity can be evaluated directly over the relevant range of  $\omega$ , supplemented by analytic behavior

as  $\omega \rightarrow 0$  and  $\omega \rightarrow \infty$ . As noted above, this condition is specific to our use of raw-support variance as a first-stage moment rather than a fundamental requirement for identification.

Second, the branch structure of Corollary C.1 is governed by the cubic (C.18). Computing all roots of  $G_\varsigma$  over a grid of  $\varsigma$  and retaining those satisfying the admissibility restrictions traces the number, location, and extent of the candidate branches, including any fold points or detached components beyond the parity threshold  $\varsigma_{hi}$ . This refines the analytical bound of at most three candidate roots at each  $\varsigma$  to the configuration that obtains at the estimated reduced forms.

Third, we can assess directly how the joint moments separate these branches. Along each admissible branch, we compute the scalar  $\varrho$ , the implied vote–support covariances, and the mean co-voting moments. The vote–support moments should vary monotonically with  $\varrho$ , while mean co-voting should vary monotonically with  $\sigma_{u_i}$  as established in Lemma C.6. When the quadratic (C.28) admits an admissible conjugate, this exercise also records the distance between the co-voting moments generated by the two points, providing a direct numerical measure of the separation supplied by the identifying co-voting block.

Fourth, local identification can be assessed from the Jacobian of the full identifying moment map at the estimates. Evaluating this Jacobian numerically, for example by finite differences, allows us to verify that it has full column rank  $N_\Theta$ ; its smallest singular value provides a direct measure of proximity to rank deficiency (Rothenberg, 1971). We report these numerical diagnostics with the empirical implementation.

## D. Robustness Tests

### D.1. Validation of Pivotal Conditioning

For each blockholder–proposal pair  $(b, j)$ , we construct the model-implied probability that blockholder  $b$  is decisive, conditional on the observed recommendation  $S_j$  and the proposal’s ownership configuration  $\Psi_j$ .

Fix a profile  $v \in \{0, 1\}^{n_j-1}$  of the other blockholders’ votes. Let

$$\Psi_{\text{for}}(v) = \sum_{\ell \neq b} \psi_{\ell j} v_\ell$$

denote the total stake of rival blockholders voting For, and let

$$\Psi_{Dj} = 1 - \sum_c \psi_{cj}$$

denote the dispersed ownership weight. Because proposal  $j$  passes when total support reaches  $\lambda^*$ , blockholder  $b$  is decisive exactly when dispersed support lies in

$$\tau_j \in [\tau_L(v), \tau_H(v)), \quad \tau_L(v) = \frac{\lambda^* - \psi_{bj} - \Psi_{\text{for}}(v)}{\Psi_{Dj}}, \quad \tau_H(v) = \frac{\lambda^* - \Psi_{\text{for}}(v)}{\Psi_{Dj}}. \quad (\text{D.35})$$

Below this interval, the proposal fails regardless of  $b$ 's vote; at or above it, the proposal passes regardless. Thus, conditional on rival votes, the pivotal window is determined entirely by the observed ownership configuration.

The estimated model supplies the joint distribution of rival votes and dispersed support within this window. Proposal quality is drawn as  $x_j \sim N(0, 1)$ , and the public report satisfies

$$s_j = x_j + u_{Ij},$$

with  $s_j$  restricted to the region  $S(S_j)$  consistent with the observed recommendation, namely  $s_j > \xi$  when  $S_j = 1$  and  $s_j \leq \xi$  when  $S_j = 0$ . Conditional on  $(x_j, s_j)$ , each rival blockholder  $\ell$  votes For with model-implied probability

$$\pi_\ell(x_j, s_j) = \Pr(V_{\ell j} = 1 \mid x_j, s_j),$$

obtained from its estimated voting cutoff and signal precision. Conditional independence of blockholder signals implies

$$\Pr(V_{Bj}^{-b} = v \mid x_j, s_j) = \prod_{\ell \neq b} \pi_\ell(x_j, s_j)^{v_\ell} [1 - \pi_\ell(x_j, s_j)]^{1-v_\ell}. \quad (\text{D.36})$$

In the large-dispersed-shareholder limit, dispersed support  $\tau_j$  is a deterministic function of proposal quality and the dispersed signal, evaluated at the estimated dispersed voting cutoff

$k_D$ . Conditional on  $(x_j, s_j)$ , we therefore compute

$$\Pr(\tau_j \in [\tau_L(v), \tau_H(v)) \mid x_j, s_j)$$

by integrating over the model-implied conditional distribution of the dispersed signal.

Combining these objects, the pivotal probability is

$$\widehat{\text{piv}}_{bj} = \frac{\sum_{v \in \{0,1\}^{n_j-1}} \mathbb{E} [\Pr(V_{Bj}^{-b} = v \mid x_j, s_j) \Pr(\tau_j \in [\tau_L(v), \tau_H(v)) \mid x_j, s_j) \mathbf{1}[s_j \in S(S_j)]]}{\Pr(s_j \in S(S_j))}, \quad (\text{D.37})$$

where the expectation is taken over the estimated joint distribution of  $(x_j, s_j)$ . Operationally, for every draw of  $(x_j, s_j)$  consistent with the observed recommendation, we: (i) calculate the probability of each rival-vote profile; (ii) calculate the corresponding pivotal window from the observed stakes; (iii) calculate the probability that dispersed support falls in that window; and (iv) sum across rival profiles and integrate across the latent state and public report.

The resulting  $\widehat{\text{piv}}_{bj}$  is specific to the blockholder–proposal pair. It varies with blockholder  $b$ 's own stake, which determines the width of the pivotal window; the stakes and voting probabilities of the rival blockholders, which determine the location and likelihood of the window; and the recommendation, which changes the conditional distribution of proposal quality and dispersed support. Blockholder  $b$ 's own voting cutoff and signal precision do not enter the predictor. Its own behavior is therefore not used to construct the probability intended to predict its vote. Moreover, ownership is not used in estimating the model parameters, so the relationship between voting and  $\widehat{\text{piv}}_{bj}$  is not directly targeted by the estimation moments.

To avoid using outcomes from the year being predicted, we construct  $\widehat{\text{piv}}_{bj}$  by leave-one-year-out estimation. For each year from 2018 through 2024, the model is re-estimated using all other years, holding the full-sample weighting matrix fixed. The cross-fitted predictor is highly stable: its correlation with the corresponding full-sample predictor exceeds 0.99.

We estimate

$$V_{bj} = \alpha_{b \times S_j} + \beta \widehat{\text{piv}}_{bj} + \gamma' w_{bj} + \varepsilon_{bj}, \quad (\text{D.38})$$

where  $\alpha_{b \times S_j}$  denotes blockholder-by-recommendation fixed effects and  $w_{bj}$  contains own stake,

the total stake of the other blockholders, the number of blockholders present, and realized dispersed support. Standard errors are clustered by proposal, with firm-clustered standard errors reported as a robustness check.

The Model coefficient is obtained by simulating votes from the estimated model after resolving each blockholder's equilibrium voting condition at the proposal's observed ownership configuration. Equation (D.38) is then estimated on each simulated panel using the same observations, controls, and fixed effects as in the data. We report the mean coefficient across simulations and its simulation standard deviation.

The estimation sample contains 20,007 blockholder–proposal observations for which the predictor is defined. The restricted sample excludes the two near-unanimous blockholder-by-recommendation cells and contains 9,078 observations. We exclude proposals with missing years, non-positive dispersed ownership weights, or invalid recorded dispersed-support values.

## D.2. Estimation with a Common Preference Shock

We augment the blockholder voting rule with a proposal-specific component common to all blockholders:

$$V_{bj} = \mathbb{1} [m_{bj} + v_j \geq k_b], \quad v_j \sim N(0, \sigma_v^2), \quad (\text{D.39})$$

where  $v_j$  is independent of proposal quality  $x_j$ , the advisor report, dispersed information, and blockholder private signals. The shock is absent from the dispersed-shareholder voting rule. It therefore captures a common proposal-level inclination of institutions to vote For, expressed in cutoff units.

Conditional on  $(\tau_j, S_j)$ ,  $v_j$  enters each blockholder's latent voting index additively. Because it is normal and independent of the remaining latent variables, it can be integrated out analytically. The conditional voting probability becomes

$$\Pr(V_{bj} = 1 \mid \tau_j, S_j) = \Phi(Q_{bj}^v), \quad Q_{bj}^v = \frac{\sigma_b \Lambda_b (a_b \mu_{x,j} + b_b \mu_{u,j} - k_b)}{\sqrt{1 + (\sigma_b \Lambda_b)^2 (\mathcal{V}_{bj} + \sigma_v^2)}}. \quad (\text{D.40})$$

Thus,  $\sigma_v^2$  adds to the variance of every blockholder latent index.

For a pair of blockholders  $(b, b')$ , the common shock also adds  $\sigma_v^2$  to their latent covariance. Their conditional joint voting probability remains a bivariate-normal probability with correlation

$$r_{bb',j}^v = \frac{(\sigma_b \Lambda_b)(\sigma_{b'} \Lambda_{b'}) (\mathcal{V}_{bb',j} + \sigma_v^2)}{\sqrt{1 + (\sigma_b \Lambda_b)^2 (\mathcal{V}_{bj} + \sigma_v^2)} \sqrt{1 + (\sigma_{b'} \Lambda_{b'})^2 (\mathcal{V}_{b'j} + \sigma_v^2)}}. \quad (\text{D.41})$$

Equations (D.40)–(D.41) reduce exactly to the baseline moment formulas at  $\sigma_v = 0$ .

The extension affects the blockholder vote-rate, aggregate-voting, and co-voting moments. It does not directly affect the dispersed-shareholder moments or the distribution of proposal quality and public information. In particular, because  $v_j$  is independent of dispersed support, it raises institutional co-voting without producing the corresponding blockholder vote–dispersed support covariance generated by shared information. This difference identifies  $\sigma_v$  relative to the information parameters.

We estimate the extension in two ways. First, we profile the criterion over a grid of values for  $\sigma_v$ , re-optimizing all baseline parameters at each grid point. Second, we estimate  $\sigma_v$  jointly with the baseline parameters. Both exercises use the same moment vector and the same data-based weighting matrix as the baseline estimation, so the criterion values are directly comparable.

The joint estimate is

$$\hat{\sigma}_v = 0.048,$$

and lowers the criterion by only 0.07 relative to the restriction  $\sigma_v = 0$ . The profile-based 95% upper bound is  $\sigma_v = 0.152$ . The profile then rises rapidly: relative to its minimum, the criterion increases by 8.2 at  $\sigma_v = 0.20$ , by 36 at 0.30, and by 122 at 0.45.

The information estimates remain stable over the admissible portion of the profile:  $\sigma_{u_i}$  remains between 1.149 and 1.161, and the public-information correlation remains between 0.177 and 0.186. At the joint estimate, the common preference component accounts for less than one percent of predicted blockholder co-voting.

The test bounds a common institutional preference component that is orthogonal to proposal quality and information. A proposal-level preference component correlated with quality would not be separately distinguishable from information using these moments. We therefore

report the bound in cutoff units and do not rely on a translation into the structural preference parameter.