Information and Preferences in Shareholder Voting*

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Abstract

We develop a structural model of shareholder voting with incomplete information about proposal quality. Shareholders differ in their ownership stake, private information precision, and unconditional preference for passage. Equilibrium voting reflects both fundamentals and strategic inference from other shareholders' behavior. We estimate the model using voting records of US mutual funds and recover institution-level information and preference parameters. Preference-implied support can diverge sharply from realized support, showing that vote records alone are insufficient to measure investor preferences. We further quantify the impact of strategic voting and find that it materially lowers overall support and increases the share of vote results near the passing threshold.

Keywords: corporate governance, shareholder voting, institutional investors, strategic voting

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1. Introduction

Institutional investors occupy blockholder positions in practically all listed firms in the US. 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, which may be interpreted as evidence of preference towards management. Implicit in this interpretation is that support rates are sufficient statistics for investor preferences.

An important point is that investors vote without observing a proposal's true value; a rational investor forms beliefs about whether the proposal passing will increase or decrease firm value by observing public information (via proxy statements and advisor recommendations, for example), their own private information, and information embedded in the voting environment itself. As a result, the same investor may vote differently on otherwise similar proposals than their unconditional preference for the proposal would suggest.

In this paper, we develop a structural model in which firms are held by block and dispersed shareholders who vote on management-sponsored proposals. Proposal quality is uncertain at the time of the vote. Shareholders may have heterogeneous information about proposal quality and may also have heterogeneous preferences for passage, modeled as an extra utility from the proposal passing (or failing) independent of fundamentals. In equilibrium, each shareholder supports the proposal when their posterior belief exceeds an endogenous, shareholder-specific cutoff. We use the model to study how preferences and information jointly shape equilibrium voting behavior and observed voting outcomes.

A stylized example clarifies the mechanism. Suppose we observe many management proposals across firms with a common blockholder and many dispersed shareholders, and we see that the blockholder supports more proposals than smaller shareholders. This implies that the blockholder supports some proposals even when it receives a low signal, and one might conclude that the blockholder receives extra payoff when the payoff passes to offset potential decreases in firm value, i.e., the blockholder is biased towards management.

This reasoning is incomplete because the blockholder votes strategically, by anticipating the states of the world in which she will swing the outcome of the vote. Therefore, the blockholder ought to vote as if the support rate is close to the passing threshold: as if she is pivotal. The event of being pivotal itself is a signal about the proposal's quality, which the blockholder incorporates into their decision. Because the remaining shareholders vote conservatively, supporting fewer proposals than the blockholder on average, they wait for a (relatively) high signal before voting for the proposal. When the blockholder is pivotal, she rationally acts as if she also received a high signal. This *strategic effect* inherent in voting games means that a shareholder's observed equilibrium voting behavior is not only a function of her own information and preferences, but also those of other shareholders. Importantly, this equilibrium strategic interdependence differs from the *signal effect*, which impacts the blockholder's through her own private information and shared public information.

Given these effects, what can we infer about the blockholder's preference towards supporting management proposals? If the remaining shareholders' signals are uncorrelated, the strategic effect is equivalent to the blockholder receiving a precise signal that the proposal increases firm value: an individual shareholder might vote for a bad proposal idiosyncratically, but the probability that most of them make the same error is small. Therefore, the strategic effect can offset the signal effect. Even though the blockholder supports some proposals that its private signal suggests are more likely to be bad (the signal effect), this is offset by the fact that when she is pivotal, the proposal is more likely to be good (the strategic effect). In this case, the blockholder may not be biased: it rationally supports more proposals because when its vote matters, the proposal is likely to increase firm value.

In practice, shareholders' information is correlated. For example, both small and large shareholders rely on proxy advisor recommendations when voting. We allow this to enter our model by letting shareholders see common signals about proposal quality; in particular, we allow dispersed and block shareholders see a proxy advisor "report" with different precisions and allow this common, group-specific information to influence voting decisions.

Importantly, strategic effects attenuate when signals are highly correlated. In the example above, a precise common proxy advisor signal means that the votes of other shareholders convey less information. The blockholder places more weight on its own signal, and since it waits only for a low signal before supporting management, it votes for some proposals likely to decrease value. This implies that the blockholder is biased, because the additional payoff it earns when the proposal passes offsets these bad proposals.

These observations imply that comparing blockholder support rates to those of smaller shareholders can lead to incorrect inferences about preferences. An unbiased blockholder can appear more supportive because of information aggregation in the state when she is pivotal, while a blockholder with a preference for passage can appear similar to others when signals are highly correlated. These ambiguities extend to the more empirically relevant setting with multiple blockholders. For credible inference on shareholder preferences, an estimator must correct for strategic and informational interactions.

We estimate our model using data on compensation proposals and recover latent preferences and information parameters. We include six large mutual fund blockholders as actors in the empirical implementation: Vanguard, BlackRock, State Street, Dimensional, Fidelity, and T. Rowe Price. We use the information about proposal quality revealed by ISS recommendations to discipline the public information component of beliefs, and we jointly match proposal-level moments (including dispersed support and ISS recommendations) together with blockholder-specific vote moments.

Our estimation procedure recovers two sets of objects for each blockholder: (i) information parameters governing the precision of private and common signals, and (ii) preference parameters that are corrected for correlated information and strategic voting incentives. In particular, because equilibrium voting depends on beliefs formed from both public signals and inference about other shareholders' behavior, the recovered preferences reflect information-adjusted attitudes toward management proposals rather than raw vote propensities. The resulting estimates imply sizable differences between observed and preference-implied support. While most blockholders exhibit high unconditional approval rates in the data, their preference-implied support is much closer in magnitude to that of dispersed shareholders.[1]

Our empirical results highlight the model's central mechanism: higher observed support for proposals does not necessarily represent a stronger preference toward passing. Strategic

[1]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.

effects and information asymmetry generate an equilibrium in which investors with more precise signals or greater voting weight may appear more supportive toward management even if their preferences may not make them materially more supportive of management.

We provide direct structural evidence on how strategic voting shapes shareholder voting outcomes. We implement a counterfactual that isolates strategic voting, holding fixed preferences and information. In equilibrium, investors condition on being pivotal, so their beliefs incorporate what other shareholders' preferences and information imply about the state. When most large holders have a pro-management baseline (as we estimate), pivotality is more likely in states where others have received negative signals. The resulting pivotality-adjusted posterior belief makes equilibrium voting more conservative (lower support) and increases the incidence of close outcomes (votes within 5 percentage points of the passing threshold).

We find that, relative to a counterfactual in which shareholders do not update based on being pivotal, strategic voting raises the proportion of votes that pass by about 10.4 percentage points (from roughly 85.4% to 95.7% in our estimation sample). It also nearly doubles the rate of close votes, from 7.8% to 14.6%.

These results contribute to our understanding of shareholder voting. Observed support rates are not sufficient statistics for investor preferences in a strategic voting environment: shareholders infer proposal quality from the voting state and from others' behavior, so equilibrium support conflates preference with information and pivotality. By structurally separating these channels, our framework identifies information-adjusted preferences toward management proposals and reinterprets why large blockholders may appear systematically more supportive even when their underlying preferences are closer to those of dispersed shareholders. To our knowledge, we are among the first studies to provide direct empirical evidence on the quantitative impact of strategic voting on shareholder voting outcomes.

The paper is organized as follows. The rest of this section discusses the literature. Section 2 outlines the model. Section 3 gives the estimation strategy and Section 4 describes the data. Section 5 presents results of the estimation. Finally, Section 6 concludes.

Literature review. This paper contributes to debates about how large diversified investors affect corporate governance, and to the study of voting under incomplete information. Legal and governance scholarship offers different views of large passive institutions. Bebchuk and Hirst (2019) argue that low-fee business models and potential conflicts can tilt preferences toward passage. Kahan and Rock (2020) and Fisch et al. (2019) emphasize that scale can strengthen stewardship incentives. The analysis here complements these perspectives by showing that observed support rates need not map into preferences once strategic pivotality and information aggregation are taken into account.

The paper relates to theoretical models of voting with common values and private signals, including Austen-Smith and Banks (1996), Feddersen and Pesendorfer (1997), and Levit and Malenko (2011). We incorporate blockholder ownership and allow for a preference-for-passage component, and We study how correlated signals attenuate the informativeness of the pivotal event. The interpretation of correlation follows Malenko and Malenko (2019), who analyze the effect of proxy-advisor recommendations on information aggregation. Bar-Isaac and Shapiro (2020) examine participation versus abstention with blockholders; Levit et al. (2025) study trading before the vote with public information; Malenko et al. (2025) consider the design of proxy-advisor products. My focus is on how preferences and information jointly determine equilibrium cutoff strategies and observed support.

Empirical work has sought to measure investor philosophies from votes. Bubb and Catan (2022) use principal components to identify dimensions of governance preferences; Bolton et al. (2020) place mutual fund families along an ideological spectrum; Yi (2021) uses a Bayesian approach to characterize preferred governance structures. My approach is complementary. We recover preference-for-passage and information parameters by estimating equilibrium strategies and inverting best responses, which directly adjusts for strategic and informational interactions.

Finally, we relate to structural work on turnout in shareholder voting. Zachariadis et al. (2020) estimate a model of participation decisions in large electorates and study strategic effects in turnout. We treat turnout as exogenous and focus on how private information, correlated signals, and payoff shifters map into cutoff strategies and support rates. Both margins are important for corporate governance, and the identification strategies differ because the economic questions differ.

2. Model

This section outlines the model. The framework is deliberately parsimonious: we consider ownership of a single firm, held by multiple investors, and voting on a single management proposal of uncertain quality. This minimal structure allows us to isolate the informational and strategic forces that shape shareholders' voting behavior. Later, when we estimate the model, we extend it to a panel of firms and proposals.

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 ψ_b of outstanding shares, such that total blockholder ownership is $\Psi_B = \sum_{b=1}^{N_B} \psi_b$. The remaining shares $\Psi_D = 1 - \Psi_B$ 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. 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.[2] Management provides a recommendation for the proposal; voting in favor corresponds to supporting management's recommendation.

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

[2]The use of a standard Normal distribution is for convenience; in the estimation, we will relax this assumption.

Given the outcome of the vote $\mathrm{P}_j \in \{0, 1\}$, shareholder i's payoff is

$$U_i(\mathrm{P}_j, x_j, \delta_i) = \mathrm{P}_j \times (x_j + \delta_i), \tag{2}$$

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 δ_i.

All dispersed shareholders share the same preference parameter δ_D, while each blockholder $b \in \{1, \dots, N_B\}$ has its own δ_b. The complete preference environment is thus given by $\Delta = \{\delta_D, \{\delta_b\}_{b=1}^{N_B}\}$. To facilitate interpretation, note that

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

where $\Phi(\cdot)$ is the standard normal cumulative distribution function (CDF). This quantity gives each shareholder's baseline approval probability. We refer to $\Phi(\delta_i)$ as shareholder i's preference-implied support rate.

We assume full vote turnout for analytical clarity, though when we estimate the model we allow for abstentions. The proposal passes, $\mathrm{P}_j = 1$, if the total support rate exceeds the passing threshold λ^*, and fails, $\mathrm{P}_j = 0$, otherwise. Under a majority rule, for example, $\lambda^* = 0.5$, whereas under a supermajority $\lambda^* > 0.5$.

Let $V_{bj} \in \{0, 1\}$ denote blockholder b's vote, and define the vector of blockholder votes $\mathbf{V}_{Bj} = [V_{1j}, \dots, V_{N_B j}]$ and the vector of ownership weights $\mathbf{\Psi}_B = [\psi_1, \dots, \psi_{N_B}]$. Given $\mathbf{V}_{Bj}$, the share of total votes cast in favor by blockholders is $s_{Bj} = \mathbf{V}_{Bj}\mathbf{\Psi}'_B$. Let τ_j denote the fraction of dispersed shareholders who vote for the proposal. The total support rate is therefore

$$\lambda_j = s_{Bj} + \tau_j = \mathbf{V}_{Bj}\mathbf{\Psi}'_B + \tau_j \Psi_D, \tag{4}$$

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

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:

$$s_j = x_j + u_{Ij}, \qquad u_{Ij} \sim N(0, \sigma_I^2), \tag{5}$$

where σ_I^2 represents the quality of the proxy advisor's information. We interpret s_j as the proxy advisor's underlying research report that shareholders may access, but we assume that dispersed and block shareholders see different versions of the report. More concretely, these two types of shareholder form group-specific noisy public assessments of proposal quality based on this report and other public information. Dispersed shareholders use

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

while blockholders use

$$\eta_{Bj} = s_j + v_{Bj}, \qquad v_{Bj} \sim N(0, \sigma_{vB}^2). \tag{7}$$

The group-specific noise terms v_{Dj} and v_{Bj} capture differences in how precisely dispersed shareholders and blockholders can observe or process the proxy advisor's report and related public disclosures. Since $s_j = x_j + u_{Ij}$, we can equivalently write the public signals in reduced form as

$$\eta_{Dj} = x_j + u_{Dj}, \qquad u_{Dj} := u_{Ij} + v_{Dj},$$

$$\eta_{Bj} = x_j + u_{Bj}, \qquad u_{Bj} := u_{Ij} + v_{Bj},$$

with u_{Ij}, v_{Dj}, and v_{Bj} mutually independent and independent of x_j. Hence

$$\sigma^2_{u_D} = \sigma^2_I + \sigma^2_{vD}, \qquad \sigma^2_{u_B} = \sigma^2_I + \sigma^2_{vB},$$

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

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

$$S_j = \mathbb{1}\left[s_j > \xi\right], \tag{8}$$

where ξ is a fixed threshold which can be interpreted as the headline "For/Against" recommendation of a proxy advisor such as ISS. In the data, the econometrician observes this binary signal S_j ex post, but not the underlying continuous report s_j or the separate noise components in investors' public signals. One could explicitly incorporate S_j into shareholders' information sets, but doing so would replace the Gaussian updating structure with a truncated-normal problem and greatly obscure how shareholders update beliefs in equilibrium. Instead, we summarize the effect of the proxy advisor's analysis through the reduced-form public signals η_{Dj} and η_{Bj} and use the observed binary recommendation S_j in the estimation to help identify the information environment.[3]

2.2.2. Private signals

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

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

[3] Because the econometrician observes only the binary recommendation S_j and voting outcomes, the data identify only the composite variances $\sigma^2_{u_D}$ and $\sigma^2_{u_B}$; we cannot separately recover σ^2_I and the group-specific components σ^2_{vD} and σ^2_{vB}, though we can recover a correlation between s_j and η_{Dj}. We return to this point in the estimation section.

where $\varepsilon_{ij} \sim N(0, \sigma^2_{\varepsilon_i})$ 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, $1/\sigma^2_{\varepsilon_i}$, capture heterogeneity in shareholders' information quality.

Dispersed shareholders share a common private signal precision,

$$\sigma^2_{\varepsilon_i} = \sigma^2_{\varepsilon_D} \quad \text{for all dispersed } i, \tag{9}$$

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

$$\sigma^2_{\varepsilon_i} = \sigma^2_{\varepsilon_b} \quad \text{for blockholder } b. \tag{10}$$

This structure implies that all shareholders start from a common prior and update using both public and investor-specific information. Dispersed shareholders observe (η_{Dj}, z_{ij}) and blockholders observe (η_{Bj}, z_{bj}). The shared component s_j induces correlation in posterior beliefs across shareholders, whereas private signals z_{ij} introduce idiosyncratic variation that can generate disagreement across investor type.

2.3. Voting Strategy

Given the information environment described above, each shareholder observes a group-specific continuous public signal $\eta_{ij} \in \{\eta_{Dj}, \eta_{Bj}\}$, as well as her private signal z_{ij}. In our reduced-form representation, we summarize all public information relevant for shareholder i's decision by the continuous public signal η_{ij}, with $\sigma^2_{u_i} \in \left\{ \sigma^2_{u_D}, \sigma^2_{u_B} \right\}$ denoting its noise variance. 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:

$$V_{ij} = 1 \quad \Longleftrightarrow \quad \mathbb{E}[x_j \mid \eta_{ij}, z_{ij}] > k_i. \tag{11}$$

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 δ_i need not move in unison, as we show below.

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

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

where the posterior mean for shareholder i is

$$m_{ij} \ \equiv\ \mathbb{E}[x_j \mid \eta_{ij}, z_{ij}] \ =\ \frac{\dfrac{\eta_{ij}}{\sigma^2_{u_i}} + \dfrac{z_{ij}}{\sigma^2_{\varepsilon_i}}}{\Lambda_i}, \qquad \Lambda_i \equiv 1 + \frac{1}{\sigma^2_{u_i}} + \frac{1}{\sigma^2_{\varepsilon_i}} \tag{12}$$

Here $\sigma^2_{u_i}$ is the variance of the reduced-form public signal noise relevant for shareholder i, and $\sigma^2_{\varepsilon_i}$ is the variance of her private signal noise. Conditional on the true proposal quality x_j and the public signal η_{ij}, the only source of randomness is the idiosyncratic noise ε_{ij} in the private signal. Substituting $z_{ij} = x_j + \varepsilon_{ij}$ and noting that $\varepsilon_{ij} \sim N(0, \sigma^2_{\varepsilon_i})$ gives:

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

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

$$\Pr(V_{ij} = 1 \mid x_j, \eta_{ij}) = \Pr\left(m_{ij} > k_i \mid x_j, \eta_{ij}\right) = \Phi\left(\sigma_{\varepsilon_i}\left[\frac{\eta_{ij}}{\sigma^2_{u_i}} + \frac{x_j}{\sigma^2_{\varepsilon_i}} - k_i\Lambda_i\right]\right), \tag{13}$$

where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function. Equation (13) shows that a shareholder is more likely to vote in favor when her public signal η_{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 ($\sigma^2_{u_i}$), private signal precisions ($\sigma^2_{\varepsilon_i}$), 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. Each shareholder votes strategically, recognizing that her action affects payoffs only in states where it changes the voting outcome. In other words, 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

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

where $v_i \in \{0, 1\}$ is shareholder i's vote, ψ_i is her voting weight, V_{Bj}^{-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 τ_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:

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

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 ψ_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

$$\Psi_{\text{for}}(V_{Bj}) + \Psi_D\,\tau_{-i,j} \;<\; \lambda^* \;\le\; \Psi_{\text{for}}(V_{Bj}) + \Psi_D\,\tau_{-i,j} + \psi_D \qquad \Longleftrightarrow$$
$$\tau_{-i,j} \in \left[\frac{\lambda^* - \Psi_{\text{for}}(V_{Bj}) - \psi_D}{\Psi_D},\; \frac{\lambda^* - \Psi_{\text{for}}(V_{Bj})}{\Psi_D}\right).$$

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 is formalized in the following best response condition:

$$\mathrm{E}\left[\, x_j \;\middle|\; \eta_{ij},\; m_{ij} = k_i,\; \text{piv}_{ij} \right] = -\,\delta_i, \tag{14}$$

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

$$\mathrm{E}\left[\, x_j \;\middle|\; \eta_{ij},\; z_{ij} = z^\star_{ij}(\eta_{ij}),\; \text{piv}_{ij} \right] = -\,\delta_i, \tag{15}$$

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

$$z^\star_{ij}(\eta_{ij}) = \sigma^2_{\varepsilon_i}\left(\Lambda_i\, k_i - \frac{\eta_{ij}}{\sigma^2_{u_i}}\right), \qquad \Lambda_i = 1 + \frac{1}{\sigma^2_{u_i}} + \frac{1}{\sigma^2_{\varepsilon_i}}.$$

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 δ_i. Equation (15) therefore characterizes the equilibrium cutoff k_i that makes shareholder i just indifferent when her vote is decisive.

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

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

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

$$f\left(x_j \mid \eta_{ij}, z_{ij}, \mathrm{piv}_{ij}\right) \;\propto\; f(x_j) \;\; \underbrace{f(\eta_{ij} \mid x_j)}_{\text{public signal effect}} \;\; \underbrace{f(z_{ij} \mid x_j)}_{\text{private signal effect}} \;\; \underbrace{\Pr\left(\mathrm{piv}_{ij} \mid x_j, \eta_{ij}\right)}_{\text{strategic effect}}. \tag{16}$$

The first two braced terms form the *signal effect*: they summarize what the shareholder learns about proposal quality from her own signals, (η_{ij}, z_{ij}). Because dispersed shareholders observe η_{jD} and all blockholders observe the common blockholder signal η_{jB}, the public signal component is group-specific.

The final term, $\Pr(\mathrm{piv}_{ij} \mid x_j, \eta_{ij})$, 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 η_{jB}), the strategic effect implicitly integrates over the unobserved public signals of the other investor groups. 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 (η_{ij}, z_{ij}).

2.4.2. Posterior beliefs about proposal quality

Determining equilibrium voting strategies requires evaluating the posterior in (16) 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: η_{jD} for dispersed shareholders and η_{jB} for blockholders. Following Myatt (2015) and Zachariadis et al. (2020), we derive the limit of the game as N_D grows large. We give explicit expressions of (16) for dispersed shareholders and blockholders separately in the following proposition.

Proposition 1a: Dispersed shareholder posterior density

Symmetry in strategies, information, and preferences implies that each dispersed shareholder's best-response condition is the same, so there is a single limit to derive. As $N_D \to \infty$, the posterior density for any x_j converges as follows:

$$\lim_{N_D\to\infty} \; f\left(x_j \mid z_{Dj},\, \eta_{jD},\, \mathrm{piv}_{Dj}\right) \propto$$

$$f(x_j \mid \eta_{jD}) \sum_{V_{Bj}} \underbrace{f\left(z_{Dj} \mid x_j\right)}_{\textit{signal effect}} \; \underbrace{\Pr\left(V_{Bj} \mid x_j\right)}_{\textit{strategic effect}} \; \underbrace{\mathrm{dirac}\left(p_D(x_j, \eta_{jD}) - \tau^{V_{Bj}}\right)}_{\textit{pivotal constraint}} \; = \tag{17a}$$

$$\sum_{V_{Bj}} \underbrace{f\left(x_{\eta_{jD}}^{V_{Bj}} \mid \eta_{jD}\right)}_{\textit{prior (given } \eta_{jD})} \; \underbrace{f\left(z_{Dj} \mid x_{\eta_{jD}}^{V_{Bj}}\right)}_{\textit{signal effect}} \; \underbrace{\chi^{V_{Bj}}}_{\textit{Jacobian}} \; \underbrace{\Pr\left(V_{Bj} \mid x_{\eta_{jD}}^{V_{Bj}}\right)}_{\textit{strategic effect}} \; \mathrm{dirac}\left(x_j - x_{\eta_{jD}}^{V_{Bj}}\right). \tag{17b}$$

The following objects are required:

- ***Dispersed voting probability:***

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

  where σ_D^2 is the variance of dispersed shareholders' private signal noise and $\sigma_{u_D}^2$ is the variance of their public signal noise.

- ***Value of** x_j **when a dispersed shareholder is pivotal, given profile** V_{Bj} (i.e., the solution to $p_D(x_j, \eta_{jD}) = \tau^{V_{Bj}}$):*

$$x_{\eta_{jD}}^{V_{Bj}} = \sigma_D^2\left(\Lambda_D k_D - \frac{\eta_{jD}}{\sigma_{u_D}^2} + \frac{q^{V_{Bj}}}{\sigma_D}\right), \qquad q^{V_{Bj}} \equiv \Phi^{-1}\left(\tau^{V_{Bj}}\right).$$

- ***Jacobian correction term** $\mathrm{dirac}\left(p_D(x_j, \eta_{jD}) - \tau^{V_{Bj}}\right) \mapsto x_j = x_{\eta_{jD}}^{V_{Bj}}$:*

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

- ***Threshold dispersed share:***

$$\tau^{V_{Bj}} \; = \; \frac{\lambda^* - \Psi_{for}(V_{Bj})}{\Psi_D},$$

which is the dispersed support rate required for the proposal to pass given the blockholder vote profile V_{Bj}.

- ***Blockholder vote profile likelihood (integrating over unobserved η_{jB}):***

Blockholders observe a common public signal

$$\eta_{jB} = x_j + u_{jB}, \qquad u_{jB} \sim N(0, \sigma^2_{u_B}),$$

which dispersed shareholders do not observe. Conditional on (x_j, η_{jB}), the likelihood of a blockholder vote profile V_{Bj} is

$$\Pr\left(V_{Bj} \mid x_j, \eta_{jB}\right) \; = \; \prod_{b=1}^{N_B} \left[\Phi\big(A_b \eta_{jB} + B_b x_j - C_b\big)\right]^{V_{Bj}(b)} \left[1 - \Phi\big(A_b \eta_{jB} + B_b x_j - C_b\big)\right]^{1-V_{Bj}(b)},$$

where

$$A_b \; = \frac{\sigma_b}{\sigma^2_{u_B}}, \qquad B_b \; = \frac{1}{\sigma_b}, \qquad C_b \; = \sigma_b \Lambda_b k_b, \qquad \Lambda_b \; = 1 + \frac{1}{\sigma^2_{u_B}} + \frac{1}{\sigma^2_b},$$

and σ^2_b is blockholder b's private signal variance.

From the perspective of a dispersed shareholder (who does not observe η_{jB}), the relevant strategic weight is the profile likelihood integrated over *the unobserved blockholder public signal:*

$$\Pr\big(V_{Bj} \mid x_j\big) = \int \Pr\left(V_{Bj} \mid x_j, \eta_{jB}\right) f(\eta_{jB} \mid x_j)\, d\eta_{jB},$$

where $f(\eta_{jB} \mid x_j)$ is the Gaussian density implied by $\eta_{jB} = x_j + u_{jB}$ and $u_{jB} \sim N(0, \sigma^2_{u_B})$.

Proof. See Appendix A. ■

Remark on Proposition 1a. The Dirac delta function in (17a) 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 $p_D(x_j, \eta_{jD})$ equals the threshold share $\tau^{V_{Bj}}$ associated with a particular blockholder vote profile V_{Bj}. Intuitively, as $N_D \to \infty$, there is a unique draw of x_j (conditional on the dispersed public signal η_{jD}) 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 $x_{\eta_{jD}}^{V_{Bj}}$. Its contribution is weighted by the (conditional) prior density $f(x_{\eta_{jD}}^{V_{Bj}} \mid \eta_{jD})$, the likelihood of the dispersed private signal $f(z_{Dj} \mid x_{\eta_{jD}}^{V_{Bj}})$, the Jacobian term $\chi^{V_{Bj}}$, and the strategic likelihood $\Pr\left(V_{Bj} \mid x_{\eta_{jD}}^{V_{Bj}}\right)$, which already averages over the unobserved blockholder public signal η_{jB}.

Proposition 1b: Blockholder posterior density

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

$$\lim_{N_D \to \infty} f\left(x_j \mid z_{bj}, \eta_{jB}, \mathrm{piv}_{bj}\right) \propto f(x_j \mid \eta_{jB}) \underbrace{f\left(z_{bj} \mid x_j\right)}_{\textit{signal effect}} \sum_{V_{B,-b,j}} \underbrace{\Pi^{V_{B,-b,j}}(x_j)}_{\textit{pivotality}} \underbrace{\Pr\left(V_{B,-b,j} \mid x_j, \eta_{jB}\right)}_{\textit{strategic effect}}. \tag{18}$$

Here $f(x_j \mid \eta_{jB})$ is the normal posterior implied by the prior $x_j \sim N(0,1)$ and the blockholder public signal η_{jB}.

The objects appearing in (18) are:

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

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

  Blockholder b is pivotal when the dispersed support rate satisfies $\tau_j \in [\tau_L^{V_{B,-b,j}}, \tau_H^{V_{B,-b,j}}]$.

- ***Dispersed voting probability:*** *for any (x_j, η_{jD}), the limiting dispersed support rate is*

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

  where σ_D^2 is the dispersed private signal variance.

- ***Pivotality probability for blockholder b:*** *in the large-N_D limit, the dispersed support satisfies $\tau_j = p_D(x_j, \eta_{jD})$ almost surely. For a given blockholder profile $V_{B,-b,j}$, the probability that*

b is pivotal depends on x_j only through

$$\Pi^{V_{B,-b,j}}(x_j) = \Pr\Big(\tau_j \in [\tau_L^{V_{B,-b,j}},\ \tau_H^{V_{B,-b,j}}] \;\Big|\; x_j \Big).$$

Because $p_D(x_j, \eta_{jD})$ is strictly increasing in η_{jD} for fixed x_j, this condition is equivalent to η_{jD} lying in an interval $[\eta_L^{V_{B,-b,j}}(x_j),\ \eta_H^{V_{B,-b,j}}(x_j)]$, where

$$\eta_L^{V_{B,-b,j}}(x_j) = \sigma_{u_D}^2 \left(\Lambda_D k_D - \frac{x_j}{\sigma_D^2} + \frac{q_L^{V_{B,-b,j}}}{\sigma_D} \right), \qquad \eta_H^{V_{B,-b,j}}(x_j) = \sigma_{u_D}^2 \left(\Lambda_D k_D - \frac{x_j}{\sigma_D^2} + \frac{q_H^{V_{B,-b,j}}}{\sigma_D} \right),$$

with $q_L^{V_{B,-b,j}} = \Phi^{-1}\big(\tau_L^{V_{B,-b,j}}\big)$ and $q_H^{V_{B,-b,j}} = \Phi^{-1}\big(\tau_H^{V_{B,-b,j}}\big)$. Let $f(\eta_{jD} \mid x_j)$ denote the conditional density of the dispersed public signal implied by $\eta_{jD} = x_j + u_{jD}$. Then

$$\Pi^{V_{B,-b,j}}(x_j) = \int_{\eta_L^{V_{B,-b,j}}(x_j)}^{\eta_H^{V_{B,-b,j}}(x_j)} f(\eta_{jD} \mid x_j)\, d\eta_{jD}.$$

- ***Blockholder voting profile (excluding b) likelihood, conditional on (x_j, η_{jB}):** blockholders share the common public signal η_{jB} and have private signal variances $\{\sigma_{b'}^2\}_{b'=1}^{N_B}$. Conditional on (x_j, η_{jB}), the likelihood of observing a vote profile $V_{B,-b,j}$ from the other blockholders is*

$$\Pr\left(V_{B,-b,j} \mid x_j, \eta_{jB}\right) = \prod_{\substack{b'=1 \\ b' \neq b}}^{N_B} \Big[\Phi\big(A_{b'}\eta_{jB} + B_{b'}x_j - C_{b'}\big)\Big]^{V_{B,-b,j}(b')} \Big[1 - \Phi\big(A_{b'}\eta_{jB} + B_{b'}x_j - C_{b'}\big)\Big]^{1 - V_{B,-b,j}(b')},$$

where

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

Proof. See Appendix A. ■

Remark on Proposition 1b. Given the voting profile of the other blockholders $\mathbf{V}_{B_j}^{-b}$, the fraction of shares cast in favor by all shareholders excluding b is $s_B^{-b} + \tau_j \Psi_D$. 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 $\tau_j = p_D(x_j, \eta_{jD})$ for a given (x_j, η_{jD}).

However, the blockholder does not observe η_{jD}; instead, she knows its distribution conditional on x_j through the dispersed public signal process. Thus, from her perspective, pivotality for a given blockholder profile $V_{B,-b,j}$ occurs with probability $\Pi^{V_{B,-b,j}}(x_j)$, which integrates over the range of dispersed public signals that would make her pivotal.

The posterior in (18) therefore has three components: (i) a prior $f(x_j \mid \eta_{jB})$ shaped by the blockholder's own public signal, (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, η_{jB}) with the pivotality probability $\Pi^{V_{B,-b,j}}(x_j)$, which summarizes how dispersed public information affects the event that blockholder b is decisive.

2.4.3. Equilibrium Definition

Maintaining the information and preference environments from above, the equilibrium concept is pure-strategy Bayesian–Nash: each shareholder chooses a cutoff strategy that maximizes expected utility given her information set (which conditions on the state of the world when she is pivotal), along with her innate preference towards the proposal passing.

Each dispersed shareholder observes (η_{Dj}, z_{dj}), while blockholder b observes (η_{Bj}, z_{bj}). Each shareholder votes "For" if the expected quality of the proposal at the pivotal margin, net of her private preference, is nonnegative. In equilibrium this can be expressed as a cutoff rule in terms of her posterior mean m_{ij}, for (12):

$$\mathrm{E}\left[x_j \mid \eta_{Dj}, z_{Dj}, \mathrm{piv}_{Dj}\right] + \delta_D \geq 0 \iff m_{Dj} \geq k_D, \tag{19}$$

$$\mathrm{E}\left[x_j \mid \eta_{Bj}, z_{bj}, \mathrm{piv}_{bj}\right] + \delta_b \geq 0 \iff m_{bj} \geq k_b, \quad \forall b \in \{1, \dots, N_B\}, \tag{20}$$

where k_D is the common dispersed cutoff and k_b is blockholder b's cutoff. The effect of pivotality is captured entirely by these equilibrium cutoffs. The equilibrium can be equivalently written as a system of indifference conditions at the cutoffs:

$$\mathrm{E}\left[x_j \mid \eta_{Dj},\ m_{Dj} = k_D,\ \mathrm{piv}_{Dj}\right] = -\,\delta_D,$$

$$\mathrm{E}\left[x_j \mid \eta_{Bj},\ m_{bj} = k_b,\ \mathrm{piv}_{bj}\right] = -\,\delta_b, \quad \forall b \in \{1, \dots, N_B\}.$$

Cutoffs k_i therefore reflect shareholders' strategic inference under the event of being pivotal, which depends on the aggregate support implied by others' strategies and information.

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

$$\Pr(V_{ij} = 1) \;=\; \Pr\left(m_{ij} \geq k_i\right) \;=\; \iint 1\left\{ m_{ij}(\eta, z) \geq k_i \right\} f_i(\eta)\, f_i(z \mid \eta)\, d\eta\, dz, \tag{21}$$

where $f_i(\eta)$ and $f_i(z \mid \eta)$ denote the public and private signal densities implied by $(\sigma^2_{u_i}, \sigma^2_{\varepsilon_i})$ in the information environment.[4] 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. Identification and Estimation

We now describe the identification and estimation routines. The data used for estimation are described in detail in Section 4. For the purpose of illustrating identification, 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 τ_j, and blockholder-level information on ownership stakes and voting decisions. As we will show, this information is sufficient to fully identify the model.

3.1. Identification

For each proposal j, the econometrician observes the proxy advisor's binary recommendation $S_j = \mathbb{1}\left[s_j > \xi\right]$, the dispersed support rate τ_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 continuous proxy assessment s_j, and the group-specific public signals (η_{Dj}, η_{Bj}) are unobserved. We use the joint cross-sectional distribution of $(S_j, \tau_j, \{V_{bj}\}, \{\psi_b\})$ to identify the information environment Σ and preferences Δ.

Identification rests on three restrictions. First, the cutoff profile $\mathbf{k} = \{k_D, \{k_b\}_{b=1}^{N_B}\}$ arises

[4] For dispersed shareholders, $(\sigma^2_{u_i}, \sigma^2_{\varepsilon_i}) = (\sigma^2_{u_D}, \sigma^2_{\varepsilon_D})$ and $\eta = \eta_{Dj}$; for blockholder b, $(\sigma^2_{u_i}, \sigma^2_{\varepsilon_i}) = (\sigma^2_{u_B}, \sigma^2_{\varepsilon_b})$ and $\eta = \eta_{Bj}$.

from a pure-strategy Bayesian–Nash equilibrium and satisfies the model's best-response conditions. Second, the proxy advisor's binary recommendation is treated as a thresholding of a latent continuous assessment, $S_j = \mathbb{1}\left[s_j > \xi\right]$. Third, the remaining within-S_j variation in dispersed and blockholder voting is fully captured by the latent quality x_j and the public and private signal shocks in the information environment.

3.1.1. Proxy Advisor Parameters

We identify two parameters governing proxy advisor information: the recommendation threshold ξ and the alignment parameter $\rho = \text{Corr}(s_j, \eta_{Dj})$ between the advisor's latent assessment and the dispersed voting index, which we denote by $T_j \equiv \Phi^{-1}(\tau_j)$, along with the standardized version, $\tilde{T}_j$. The proxy advisor's rule is

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

where s_j is the latent advisor signal. Given that T_j is normal in the limit, we have the following probit relation between advisor recommendations and the dispersed index:

$$\Pr(S_j = 1 \mid \tilde{T}_j = t) = \Phi(\gamma_0 + \gamma_1 t),$$

with (γ_0, γ_1) nonlinearly related to (ρ, ξ). In particular,

$$\rho = \frac{\gamma_1}{\sqrt{1+\gamma_1^2}}, \qquad \xi = -\gamma_0\sqrt{1-\rho^2}.$$

From the econometrician's perspective, (ξ, ρ) govern what can be learned from the recommendation once we condition on dispersed voting. The threshold ξ determines how the observed split into $S_j = 0$ and $S_j = 1$ selects proposals, and therefore how the distributions of T_j and $\{V_{bj}\}_b$ shift across recommendation groups. The alignment ρ then determines the incremental information in S_j about x_j beyond τ_j. Together, these two parameters pin down the posterior $x_j \mid (\tau_j, S_j)$ that enters blockholders' beliefs and thus is required to identify blockholder information parameters.

3.1.2. Dispersed Shareholder Parameters

We use the joint behavior of (T_j, S_j) to identify dispersed information $(\sigma^2_{uD}, \sigma^2_{\varepsilon D})$ and the dispersed cutoff k_D. Under the model, the advisor recommendation induces a truncation of the distribution of T_j into the $S_j = 0$ and $S_j = 1$ subsamples. The resulting shift in the distribution is governed by the strength of co-movement between T_j and s_j, which is pinned down by $\sigma^2_{u_D}$.

Once ξ and $\sigma^2_{u_D}$ are identified, the joint law of (x_j, η_{Dj}) is pinned down. The dispersed voting rule in (13) implies that the dispersed support rate satisfies

$$\tau_j = p_D(x_j, \eta_{Dj}) = \Phi\left(\sigma_{\varepsilon_D}\left[\frac{\eta_{Dj}}{\sigma^2_{u_D}} + \frac{x_j}{\sigma^2_{\varepsilon_D}} - k_D\Lambda_D\right]\right)$$

in the limit, with $\Lambda_D = 1 + 1/\sigma^2_{u_D} + 1/\sigma^2_{\varepsilon_D}$. The inverse probit $T_j = \Phi^{-1}(\tau_j)$ has coefficients that depend only on $(\sigma^2_{u_D}, \sigma^2_{\varepsilon_D}, k_D)$. Given the known joint distribution of (x_j, η_{Dj}), the variance of T_j across proposals identifies $\sigma^2_{\varepsilon_D}$, while the location of the T_j distribution pins down k_D uniquely.

3.1.3. Blockholder Parameters

Conditional on the estimated advisor and dispersed parameters, we use blockholder voting to identify the blockholder information environment: the common public variance σ^2_{uB} and each blockholder's private variance and cutoff $(\sigma^2_{\varepsilon_b}, k_b)$.

In the appendix, we derive the posterior

$$x_j \mid (\tau_j, S_j) \sim N\big(\mu_{x|(\tau_j,S_j)},\ \sigma^2_{x|(\tau_j,S_j)}\big)$$

in closed form. Blockholders observe a reduced-form public signal $\eta_{Bj} = x_j + u_{Bj}$ with $u_{Bj} \sim N(0, \sigma^2_{uB})$, so

$$\eta_{Bj} \mid (\tau_j, S_j) \sim N\Big(\mu_{x|(\tau_j,S_j)},\ \sigma^2_{x|(\tau_j,S_j)} + \sigma^2_{uB}\Big).$$

Thus, conditional on (τ_j, S_j), the only remaining unknown in the blockholder public information is σ^2_{uB}, which governs how closely blockholder assessments lie around the posterior of x_j implied by (τ_j, S_j).

We do not observe η_{Bj}, but under the equilibrium cutoff rule blockholder voting (and hence s_{Bj}) is monotone in blockholders' posterior means. The sensitivity of blockholder voting to (τ_j, S_j) therefore disciplines σ^2_{uB}.

Finally, integrating out unobserved signals conditional on (τ_j, S_j), we obtain for each blockholder b,

$$\Pr(V_{bj} = 1 \mid \tau_j, S_j) = \Phi\left(\alpha_{b0} + \alpha_{b1}\, T_j + \alpha_{b2}\, S_j\right),$$

for coefficients $(\alpha_{b0}, \alpha_{b1}, \alpha_{b2})$ that are smooth functions of $(\sigma^2_{uB}, \sigma^2_{\varepsilon_b}, k_b)$ and the already-known dispersed parameters (Lemma 4). Because σ^2_{uB} is common across blockholders while $(\sigma^2_{\varepsilon_b}, k_b)$ are block-specific, the cross-block pattern of slopes on both T_j and S_j provides overidentifying restrictions that pin down σ^2_{uB} and then identify each $(\sigma^2_{\varepsilon_b}, k_b)$ by inversion.

3.1.4. Preferences

Finally, we identify the preference parameters

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

from the best-response conditions at the cutoffs. For dispersed shareholders,

$$E\left[x_j \mid m_{Dj} = k_D,\ \mathrm{piv}_{Dj}\right] + \delta_D = 0,$$

and the argument is analogous for each blockholder b.

3.1.5. Formal Identification

We formalize the identification claim with the following proposition.

Proposition 2: Identification of model parameters

Let the structural parameter vector be

$$\Theta \equiv \left(\rho, \xi, \sigma^2_{uD}, \sigma^2_{uB}, \sigma^2_{\varepsilon D}, \{\sigma^2_{\varepsilon_b}\}_{b=1}^{N_B}, k_D, \{k_b\}_{b=1}^{N_B}, \delta_D, \{\delta_b\}_{b=1}^{N_B}\right),$$

where ρ is the proxy advisor's alignment with the dispersed index, ξ is the recommendation *threshold, σ^2_{uD} and σ^2_{uB} are the reduced-form public-signal variances for dispersed shareholders and blockholders, $\sigma^2_{\varepsilon D}$ and $\{\sigma^2_{\varepsilon_b}\}_b$ are private-signal variances, k_D and $\{k_b\}_b$ are voting cutoffs, and δ_D and $\{\delta_b\}_b$ are preference parameters.*

Given the joint cross-sectional distribution of

$$\left\{ \tau_j, S_j, \{V_{bj}\}_{b=1}^{N_B} \right\}_j$$

across proposals (together with the ownership weights $\{\psi_b\}_{b=1}^{B}$ and the model's voting rule), the parameter vector Θ is identified.

Proof. See Appendix B. ■

3.2. Estimation Routine

We take the subset of moment restrictions implied by the identification argument above and stack them into a single sample moment vector. That is, at the proposal-level, we match the conditional means and variances of the inverse-probit dispersed support index $T_j = \Phi^{-1}(\tau_j)$ by ISS recommendation group, $\mathbb{E}[T_j \mid S_j]$ and $\mathrm{Var}(T_j \mid S_j)$ for $S_j \in \{0, 1\}$, together with the probit slope β^T_{ISS} from predicting S_j using T_j. At the blockholder level, we match the moment restrictions implied by each blockholder's vote probit. Specifically, $\mathbb{E}[V_{bj}]$ matches the probit intercept, $\mathbb{E}[V_{bj}T_j]$ matches the loading on T_j, and $\mathbb{E}[V_{bj}S_j]$ matches the loading on S_j in the probit index. We also include the triple interaction moment $\mathbb{E}[V_{bj}T_jS_j]$, which does not introduce an additional free coefficient in the baseline probit but provides an overidentifying restriction that disciplines the model's joint fit of the (T_j, S_j) interaction.

Estimation then proceeds via a standard two-step GMM routine: we obtain a first-step estimate using an initial weighting matrix, form the optimal weighting matrix from the estimated moment covariance, and re-estimate in a second step. Appendix B.2 details in full.

4. Institutional Details and Data

4.1. Institutional Background

The largest diversified asset managers—most notably Vanguard, BlackRock, and State Street—routinely hold economically meaningful stakes in public firms and therefore play an outsized role in proxy voting. In practice, these institutions typically retain voting rights over the shares they manage and implement voting through centralized stewardship teams and firm-wide policies (Fichtner et al., 2017). Because retail shareholder participation in proxy voting is low and uneven (Brav et al., 2022), the effective influence of large institutions in close votes can substantially exceed what their nominal ownership shares alone would suggest.

A prominent empirical literature finds that passive funds support management more frequently than other shareholders in settings where votes are close and potentially consequential. For example, Heath et al. (2022) show that passive funds are more likely to side with management in close governance votes, while Brav et al. (2024) document a similar pattern in proxy contests.[5] Several mechanisms could generate pro-management voting patterns among large asset managers. Bebchuk and Hirst (2019) argue that large managers may be "excessively deferential" to management, including due to conflicts arising from business ties with portfolio firms (Davis and Kim, 2007; Cvijanović et al., 2016) or concerns about political backlash (Roe, 1991). Rather than taking a stand on the underlying mechanism, our contribution is to measure differences in preferences and information in a framework that explicitly accounts for strategic voting incentives.

Our model implies that observed vote choices need not map one-to-one into underlying preferences for passage. In equilibrium, a shareholder's vote reflects both its intrinsic taste for passage and its inference about proposal quality given public information, private signals, and the voting environment. As a result, there is an ambiguous relationship between the fraction of proposals a shareholder believes should pass and the fraction it supports in equilibrium. We therefore estimate the model structurally to uncover whether the Big Three and other large mutual funds exhibit a strong pro-management bias.

[5] The authors emphasize, however, that passive funds may express dissent through channels other than voting for dissidents outright.

To estimate the model, we focus on executive compensation proposals ("Say-on-Pay"), in which shareholders cast advisory votes on management's disclosed compensation program. These are management-sponsored proposals, so a "For" vote is naturally interpreted as support for management. Because SOP is advisory, there is no statutory voting threshold that compels the compensation committee to revise pay. Instead, what matters is the level of dissent at which key governance intermediaries and boards treat the outcome as a negative signal. A central benchmark is 70% support. In particular, Institutional Shareholder Services (ISS) treats SOP support below 70% as a low-support outcome that triggers heightened scrutiny of the firm's response and may lead ISS to recommend votes against the subsequent SOP proposal and/or directors (ISS, 2022, Section 5, "Compensation").[6] For these reasons, we use 70% as the passing threshold in the empirical analyses.

4.2. Sample Construction

We use the ISS Voting Results dataset to gather a universe of Say-on-Pay proposals held at annual meetings in 2020. We identify Say-on-Pay votes using the ISS Agenda Item ID "M0550." For each proposal, we collect identifying information about the firm, the date of the meeting, the number of shares voted for/Against/abstain, ISS's voting recommendation, and additional variables related to voting procedures. We keep only proposals with voting bases "For + Against + Abstain" or "For + Against." We merge share price information from the CRSP monthly stock file, matching on the month-end prior to the meeting date. We compute the proposal's total support rate, λ_j, following:

$$\lambda_j = \begin{cases} \dfrac{\text{\# shares for}}{\text{\# shares for} + \text{\# shares Against}}, & \text{if base = "For + Against,"} \\[2ex] \dfrac{\text{\# shares for}}{\text{\# shares for} + \text{\# shares Against} + \text{\# shares abstain}}, & \text{if base = "For + Against + Abstain".} \end{cases}$$

[6]Consistent with this, firms experience sharp changes in institutional investor engagement around the 70% cutoff, while placebo threshold analyses do not show comparable discontinuities at alternative cutoffs such as 50% support (Dey et al., 2024). More broadly, low SOP support is widely viewed as a signal of shareholder dissatisfaction and can trigger engagement and compensation changes (Ertimur et al., 2013). Moreover, Barry (2026) shows that 70% support is an important threshold in influencing compensation policy.

We follow the approach in Bubb and Catan (2022) and Bolton et al. (2020) and filter to proposals receiving less than 95% support. We also compute turnout, χ_j:

$$\chi_j = \begin{cases} \dfrac{\#\text{ shares for} + \#\text{ shares Against}}{\#\text{ shares outstanding}}, & \text{if base = “For + Against,”} \\ \dfrac{\#\text{ shares for} + \#\text{ shares Against} + \#\text{ shares abstain}}{\#\text{ shares outstanding}}, & \text{if base = “For + Against + Abstain”.} \end{cases}$$

We drop proposals with less than 50% turnout. For each Say-on-Pay proposal, we download all mutual fund voting records. We collect the name and ISS identifier of the mutual fund, the mutual fund family, and the vote cast. We keep only for/Against/abstain votes. We aggregate fund-level votes to the family-level, deeming a family to vote for the proposal if a majority of its funds support it. We download institutional ownership data from the Thomson Reuters 13F dataset, merging on the quarter prior to the meeting date. We compute each manager's ownership by dividing the number of shares held by the number of shares outstanding.

We now turn to how we map the raw data to the structure assumed in the model. First, we compute each 13F manager's turnout-adjusted ownership by dividing their raw ownership by the turnout rate χ_j. We deem a manager to be a blockholder if its turnout-adjusted ownership is at least five percent. Next, we match 13F manager names to ISS fund family names to record each blockholder's vote.[7] For each proposal, this step produces a set of blockholders, their votes, and their turnout-adjusted ownership. We construct the vector of blockholder ownership, ψ^{χ}_{Bj}, and the vector of blockholder votes, V^B_j, where the number of blockholders N_B is the count of unique blockholders across all proposals. Given the total support rate, λ_j, we impute the dispersed shareholders' support rate, τ_j, following

$$\tau_j = \frac{\lambda_j - V_j^{B\top} \psi^{\chi}_{Bj}}{\Psi^{\chi}_{Dj}}.$$

Here, Ψ^{χ}_{Dj} denotes the dispersed shareholders' turnout-adjusted ownership share in proposal j. This step produces a series of voting results $\{\tau_j, V^B_j\}$ and ownership structures $\{\Psi_j\}$ suitable as inputs to the procedure described in Section 3.

[7]In the underlying data, we keep only for/Against/abstain votes; fund-level votes are aggregated to the family level.

4.2.1. Sample summary

We summarize our sample of 993 Say-on-Pay votes in Table 1. The average firm has 2.89 blockholders, with combined ownership of 29.53%. Average total support is 83.65%. Support is lower among dispersed shareholders, with an average dispersed support rate of 81.56%, while blockholders are more supportive on average: conditional on being a blockholder, the mean blockholder support rate is 86.92%. Using the standard convention that votes with less than 70% support are considered failures, 85.90% of proposals pass.

Panel B summarizes ownership and voting behavior for the largest blockholders. Vanguard is the most frequent blockholder, appearing in 909 votes, while BlackRock appears in 800. State Street appears in 291 votes, consistent with its smaller average stake. The Big Three hold economically large positions: average ownership is 10.65% for Vanguard, 11.62% for BlackRock, and 6.63% for State Street. All three are more supportive than dispersed shareholders on average: Vanguard supports 90.21% of proposals, BlackRock supports 95.00%, and State Street supports 90.38%. Pivot probabilities vary meaningfully across investors, reflecting both differences in stake sizes and voting behavior: the average pivot probability is 12.54% for Vanguard and 17.00% for BlackRock, compared to 4.12% for State Street.

5. Results

5.1. Model fit

Table 2 displays the results of the GMM estimation. Overall, the model fits the data well. Moments relating to dispersed shareholder parameters are very closely matched (Panel A). The slope relation between the ISS recommendation and T_j is also closely matched, suggesting that the model is able to replicate the correlation between latent advisor recommendations and latent dispersed public information.

In Panel B, we display the targeted moments for each of the six blockholders. The model is able to replicate key moments for all blockholders. It is notable that the fit remains close even for Dimensional, whose particular stewardship strategy separates it from other managers.

5.1.1. Model Fit on Untargeted Moments

Table 3 displays model fit on moments we do not explicitly target in hte estimation. At the proposal-level (Panel A), the table shows that we match total support. It also shows that the proportion of passing and close votes is very similar to the data.

In Panel B, we report each blockholder's voting probability conditional on the ISS recommendation, along with its estimated pivot probability (i.e., the share of proposals for which switching that blockholder's vote would change the outcome). Overall, the model matches these blockholder-level moments closely.

One notable deviation is that the model assigns a higher pivot probability to Dimensional in the model. This discrepancy is economically interpretable: we estimate that Dimensional has the strongest anti-management preference among blockholders, which makes its vote most likely to be decisive in proposals that generate pivotal events. In other words, the model's tendency to overstate Dimensional's pivotality reflects an implication of the preference estimates, when an investor is systematically more willing to oppose management, it endogenously becomes pivotal more often.

Figure 1 displays simulated total support from the model as compared to the data. We display the densities of support conditional on the ISS recommendation. The figure shows that the model is able to closely capture the data generating process for support rates. However, the model cannot perfectly replicate the peakedness of support in the data around the mean.

5.2. Parameter Estimates

Table 4 reports the estimated parameters. The proxy advisor signal is aligned with the information of dispersed shareholders: the estimated correlation is $\rho = 0.774$. This implies that the advisor recommendation is not an orthogonal third signal, but rather a noisy public summary that loads heavily on the same underlying component of proposal quality that dispersed investors would infer from their own information. Put differently, shifts in the recommendation are informative because they move in tandem with what the broader investor base believes.

Second, the model estimates meaningful heterogeneity in public information precision across voter types. Dispersed shareholders' public signal is relatively noisy ($\sigma_{u_D} = 6.67$), whereas blockholders observe a more precise public signal ($\sigma_{u_B} = 3.31$). This gap suggests that large institutions effectively operate with a richer public-information set—consistent with centralized stewardship resources and systematic monitoring.

Turning to private information, the pattern goes in the opposite direction: blockholders' private signals are substantially more precise than those of dispersed shareholders. Dispersed shareholders have $\sigma_D = 3.41$, while most blockholders have much lower private signal volatility—σ_b between 0.83 and 1.10 for Vanguard, BlackRock, State Street, Dimensional, and Fidelity, with T. Rowe an outlier at $\sigma = 1.95$. This implies that, conditional on the public information environment, large institutions (especially the Big Three and Dimensional) place greater weight on their own private assessments of proposal quality than does the dispersed mass. The model therefore does not require an "uninformed indexer" mechanism to rationalize blockholder voting: their strong co-movement with the proxy advisor recommendation can arise even when they are well-informed privately, because the recommendation is highly correlated with the dispersed-information component of fundamentals (high ρ) and therefore forecasts how the broader voting base is likely to move.

Finally, the estimated preference parameters reveal heterogeneity in underlying voting tastes. In our normalization, δ_i shifts a shareholder's ideal point toward passage, and $\Phi(\delta_i)$ provides a convenient probability-scale summary of this baseline pro-passage orientation.[8] Dispersed shareholders are moderately pro-passage, with $\Phi(\delta_D) = 66.56\%$. Most large blockholders are more pro-passage than dispersed: Vanguard (72.45%), BlackRock (75.60%), State Street (71.33%), and T. Rowe (70.92%)—while Fidelity is close to dispersed shareholders (67.03%).

Importantly, these preference indices are not the same object as raw voting frequencies: Table 2 shows that unconditional vote-for rates $\mathbb{E}[V_i]$ are substantially higher for several investors (e.g., Vanguard 90.2% and BlackRock 95.0%) than their corresponding $\Phi(\delta_i)$ values, underscoring the paper's central message that equilibrium support need not move one-for-one with underlying preferences.

[8]This quantity is a preference index and should not be compared to the 70% support threshold used to classify Say-on-Pay outcomes.

5.3. Decomposing Voting: Strategic Incentives and Information

To quantify the contribution of strategic effects to observed voting outcomes, we compare the estimated equilibrium to a "non-strategic" counterfactual that holds fixed the information environment, and hence the posterior means $m_{ij} = E[x_j \mid \eta_j, z_{ij}]$, but removes the effect of pivotality on shareholder voting decisions.

In the full model, shareholder i votes

$$V_{ij} = \mathbf{1}\{ m_{ij} \geq k_i \},$$

in which k_i is pinned down by $E[x_j \mid \eta_j, m_{ij} = k_i, \text{piv}_{ij}] = -\delta_i$. In the non-strategic counterfactual, we instead force shareholder i to use a "sincere" preference threshold implied by δ_i:

$$V_{ij}^{NS} = \mathbf{1}\{ m_{ij} \geq -\delta_i \}.$$

That is, the cutoff in posterior-mean space is $-\delta_i$ rather than the equilibrium cutoff k_i, but we allow the shareholder to condition on the information they observe. This isolates the impact of strategic voting because the only aspect that changes from the baseline equilibrium to the counterfactual is that shareholders no longer condition on the event of being pivotal.

Table 5 shows the impact on shareholder voting strategies. Specifically, it displays the observed support probabilities in the data and baseline estimated model for each shareholder. Then, it displays the "non-strategic" counterfactual support probability. Panel A displays for all proposals, whereas Panel B splits by ISS recommendation.

The table shows that strategic voting can have a marked impact on shareholder voting. In the model, equilibrium cutoffs k_i are disciplined by the pivotality condition: at the margin $m_{ij} = k_i$, shareholders condition on being pivotal, and this pivotal conditioning tilts beliefs toward lower-quality (more contested) proposals. Relative to the sincere benchmark $m_{ij} \geq -\delta_i$, this shading makes equilibrium voting more conservative and lowers support rates.

Consistent with this mechanism, removing pivotality increases vote-for probabilities across most shareholder types. The effect is largest where pivotality is most consequential for the marginal decision: dispersed shareholders' support rises from 81.56% in the full model to

95.92% in the non-strategic counterfactual, and Dimensional's rises from 48.85% to 69.20%. By contrast, the Big Three move relatively little in aggregate—Vanguard increases from 90.24% to 92.45%, BlackRock changes minimally (94.99% to 94.57%), and State Street rises from 90.51% to 94.82%—reflecting that their observed support is already concentrated in states where the proposal-quality posterior is comfortably above the relevant threshold. Overall, the table illustrates the central theoretical point: conditioning on pivotality makes voters behave as if proposals are different at the margin, materially affecting equilibrium support relative to the non-strategic counterfactual.

Table 6 aggregates these effects to the proposal level. Eliminating pivotality-driven incentives leads to substantially higher passage and fewer close votes. In the non-strategic counterfactual, the passing rate rises to 95.77%, implying that strategic voting accounts for roughly a 10 percentage point reduction in the fraction of SOP proposals that clear the passing threshold. The close vote rate falls by nearly half, from 14.60% to 7.75%. All told, the results suggest that strategic incentives, or shareholders incorporate the beliefs and preferences of others optimally into their voting decisions, has a tangible impact on shareholder voting outcomes.

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 can diverge sharply from realized support. Large asset managers that appear uniformly pro-management in raw voting data exhibit much more moderate baseline preferences once correlated information and pivotality incentives are accounted for. At the same time, the estimates imply substantial heterogeneity in information: large institutions operate with meaningfully more precise effective public information and private assessments than dispersed shareholders, so higher observed support need not reflect weaker monitoring or a stronger taste for passage.

Counterfactuals that remove pivotality-driven incentives while holding preferences and the information environment fixed highlight the first-order role of strategic voting in shaping outcomes. Strategic conditioning makes voting more conservative in contentious states, lowering overall support and increasing the incidence of close votes. In the estimation sample, eliminating strategic voting raises the passing rate from about 85% to nearly 96%, while cutting the close-vote rate roughly in half. Taken together, the results imply that interpreting shareholder voice requires disentangling information from preferences and recognizing that the voting environment itself materially shapes voting outcomes.

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Figure 1. 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(τ_j, S_j), we generate blockholder support using the blockholder-level model-implied voting probabilities; total support is then $\tau_j + s_{Bj}$.

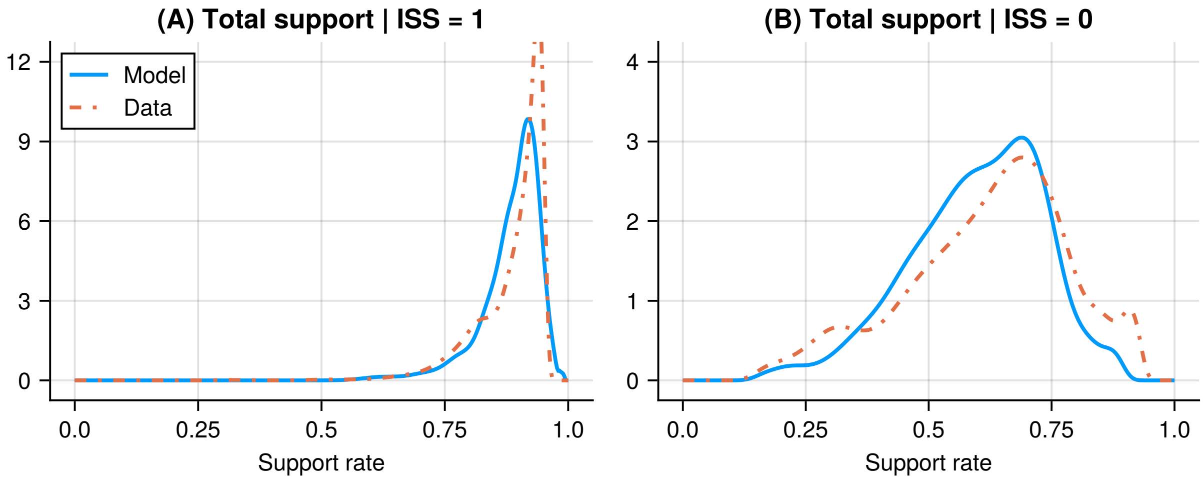

Table 1. Summary statistics

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 a dummy variable equal to one if the proposal's support rate is between 65% and 75%. 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	993	2.89	1.08	2	3	4
Blockholder ownership	993	29.53%	12.86%	20.16%	28.92%	38.27%
Total support	993	83.65%	14.11%	79.67%	89.53%	93.24%
Blockholder support	993	86.92%	25.65%	82.58%	100.00%	100.00%
Dispersed support	993	81.56%	14.40%	77.46%	87.12%	90.86%
Passing vote	993	85.90%				
Close vote	993	8.86%				

Panel B. Blockholder-level

	(1)	(2)	(3)	(4)	(5)	(6)
	Vanguard	BlackRock	State Street	Dimensional	Fidelity	T. Rowe
Number of votes	909	800	291	285	130	118
Average ownership	10.65%	11.62%	6.63%	8.49%	9.65%	9.83%
Support rate	90.21%	95.00%	90.38%	48.77%	83.85%	92.37%
Pivot probability	12.54%	17.00%	4.12%	7.02%	16.92%	11.02%

Table 2. Estimated moments

This table summarizes the fit of the structural voting model estimated by GMM. Panel A reports dispersed-side moments based on the joint distribution of the inverse–probit index $T = \Phi^{-1}(\tau)$ and the ISS recommendation S: the conditional means and variances $\mathrm{E}[T \mid S = x]$ and $\mathrm{Var}(T \mid S = x)$ for $x \in 0, 1$, and the probit slope β_T^{ISS} from regressing S on T. Panel B reports blockholder moments used in estimation. For each blockholder b, we report the moments $\mathrm{E}[V_b]$, $\mathrm{E}[V_b \cdot T]$, and $\mathrm{E}[V_b \cdot S]$ (and their model-implied counterparts), which capture the level of support, the comovement of blockholder voting with dispersed support, and the incremental shift associated with the ISS recommendation. These moments are the GMM analogs of an auxiliary probit representation of blockholder voting in (T, S).

Panel A. Dispersed and advisor Moments

	(1) Data	(2) Model
$\mathbb{E}[T \mid \mathrm{ISS} = 1]$	1.150	1.145
$\mathrm{Var}(T \mid \mathrm{ISS} = 1)$	0.129	0.138
$\mathbb{E}[T \mid \mathrm{ISS} = 0]$	0.352	0.351
$\mathrm{Var}(T \mid \mathrm{ISS} = 0)$	0.315	0.318
β_{ISS}^{T}	1.939	1.941

Panel B. Blockholder moments

	(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
$\mathbb{E}[V_b]$	0.902	0.903	0.950	0.949	0.904	0.905	0.488	0.487	0.838	0.836	0.924	0.921
$\mathbb{E}[V_b \cdot T]$	0.957	0.958	0.961	0.961	0.962	0.960	0.552	0.550	0.783	0.784	0.882	0.879
$\mathbb{E}[V_b \cdot S]$	0.805	0.813	0.819	0.813	0.849	0.850	0.484	0.483	0.708	0.690	0.805	0.784
$\mathbb{E}[V_b \cdot T \cdot S]$	0.923	0.932	0.929	0.920	0.960	0.956	0.551	0.549	0.769	0.744	0.894	0.881

Table 3. Model fit on untargeted moments

This table summarizes the fit of the structural voting model estimated by GMM. Panel A reports dispersed-side moments based on the joint distribution of the inverse–probit index $T = \Phi^{-1}(\tau)$ and the ISS recommendation S: the conditional means and variances $\mathrm{E}[T \mid S = x]$ and $\mathrm{Var}(T \mid S = x)$ for $x \in 0, 1$, and the probit slope β_T^{ISS} from regressing S on T. Panel B reports blockholder moments used in estimation. For each blockholder b, we report the moments $\mathrm{E}[V_b]$, $\mathrm{E}[V_b \cdot T]$, and $\mathrm{E}[V_b \cdot S]$ (and their model-implied counterparts), which capture the level of support, the comovement of blockholder voting with dispersed support, and the incremental shift associated with the ISS recommendation. These moments are the GMM analogs of an auxiliary probit representation of blockholder voting in (T, S).

Panel A. Proposal-level

	(1)	(2)
	Data	Model
$\mathbb{E}$ [Total support | ISS = 0]	61.79%	59.83%
Var (Total support | ISS = 0)	2.65%	1.77%
$\mathbb{E}$ [Total support | ISS = 1]	88.69%	88.51%
Var (Total support | ISS = 1)	0.49%	0.37%
Passing vote	85.90%	84.17%
Close vote	18.03%	15.93%

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
$\Pr(V_b = 1 \mid \mathrm{ISS} = 0)$	51.76%	53.75%	73.43%	75.26%	45.71%	47.02%	1.92%	1.98%	45.95%	47.93%	70.00%	71.32%
$\Pr(V_b = 1 \mid \mathrm{ISS} = 1)$	99.05%	99.18%	99.70%	99.72%	96.48%	96.95%	59.23%	63.11%	98.92%	98.79%	96.94%	96.65%
Pivot probability	12.54%	9.03%	17.00%	19.50%	4.12%	2.99%	7.02%	25.42%	16.92%	6.65%	11.02%	17.25%

Table 4. Estimated parameters

This table reports the estimated parameters of the information structure and voting behavior. Column 1 displays parameters relating to the public information environment: ξ and ρ describe the advisor threshold and the correlation of the latent advisor signal with the latent dispersed shareholder signal. σ_{u_D} and σ_{u_B} represent the idiosyncratic volatility of the (combined) public signals for dispersed and block shareholders respectively. Column 2-8 display parameters relating to each distinct shareholder type in the economy: $i \in \left\{D, \{b\}_1^B\right\}$. For example, column 2 displays dispersed shareholder parameters: the idiosyncratic volatility of the dispersed private signal σ_D, the equilibrium dispersed voting threshold k_D and the preference δ_D. In the last row, we also display each shareholder's preference-implied support rate $\Phi(\delta_i)$, which tells us, given the prior, the proportion of votes each shareholder would prefer to pass. Standard errors, clustered at the proposal level and estimated via bootstrap, are reported in parentheses; see Appendix B.2 for details.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Blockholders					
Parameter	Public information	Dispersed	Vanguard	Blackrock	State Street	Dimensional	Fidelity	T. Rowe
ξ	0.389							
	(0.074)							
ρ	0.774							
	(0.031)							
σ_{u_D}	6.670							
	(0.429)							
σ_{u_B}	3.314							
	(0.847)							
σ_i		3.411	0.904	1.037	1.102	0.828	0.886	1.948
		(0.285)	(0.159)	(0.156)	(0.207)	(0.197)	(0.246)	(0.805)
k_i		-0.167	-0.455	-0.728	-0.299	0.694	-0.379	-0.441
		(0.012)	(0.107)	(0.061)	(0.074)	(0.148)	(0.071)	(0.039)
δ_i		0.428	0.596	0.694	0.563	-0.327	0.441	0.551
		(0.032)	(0.088)	(0.060)	(0.072)	(0.243)	(0.067)	(0.103)
$\Phi(\delta_i)$		66.56%	72.45%	75.60%	71.33%	37.19%	67.03%	70.92%
		(1.16%)	(2.93%)	(1.87%)	(2.46%)	(9.19%)	(2.44%)	(3.52%)

Table 5. The impact of strategic voting on shareholder voting strategies

Panel A. All proposals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dispersed	Vanguard	BlackRock	State Street	Dimensional	Fidelity	T. Rowe
Data	81.56%	90.21%	95.00%	90.38%	48.77%	83.85%	92.37%
Full model	81.56%	90.24%	94.99%	90.51%	48.85%	83.85%	91.82%
Non-strategic	95.92%	92.45%	94.57%	94.82%	69.20%	85.27%	94.44%

Panel B. By ISS recommendation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Dispersed		Vanguard		BlackRock		State Street		Dimensional		Fidelity		T. Rowe	
	ISS = 0	ISS = 1	ISS = 0	ISS = 1	ISS = 0	ISS = 1	ISS = 0	ISS = 1	ISS = 0	ISS = 1	ISS = 0	ISS = 1	ISS = 0	ISS = 1
Data	61.82%	86.11%	51.76%	99.05%	73.43%	99.70%	45.71%	96.48%	1.92%	59.23%	45.95%	98.92%	70.00%	96.94%
Full model	61.82%	86.11%	51.76%	99.10%	73.43%	99.69%	45.71%	96.64%	1.94%	59.32%	45.94%	98.92%	70.01%	96.27%
Non-strategic	88.01%	97.74%	61.45%	99.58%	71.39%	99.62%	63.80%	99.06%	7.98%	82.87%	50.21%	99.22%	77.58%	97.88%

Table 6. The impact of strategic voting on vote outcomes

The table reports proposal-level outcomes under the estimated equilibrium and under a non-strategic benchmark that holds the information environment fixed but removes strategic voting incentives. We report the mean and variance of total support conditional on the proxy advisor recommendation (ISS $= 0, 1$), as well as the passing and close-vote rates. Column (1) reports the corresponding data moments, column (2) reports the model-implied moments under the estimated equilibrium, and column (3) reports the counterfactual moments.

	(1)	(2)	(3)
	Data	Full model	Non-strategic
$\mathbb{E}$ [Total support | ISS $= 0$]	61.79%	61.29%	78.86%
Var (Total support | ISS $= 0$)	2.65%	1.96%	1.11%
$\mathbb{E}$ [Total support | ISS $= 1$]	88.69%	88.75%	96.44%
Var (Total support | ISS $= 1$)	0.49%	0.34%	0.10%
Passing vote	85.90%	85.40%	95.77%
Close vote	18.03%	14.60%	7.75%

A. Model Appendix

A.1. Derivation of Equilibrium Posterior Density Functions

This section presents the formal proofs of Proposition 1a and 1b

Proof of Proposition 1a. 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.

Step 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 η_{jD}, and the event of pivotality piv_{Dj}. By Bayes' rule,

$$f(x_j \mid z_{Dj}, \eta_{jD}, \text{piv}_{Dj}) \;\propto\; f(x_j \mid \eta_{jD})\, f(z_{Dj} \mid x_j)\; \Pr(\text{piv}_{Dj} \mid x_j, z_{Dj}, \eta_{jD}). \tag{A.1}$$

Conditional on x_j, the dispersed private signal z_{Dj} is independent of η_{jD} and of other shareholders' votes, so $\Pr(\text{piv}_{Dj} \mid x_j, z_{Dj}, \eta_{jD}) = \Pr(\text{piv}_{Dj} \mid x_j, \eta_{jD})$. Substituting into (A.1) yields

$$f(x_j \mid z_{Dj}, \eta_{jD}, \text{piv}_{Dj}) \;\propto\; f(x_j \mid \eta_{jD})\, f(z_{Dj} \mid x_j)\; \Pr(\text{piv}_{Dj} \mid x_j, \eta_{jD}). \tag{A.2}$$

Step 2: Decomposition of pivotality across blockholder vote profiles. Let $V_{Bj} \in \{0,1\}^{N_B}$ denote the blockholder vote profile. Conditioning on V_{Bj} and using the law of total probability,

$$\Pr(\text{piv}_{Dj} \mid x_j, \eta_{jD}) = \sum_{V_{Bj}} \Pr(\text{piv}_{Dj} \mid x_j, \eta_{jD}, V_{Bj})\; \Pr(V_{Bj} \mid x_j, \eta_{jD}). \tag{A.3}$$

From the dispersed shareholder's perspective, the blockholders' public signal η_{jB} is unobserved. Under the maintained information structure, conditional on x_j the dispersed signal η_{jD} carries no additional information about η_{jB} beyond x_j; hence $\Pr(V_{Bj} \mid x_j, \eta_{jD}) = \Pr(V_{Bj} \mid x_j)$, where

$$\Pr(V_{Bj} \mid x_j) = \int \Pr(V_{Bj} \mid x_j, \eta_{jB})\, f(\eta_{jB} \mid x_j)\, d\eta_{jB}.$$

(If your model allows correlation between η_{jD} and η_{jB} conditional on x_j, the same argument goes through with $f(\eta_{jB} \mid x_j, \eta_{jD})$ instead.)

Step 3: Large-N_D limit and the pivotality constraint. Fix (x_j, η_{jD}). Given the symmetric dispersed strategy, dispersed votes are i.i.d. conditional on (x_j, η_{jD}) and satisfy

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

where $p_D(x_j, \eta_{jD})$ is the dispersed voting probability stated in the proposition. A dispersed shareholder is pivotal under profile V_{Bj} only when the dispersed support rate (excluding her own infinitesimal vote) equals the threshold share $\tau^{V_{Bj}}$. In the limit $N_D \to \infty$, this becomes the knife-edge condition

$$p_D(x_j, \eta_{jD}) = \tau^{V_{Bj}}.$$

Because this event has probability zero under a continuous signal structure, we represent the limiting contribution of pivotality using a Dirac delta. Thus,

$$\Pr(\mathrm{piv}_{Dj} \mid x_j, \eta_{jD}, V_{Bj}) \;\propto\; \mathrm{dirac}\big(p_D(x_j, \eta_{jD}) - \tau^{V_{Bj}}\big)\,.$$

Substituting into (A.2)–(A.3) yields

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

which is (17a).

Step 4: Collapse to an atomic posterior via the Dirac delta identity. For fixed η_{jD} and V_{Bj}, the mapping $x_j \mapsto p_D(x_j, \eta_{jD})$ is strictly increasing, so the equation $p_D(x_j, \eta_{jD}) = \tau^{V_{Bj}}$ has a unique solution $x_{\eta_{jD}}^{V_{Bj}}$ given in the proposition. Let $q^{V_{Bj}} = \Phi^{-1}(\tau^{V_{Bj}})$. Then at the root,

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

Moreover,

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

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

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

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

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

Substituting this into (17a) yields (17b). This completes the proof. ■

Proof of Proposition 1b. 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.

Step 1: Bayes rule. By Bayes' rule,

$$f(x_j \mid z_{bj}, \eta_{jB}, \mathrm{piv}_{bj}) \;\propto\; f(x_j \mid \eta_{jB})\, f(z_{bj} \mid x_j)\ \Pr(\mathrm{piv}_{bj} \mid x_j, z_{bj}, \eta_{jB}). \tag{A.4}$$

Conditional on x_j, the private signal z_{bj} is independent of the remaining shareholders' votes and of η_{jD}, so $\Pr(\mathrm{piv}_{bj} \mid x_j, z_{bj}, \eta_{jB}) = \Pr(\mathrm{piv}_{bj} \mid x_j, \eta_{jB})$. Hence

$$f(x_j \mid z_{bj}, \eta_{jB}, \mathrm{piv}_{bj}) \;\propto\; f(x_j \mid \eta_{jB})\, f(z_{bj} \mid x_j)\ \Pr(\mathrm{piv}_{bj} \mid x_j, \eta_{jB}). \tag{A.5}$$

Step 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,

$$\Pr(\mathrm{piv}_{bj} \mid x_j, \eta_{jB}) = \sum_{V_{B,-b,j}} \Pr(\mathrm{piv}_{bj} \mid x_j, \eta_{jB}, V_{B,-b,j})\ \Pr(V_{B,-b,j} \mid x_j, \eta_{jB}). \tag{A.6}$$

Conditional on (x_j, η_{jB}), the other blockholders' votes are independent under the cutoff (probit) strategies, which delivers the product form for $\Pr(V_{B,-b,j} \mid x_j, \eta_{jB})$ stated in the proposition.

Step 3: Characterize pivotality conditional on $V_{B,-b,j}$. Fix $(x_j, \eta_{jB}, V_{B,-b,j})$. Blockholder b is pivotal when the total fraction of shares cast in favor by all shareholders other than b lies in the interval $[\lambda^* - \psi_b, \lambda^*]$. Equivalently, the dispersed support rate τ_j must satisfy

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

where $\tau_L^{V_{B,-b,j}}$ and $\tau_H^{V_{B,-b,j}}$ are defined in the proposition.

As $N_D \to \infty$, conditional on (x_j, η_{jD}) the dispersed support rate satisfies $\tau_j = p_D(x_j, \eta_{jD})$ almost surely by the law of large numbers. The focal blockholder does not observe η_{jD}, but she knows its conditional distribution given x_j implied by $\eta_{jD} = x_j + u_{jD}$. Therefore,

$$\begin{aligned}
\Pr(\text{piv}_{bj} \mid x_j, \eta_{jB}, V_{B,-b,j}) &= \Pr\left(\tau_j \in [\tau_L^{V_{B,-b,j}}, \tau_H^{V_{B,-b,j}}] \,\middle|\, x_j, \eta_{jB}, V_{B,-b,j}\right) \\
&= \Pr\left(p_D(x_j, \eta_{jD}) \in [\tau_L^{V_{B,-b,j}}, \tau_H^{V_{B,-b,j}}] \,\middle|\, x_j\right) \equiv \Pi^{V_{B,-b,j}}(x_j), \qquad \text{(A.7)}
\end{aligned}$$

where the second equality uses that η_{jD} is conditionally independent of η_{jB} given x_j under the maintained signal structure.

Step 4: Express $\Pi^{V_{B,-b,j}}(x_j)$ **as an integral over** η_{jD}. For fixed x_j, $p_D(x_j, \eta_{jD})$ is strictly increasing in η_{jD}. Hence the event $p_D(x_j, \eta_{jD}) \in [\tau_L^{V_{B,-b,j}}, \tau_H^{V_{B,-b,j}}]$ is equivalent to $\eta_{jD} \in [\eta_L^{V_{B,-b,j}}(x_j),\ \eta_H^{V_{B,-b,j}}(x_j)]$, where $\eta_L^{V_{B,-b,j}}(x_j)$ and $\eta_H^{V_{B,-b,j}}(x_j)$ are obtained by inverting $p_D(x_j, \eta_{jD}) = \tau_L^{V_{B,-b,j}}$ and $p_D(x_j, \eta_{jD}) = \tau_H^{V_{B,-b,j}}$, respectively, yielding the expressions in the proposition. Therefore,

$$\Pi^{V_{B,-b,j}}(x_j) = \int_{\eta_L^{V_{B,-b,j}}(x_j)}^{\eta_H^{V_{B,-b,j}}(x_j)} f(\eta_{jD} \mid x_j)\, d\eta_{jD}.$$

Step 5: Combine pieces to obtain the posterior. Substituting (A.7) into (A.6) gives

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

Plugging this into (A.5) yields

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

which is exactly (18). This completes the proof. ■

B. Estimation Appendix

B.1. Identification Strategy

This section formally outlines the identification strategy. We first begin with the formal proof of Proposition 2, which references the lemmas following.

Proof of Proposition 2. The proof proceeds by showing how each block of parameters is pinned down by a particular part of the joint distribution of the observables and then invoking the corresponding lemma.

- **Advisor alignment and threshold.** Using the joint distribution of (T_j, S_j), we consider the conditional recommendation probability $P(S_j = 1 \mid T_j = t)$. Under the Gaussian structure, this is a probit in t whose slope and intercept are one-to-one functions of the advisor–alignment parameter ρ and the scaled threshold $\xi/\sqrt{1-\rho^2}$. With $\text{Var}(s_j)$ normalized, this identifies both ρ and the threshold ξ. See Lemma 1.

- **Dispersed information and cutoff.** From the dispersed support rate τ_j we construct the continuous index $T_j = \Phi^{-1}(\tau_j)$. The joint distribution of (τ_j, S_j) (equivalently (T_j, S_j)) identifies the dispersed-side information parameters $(\sigma^2_{uD}, \sigma^2_{\varepsilon D})$ and the dispersed cutoff k_D by exploiting: (i) the Gaussian index structure of T_j in the latent signals; and (ii) the way the distribution of T_j is truncated and shifted across $S_j = 0$ versus $S_j = 1$. Formally, see Lemma 2.

- **State distribution given (τ_j, S_j).** Given the identified dispersed information parameters and advisor primitives $(\sigma^2_{uD}, \sigma^2_{\varepsilon D}, k_D, \rho, \xi)$, the Gaussian structure implies that the latent state conditional on (τ_j, S_j) is normal, with mean and variance that can be written explicitly as functions of these parameters. Intuitively, (τ_j, S_j) summarize how the underlying state loads into dispersed voting and the advisor's assessment. The resulting expressions $\mu_{x|\tau,\ell}(\tau_j)$ and $\sigma^2_{x|\tau,\ell}(\tau_j)$ for $\ell \in \{0,1\}$ are given in Lemma 3.

- **Blockholder public information.** Conditional on (τ_j, S_j), the state x_j has the normal distribution characterized above. Blockholders observe a group-specific public signal $\eta_{Bj} = x_j + u_{Bj}$ with variance σ^2_{uB}. The way aggregate blockholder support $s_{Bj} = \sum_b \psi_b V_{bj}$ moves with (T_j, S_j) and how dispersed blockholder votes are around that aggregate identify the reduced-form blockholder public variance σ^2_{uB}: more precise public information (smaller σ^2_{uB}) makes s_{Bj} track (T_j, S_j) more tightly, while less precise information makes blockholder support more diffuse even conditional on (τ_j, S_j). This argument is formalized in Lemma 4.
- **Blockholder private information and cutoffs.** Once σ^2_{uB} is known, each blockholder b's vote can be written, after integrating out unobserved signals, as

$$\Pr(V_{bj} = 1 \mid T_j, S_j) = \Phi\big(\alpha_{b0} + \alpha_{b1} T_j + \alpha_{b2} S_j\big),$$

for some coefficients $(\alpha_{b0}, \alpha_{b1}, \alpha_{b2})$ that are smooth functions of $(\sigma^2_{uB}, \sigma^2_{\varepsilon_b}, k_b)$ and the already-identified dispersed parameters. The variation in (T_j, S_j) across proposals identifies $(\alpha_{b0}, \alpha_{b1}, \alpha_{b2})$ from the observed probit of V_{bj} on (T_j, S_j), and the structural mapping from $(\alpha_{b0}, \alpha_{b1}, \alpha_{b2})$ to $(\sigma^2_{\varepsilon_b}, k_b)$ is one-to-one. Thus each blockholder's private-signal variance and cutoff are identified. See Lemma 4.

- **Preferences.** Finally, given the identified information environment and cutoffs

$$(\sigma^2_{uD}, \sigma^2_{\varepsilon D}, k_D,\ \sigma^2_{uB}, \{\sigma^2_{\varepsilon_b}, k_b\}_b,\ \rho, \xi),$$

the equilibrium pivotality probabilities and the posterior distribution of the state at each cutoff are fully determined by the model. For the dispersed shareholders,

$$\delta_D = -\,\mathrm{E}\big[x_j \mid m_{Dj} = k_D,\ \mathrm{piv}_{Dj}\big],$$

where the expectation on the right-hand side is a known functional of the identified primitives (obtained by combining the Gaussian law of m_{Dj} with the equilibrium pivotality kernel). An analogous expression holds for each blockholder:

$$\delta_b = -\,\mathrm{E}\big[x_j \mid m_{bj} = k_b,\ \mathrm{piv}_{bj}\big].$$

Lemma 5 shows that these expectations are uniquely determined by the previously identified parameters, so δ_D and $\{\delta_b\}_b$ are identified.

Collecting these steps, we obtain that the mapping from the joint distribution of the observables $\{S_j, \tau_j, \{V_{bj}, \psi_b\}_b\}_j$ to the structural parameter vector is one-to-one, which establishes Proposition 2.

■

Lemma 1 (Identification of advisor alignment ρ and threshold ξ)**.** *Let $T_j = \Phi^{-1}(\tau_j)$ denote the dispersed voting index for proposal j and suppose that there exists a latent Gaussian advisor index $\tilde{s}_j = x_j + u_j$,. Given x_j is assumed standard normal and $u_j \sim N(0, \sigma_I^2)$, we can normalize $\tilde{s}_j$ using variance $1/\sqrt{1+\sigma_I^2}$ such that s_j is also standard normal. This gives a bivariate normal:*

$$\begin{pmatrix} T_j \\ s_j \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_T \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_T^2 & \rho\,\sigma_T \\ \rho\,\sigma_T & 1 \end{pmatrix}\right),$$

with unknown correlation parameter $\rho \in (-1,1)$ and variance normalization $\mathrm{Var}(s_j) = 1$. *The binary recommendation is generated by*

$$S_j = \mathbf{1}\{s_j > \xi\},$$

for some threshold $\xi \in \mathbb{R}$. The econometrician observes the joint distribution of (T_j, S_j) across proposals and knows the marginal distribution of T_j (hence μ_T and σ_T^2). Then the parameter ρ and the scaled threshold $\xi/\sqrt{1-\rho^2}$ are identified from the joint distribution of (T_j, S_j).

Sketch of proof. Standardizing T_j using its known mean and variance, define

$$\tilde{T}_j \equiv \frac{T_j - \mu_T}{\sigma_T}.$$

Then $(\tilde{T}_j, s_j)$ is bivariate normal with zero means, unit variances, and correlation ρ:

$$\begin{pmatrix} \tilde{T}_j \\ s_j \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right), \qquad S_j = \mathbf{1}\{s_j > \xi\}.$$

Conditional on $\tilde{T}_j = t$, the advisor index satisfies

$$s_j \mid \tilde{T}_j = t \sim N\big(\rho t,\ 1 - \rho^2\big),$$

so

$$\Pr(S_j = 1 \mid \tilde{T}_j = t) = \Pr(s_j > \xi \mid \tilde{T}_j = t) = \Phi\left(\frac{\rho t - \xi}{\sqrt{1 - \rho^2}} \right).$$

Define the inverse probit transform of this conditional probability,

$$g(t) \ \equiv\ \Phi^{-1}\big(\Pr(S_j = 1 \mid \tilde{T}_j = t) \big).$$

Then

$$g(t) = \frac{\rho t - \xi}{\sqrt{1 - \rho^2}} = b_0 + b_1 t,$$

with slope $b_1 = \rho / \sqrt{1 - \rho^2}$ and intercept $b_0 = -\xi / \sqrt{1 - \rho^2}$.

The joint distribution of $(\tilde{T}_j, S_j)$ identifies the function $t \mapsto \Pr(S_j = 1 \mid \tilde{T}_j = t)$ and hence identifies $g(t)$. Because $g(t)$ is affine, its slope b_1 and intercept b_0 are uniquely determined. The slope satisfies

$$b_1 = \frac{\rho}{\sqrt{1 - \rho^2}},$$

which defines a strictly monotone mapping $\rho \mapsto b_1$ on $(-1, 1)$; thus ρ is uniquely recovered from b_1, i.e.,

$$\rho = \frac{b_1}{\sqrt{1 + b_1^2}}.$$

Given ρ, the scaled threshold $\xi / \sqrt{1 - \rho^2}$ is then recovered from the intercept $b_0 = -\xi / \sqrt{1 - \rho^2}$, i.e.,

$$\xi = -b_0 \left(\sqrt{1 - \frac{b_1}{\sqrt{1 + b_1^2}}} \right).$$

Hence ρ and $\xi/\sqrt{1-\rho^2}$ are identified from the joint distribution of (T_j, S_j). ■

Lemma 2 (Identification of dispersed shareholder parameters)**.** *Suppose the primitives of the model in Section 2 hold: the latent state is $x_j \sim N(0,1)$, dispersed shareholders observe the reduced-form public signal*

$$\eta_{Dj} = x_j + u_{Dj}, \qquad u_{Dj} \sim N(0, \sigma^2_{u_D}),$$

and each dispersed shareholder i receives a private signal $z_{ij} = x_j + \varepsilon_{ij}$ with $\varepsilon_{ij} \sim N(0, \sigma^2_{\varepsilon_D})$, independent of (x_j, u_{Dj}). Let $p_D(x_j, \eta_{Dj})$ denote the dispersed voting probability implied by the voting rule in Equation (13) specialized to the dispersed type $(\sigma^2_{u_D}, \sigma^2_{\varepsilon_D}, k_D)$, and define

$$\tau_j \;=\; p_D(x_j, \eta_{Dj})$$

as the dispersed support rate for proposal j in the $N_D \to \infty$ limit.

In addition, suppose there exists a proxy advisor that forms a continuous assessment

$$s_j = x_j + u_{Ij}, \qquad u_{Ij} \sim N(0, \sigma^2_I),$$

independent of u_{Dj}, and issues the binary recommendation

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

where both the correlation between inverse probit $T_j = \Phi^{-1}(\tau_j)$ and the latent proxy advisor signal $\rho = \mathrm{Corr}\left(T_j, s_j\right)$ and ξ are identified from Lemma 1.

The econometrician observes the joint cross-sectional distribution of (τ_j, S_j) across proposals. Then the dispersed public signal variance $\sigma^2_{u_D}$, the dispersed private signal variance $\sigma^2_{\varepsilon_D}$, and the dispersed cutoff k_D are identified.

Proof. Specializing Equation (13) to the dispersed type yields, for each proposal j,

$$\tau_j = \Pr\left(V_{Dj} = 1 \mid x_j, \eta_{Dj}\right) = \Phi\left(\sigma_{\varepsilon_D}\left[\frac{\eta_{Dj}}{\sigma^2_{u_D}} + \frac{x_j}{\sigma^2_{\varepsilon_D}} - k_D\Lambda_D\right]\right), \tag{B.1}$$

with $\sigma^2_{\varepsilon_D} = \sigma^2_{\varepsilon_D}$ and $\Lambda_D = 1 + 1/\sigma^2_{u_D} + 1/\sigma^2_{\varepsilon_D}$. Applying the inverse probit transform gives

$$T_j \;\equiv\; \Phi^{-1}(\tau_j) = \sigma_{\varepsilon_D}\left[\frac{\eta_{Dj}}{\sigma^2_{u_D}} + \frac{x_j}{\sigma^2_{\varepsilon_D}} - k_D\Lambda_D\right] \;=\; a\,\eta_{Dj} + b\,x_j + c, \tag{B.2}$$

where

$$a = \frac{\sigma_{\varepsilon_D}}{\sigma^2_{u_D}}, \qquad b = \frac{1}{\sigma_{\varepsilon_D}}, \qquad c = -\,\sigma_{\varepsilon_D} k_D \Lambda_D.$$

By assumption, $x_j \sim N(0,1)$, $\eta_{Dj} = x_j + u_{Dj}$ with $u_{Dj} \sim N(0, \sigma^2_{u_D})$, and $s_j = x_j + u_{Ij}$ with $u_{Ij} \sim N(0, \sigma^2_I)$, all mutually independent. Hence (x_j, η_{Dj}, s_j) is trivariate normal with

$$\mathrm{Var}(x_j) = 1, \quad \mathrm{Var}(\eta_{Dj}) = 1 + \sigma^2_{u_D}, \quad \mathrm{Var}(s_j) = 1 + \sigma^2_I,$$

and

$$\mathrm{Cov}(x_j, \eta_{Dj}) = 1, \quad \mathrm{Cov}(x_j, s_j) = 1, \quad \mathrm{Cov}(\eta_{Dj}, s_j) = 1.$$

Equation (B.2) shows that T_j is an affine function of (x_j, η_{Dj}), so the pair (T_j, s_j) is also jointly Gaussian. The recommendation rule $S_j = \mathbb{1}\left[s_j > \xi\right]$ implies that the econometrician observes (T_j, S_j), where S_j indicates whether the latent normal s_j lies above the threshold ξ.

Let $(\mu_T, \mu_s, \sigma^2_T, \sigma^2_s, \rho_{Ts})$ denote the mean, variances, and correlation of the bivariate normal (T_j, s_j). The joint cross-sectional distribution of (T_j, S_j) identifies these five quantities. First, the marginal distribution of T_j is directly observed, so (μ_T, σ^2_T) are identified. Second, the marginal distribution of the binary S_j identifies the standardized cutoff of s_j:

$$\Pr(S_j = 1) = \Pr(s_j > \xi) = 1 - \Phi\left(\frac{\xi - \mu_s}{\sigma_s}\right),$$

so (μ_s, σ_s, ξ) are identified up to the normalization of s_j; with $\mathrm{Var}(x_j) = 1$ fixed, this pins down $\sigma^2_s = 1 + \sigma^2_I$ and the standardized threshold ξ/σ_s. Third, the conditional means and variances of T_j given $S_j = 0$ and $S_j = 1$ are identified from the joint distribution of (T_j, S_j). For a bivariate normal (T, s) truncated along the s-dimension, these conditional moments are smooth functions of $(\mu_T, \mu_s, \sigma^2_T, \sigma^2_s, \rho_{Ts})$ and the threshold ξ; inverting these relationships yields ρ_{Ts} and hence the covariance $\mathrm{Cov}(T_j, s_j)$ in addition to μ_s and σ^2_s.

We now relate $(\sigma_T^2, \mathrm{Cov}(T_j, s_j))$ to the underlying structural parameters. From (B.2) and the covariance structure of (x_j, η_{Dj}, s_j), we obtain

$$\mathrm{Var}(T_j) = a^2\,\mathrm{Var}(\eta_{Dj}) + b^2\,\mathrm{Var}(x_j) + 2ab\;\mathrm{Cov}(\eta_{Dj}, x_j) = a^2(1+\sigma_{u_D}^2) + b^2 + 2ab,$$

and

$$\mathrm{Cov}(T_j, s_j) = a\;\mathrm{Cov}(\eta_{Dj}, s_j) + b\;\mathrm{Cov}(x_j, s_j) = a\cdot 1 + b\cdot 1 = a+b,$$

where the last equality uses $\mathrm{Cov}(\eta_{Dj}, s_j) = \mathrm{Cov}(x_j, s_j) = 1$ under the assumed independence structure.[9]

The left-hand sides $(\sigma_T^2, \mathrm{Cov}(T_j, s_j))$ are identified from the joint distribution of (T_j, S_j), and the right-hand sides depend only on $(a, b, \sigma_{u_D}^2)$, with $a = \sigma_{\varepsilon_D}/\sigma_{u_D}^2$ and $b = 1/\sigma_{\varepsilon_D}$. This gives a system of two equations in the two unknowns $(\sigma_{u_D}^2, \sigma_{\varepsilon_D}^2)$; under the usual positivity restrictions on variances, the mapping

$$(\sigma_{u_D}^2, \sigma_{\varepsilon_D}^2) \mapsto (\sigma_T^2, \mathrm{Cov}(T_j, s_j))$$

is one-to-one, so $(\sigma_{u_D}^2, \sigma_{\varepsilon_D}^2)$ are identified.

Finally, the intercept c in (B.2) is the mean of T_j net of its dependence on (x_j, η_{Dj}):

$$c = \mathrm{E}[T_j] - a\,\mathrm{E}[\eta_{Dj}] - b\,\mathrm{E}[x_j] = \mu_T,$$

since $\mathrm{E}[x_j] = \mathrm{E}[\eta_{Dj}] = 0$ under our normalization. Given $(\sigma_{u_D}^2, \sigma_{\varepsilon_D}^2)$ and $\Lambda_D = 1 + 1/\sigma_{u_D}^2 + 1/\sigma_{\varepsilon_D}^2$, we have

$$c = -\,\sigma_{\varepsilon_D} k_D \Lambda_D \quad\Longrightarrow\quad k_D = -\frac{c}{\sigma_{\varepsilon_D}\Lambda_D},$$

so k_D is identified. This completes the identification of $(\sigma_{u_D}^2, \sigma_{\varepsilon_D}^2, k_D)$ from the joint cross-sectional distribution of (τ_j, S_j). ■

Lemma 3 (Conditional state distribution given (τ_j, S_j)). *Suppose the information structure in*

[9] If instead η_{Dj} is written as a noisy transformation of s_j as in the information section, the same logic applies with $\mathrm{Cov}(\eta_{Dj}, s_j)$ replaced by $\mathrm{Var}(s_j)$; the reduced-form variance $\sigma_{u_D}^2$ then absorbs the advisor and group-specific components.

Section 2 holds. In particular, for each proposal j, the latent state satisfies $x_j \sim N(0,1)$, dispersed shareholders observe

$$\eta_{Dj} = x_j + u_{Dj}, \qquad u_{Dj} \sim N(0, \sigma^2_{uD}),$$

and their private signals have variance $\sigma^2_{\varepsilon D}$. Let k_D denote the dispersed cutoff and define

$$T_j \equiv \Phi^{-1}(\tau_j), \qquad \Lambda_D \equiv 1 + \frac{1}{\sigma^2_{uD}} + \frac{1}{\sigma^2_{\varepsilon D}},$$

so that, from the dispersed voting rule,

$$T_j = \sigma_{\varepsilon D}\left[\frac{\eta_{Dj}}{\sigma^2_{uD}} + \frac{x_j}{\sigma^2_{\varepsilon D}} - k_D\Lambda_D\right]. \tag{B.3}$$

The proxy advisor observes a latent Gaussian index s_j and issues the recommendation

$$S_j = \mathbf{1}\{s_j > \xi\}.$$

We normalize $\mathrm{Var}(s_j) = 1$ and let

$$\rho \equiv \mathrm{Corr}(T_j, s_j)$$

denote the advisor–alignment parameter, which is identified from the joint distribution of (T_j, S_j) as in Lemma 1.

Then, for any proposal with interior $\tau_j \in (0,1)$ and for each $\ell \in \{0,1\}$, the conditional distribution of the state given the dispersed support rate and the recommendation is Gaussian:

$$x_j \mid (\tau_j, S_j = \ell) \sim N\left(\mu_{x|\tau,\ell}(\tau_j),\ \sigma^2_{x|\tau,\ell}(\tau_j)\right),$$

where the conditional means are

$$\mu_{x|\tau,1}(\tau_j) = \mu_{x|T}(t) + \frac{\sigma_{xs|T}}{\sigma_{s|T}}\,\lambda_1\big(\alpha(t)\big), \tag{B.4}$$

$$\mu_{x|\tau,0}(\tau_j) = \mu_{x|T}(t) - \frac{\sigma_{xs|T}}{\sigma_{s|T}}\,\lambda_0\big(\alpha(t)\big), \tag{B.5}$$

and the conditional variances are

$$\sigma^2_{x|\tau,1}(\tau_j) = \sigma^2_{x|T} - \frac{\sigma^2_{xs|T}}{\sigma^2_{s|T}}\,\delta_1\big(\alpha(t)\big), \tag{B.6}$$

$$\sigma^2_{x|\tau,0}(\tau_j) = \sigma^2_{x|T} - \frac{\sigma^2_{xs|T}}{\sigma^2_{s|T}}\,\delta_0\big(\alpha(t)\big), \tag{B.7}$$

with $t = \Phi^{-1}(\tau_j)$*, and where*

$$\begin{aligned}
\mu_T &\equiv \mathrm{E}[T_j] = -\,\sigma_{\varepsilon D} k_D \Lambda_D,\\
\sigma_{xT} &\equiv \mathrm{Cov}(x_j, T_j) = \sigma_{\varepsilon D}\left(\frac{1}{\sigma^2_{uD}} + \frac{1}{\sigma^2_{\varepsilon D}}\right),\\
\sigma^2_T &\equiv \mathrm{Var}(T_j) = \sigma^2_{\varepsilon D}\left[\left(\frac{1}{\sigma^2_{uD}} + \frac{1}{\sigma^2_{\varepsilon D}}\right)^2 + \frac{1}{\sigma^2_{uD}}\right].
\end{aligned}$$

The conditional mean and variance of x_j *given* $T_j = t$ *are*

$$\mu_{x|T}(t) = \mathrm{E}[x_j \mid T_j = t] = \frac{\sigma_{xT}}{\sigma^2_T}\,(t - \mu_T), \qquad \sigma^2_{x|T} = \mathrm{Var}(x_j \mid T_j) = 1 - \frac{\sigma^2_{xT}}{\sigma^2_T}.$$

Let $\sigma_{sT} \equiv \mathrm{Cov}(s_j, T_j) = \rho\,\sigma_T$*, so that*

$$\mu_{s|T}(t) = \mathrm{E}[s_j \mid T_j = t] = \frac{\sigma_{sT}}{\sigma^2_T}(t - \mu_T) = \frac{\rho}{\sigma_T}(t - \mu_T),$$

and

$$\sigma^2_{s|T} = \mathrm{Var}(s_j \mid T_j) = 1 - \frac{\sigma^2_{sT}}{\sigma^2_T} = 1 - \rho^2, \qquad \sigma_{s|T} \equiv \sqrt{1-\rho^2}.$$

Under the structural representation $s_j = (x_j + u_{Ij})/\sqrt{1+\sigma^2_I}$ *with* u_{Ij} *independent of* (x_j, u_{Dj})*, we have* $\mathrm{Cov}(T_j, s_j) = \mathrm{Cov}(x_j, T_j)/\sqrt{1+\sigma^2_I}$ *and* $\mathrm{Cov}(x_j, s_j) = 1/\sqrt{1+\sigma^2_I}$*, which implies*

$$\sigma_{xs} \equiv \mathrm{Cov}(x_j, s_j) = \frac{\mathrm{Cov}(T_j, s_j)}{\mathrm{Cov}(x_j, T_j)} = \frac{\rho\,\sigma_T}{\sigma_{xT}}.$$

Hence the conditional covariance between x_j *and* s_j *given* T_j *is*

$$\sigma_{xs|T} \equiv \mathrm{Cov}(x_j, s_j \mid T_j) = \sigma_{xs} - \frac{\sigma_{xT}\,\sigma_{sT}}{\sigma^2_T}$$

$$= \frac{\rho\,\sigma_T}{\sigma_{xT}} - \frac{\sigma_{xT}\,\rho\,\sigma_T}{\sigma_T^2} = \rho\,\sigma_T\,\frac{\sigma_T^2 - \sigma_{xT}^2}{\sigma_{xT}\sigma_T^2}.$$

The truncation index and inverse Mills ratios are

$$\alpha(t) = \frac{\xi - \mu_{s|T}(t)}{\sigma_{s|T}} = \frac{\xi - \frac{\rho}{\sigma_T}(t-\mu_T)}{\sqrt{1-\rho^2}},$$

$$\lambda_1(\alpha) = \frac{\phi(\alpha)}{1-\Phi(\alpha)}, \qquad \lambda_0(\alpha) = \frac{\phi(\alpha)}{\Phi(\alpha)},$$

$$\delta_1(\alpha) = \lambda_1(\alpha)\big(\lambda_1(\alpha) - \alpha\big), \qquad \delta_0(\alpha) = \lambda_0(\alpha)\big(\lambda_0(\alpha) + \alpha\big),$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the standard normal PDF and CDF, respectively. All terms in (B.4)–(B.7) *are thus explicit functions of the identified dispersed-side parameters* $(\sigma_{uD}^2, \sigma_{\varepsilon D}^2, k_D)$*, the advisor-alignment parameter ρ, and the threshold ξ.*

Proof. The linear representation (B.3) implies

$$T_j = a_x x_j + a_\eta \eta_{Dj} + c_D, \qquad a_x = \frac{1}{\sigma_{\varepsilon D}}, \quad a_\eta = \frac{\sigma_{\varepsilon D}}{\sigma_{uD}^2}, \quad c_D = -\,\sigma_{\varepsilon D} k_D \Lambda_D.$$

Since $x_j \sim N(0,1)$ and $\eta_{Dj} = x_j + u_{Dj}$ with $u_{Dj} \sim N(0, \sigma_{uD}^2)$ independent of x_j, straightforward calculations yield

$$\mu_T = \mathrm{E}[T_j] = c_D, \qquad \sigma_{xT} = \mathrm{Cov}(x_j, T_j) = a_x + a_\eta,$$

and

$$\sigma_T^2 = \mathrm{Var}(T_j) = a_x^2\,\mathrm{Var}(x_j) + a_\eta^2\,\mathrm{Var}(\eta_{Dj}) + 2a_x a_\eta\,\mathrm{Cov}(x_j, \eta_{Dj}) = \sigma_{\varepsilon D}^2\left[\left(\frac{1}{\sigma_{uD}^2} + \frac{1}{\sigma_{\varepsilon D}^2}\right)^2 + \frac{1}{\sigma_{uD}^2}\right].$$

Thus

$$\mu_{x|T}(t) = \mathrm{E}[x_j \mid T_j = t] = \frac{\sigma_{xT}}{\sigma_T^2}(t-\mu_T), \qquad \sigma_{x|T}^2 = 1 - \frac{\sigma_{xT}^2}{\sigma_T^2}$$

follow from standard Gaussian conditioning.

For the advisor, start from the structural latent index

$$\tilde{s}_j = x_j + u_{Ij}, \qquad u_{Ij} \sim N(0, \sigma_I^2),$$

independent of (x_j, u_{Dj}), and normalize $s_j = \tilde{s}_j / \sqrt{1+\sigma_I^2}$ so that $\mathrm{Var}(s_j) = 1$. Then

$$\mathrm{Cov}(x_j, \tilde{s}_j) = 1, \qquad \mathrm{Cov}(T_j, \tilde{s}_j) = \mathrm{Cov}(T_j, x_j),$$

because u_{Ij} is independent of (x_j, u_{Dj}) and T_j is linear in (x_j, u_{Dj}). Hence

$$\mathrm{Cov}(x_j, s_j) = \frac{1}{\sqrt{1+\sigma_I^2}}, \qquad \mathrm{Cov}(T_j, s_j) = \frac{\sigma_{xT}}{\sqrt{1+\sigma_I^2}}.$$

Letting $\rho = \mathrm{Corr}(T_j, s_j)$ and normalizing $\mathrm{Var}(s_j) = 1$, we have $\mathrm{Cov}(T_j, s_j) = \rho\, \sigma_T$, so

$$\frac{\sigma_{xT}}{\sqrt{1+\sigma_I^2}} = \mathrm{Cov}(T_j, s_j) = \rho\, \sigma_T \quad \Longrightarrow \quad \sqrt{1+\sigma_I^2} = \frac{\sigma_{xT}}{\rho\, \sigma_T}.$$

Substituting into $\mathrm{Cov}(x_j, s_j) = 1/\sqrt{1+\sigma_I^2}$ gives

$$\sigma_{xs} \equiv \mathrm{Cov}(x_j, s_j) = \frac{\rho\, \sigma_T}{\sigma_{xT}}.$$

Thus the joint vector (x_j, s_j, T_j) is trivariate normal with mean $(0, 0, \mu_T)'$ and covariance determined by $(\sigma_{xT}, \sigma_T^2, \rho)$ and the normalization $\mathrm{Var}(s_j) = 1$.

By the standard formula for conditioning in the multivariate normal, the conditional distribution of (x_j, s_j) given $T_j = t$ is bivariate normal with mean

$$\begin{pmatrix} \mu_{x|T}(t) \\ \mu_{s|T}(t) \end{pmatrix} = \begin{pmatrix} \sigma_{xT} \\ \sigma_{sT} \end{pmatrix} \frac{1}{\sigma_T^2}(t - \mu_T) = \begin{pmatrix} \frac{\sigma_{xT}}{\sigma_T^2}(t - \mu_T) \\ \frac{\rho}{\sigma_T}(t - \mu_T) \end{pmatrix},$$

and covariance matrix

$$\Sigma_{(x,s)|T} = \begin{pmatrix} 1 & \sigma_{xs} \\ \sigma_{xs} & 1 \end{pmatrix} - \begin{pmatrix} \sigma_{xT} \\ \sigma_{sT} \end{pmatrix} \frac{1}{\sigma_T^2} \begin{pmatrix} \sigma_{xT} & \sigma_{sT} \end{pmatrix}.$$

From this,

$$\sigma^2_{x|T} = 1 - \frac{\sigma^2_{xT}}{\sigma^2_T}, \qquad \sigma^2_{s|T} = 1 - \frac{\sigma^2_{sT}}{\sigma^2_T} = 1 - \rho^2,$$

and

$$\sigma_{xs|T} = \mathrm{Cov}(x_j, s_j \mid T_j) = \sigma_{xs} - \frac{\sigma_{xT}\sigma_{sT}}{\sigma^2_T} = \frac{\rho\,\sigma_T}{\sigma_{xT}} - \frac{\sigma_{xT}\,\rho\,\sigma_T}{\sigma^2_T} = \rho\,\sigma_T\,\frac{\sigma^2_T - \sigma^2_{xT}}{\sigma_{xT}\sigma^2_T}.$$

Finally, conditioning on (τ_j, S_j) is equivalent to conditioning on $(T_j = t, S_j = \ell)$ with $t = \Phi^{-1}(\tau_j)$ and truncating on the s_j-dimension at $s_j > \xi$ (if $\ell = 1$) or $s_j \le \xi$ (if $\ell = 0$). Since $(x_j, s_j) \mid T_j = t$ is bivariate normal, the truncated normal formulas (see, e.g., Tallis, 1961) imply that

$$\mathrm{E}[x_j \mid T_j = t, S_j = 1] = \mu_{x|T}(t) + \frac{\sigma_{xs|T}}{\sigma_{s|T}}\,\lambda_1\big(\alpha(t)\big),$$
$$\mathrm{Var}(x_j \mid T_j = t, S_j = 1) = \sigma^2_{x|T} - \frac{\sigma^2_{xs|T}}{\sigma^2_{s|T}}\,\delta_1\big(\alpha(t)\big),$$

and

$$\mathrm{E}[x_j \mid T_j = t, S_j = 0] = \mu_{x|T}(t) - \frac{\sigma_{xs|T}}{\sigma_{s|T}}\,\lambda_0\big(\alpha(t)\big),$$
$$\mathrm{Var}(x_j \mid T_j = t, S_j = 0) = \sigma^2_{x|T} - \frac{\sigma^2_{xs|T}}{\sigma^2_{s|T}}\,\delta_0\big(\alpha(t)\big),$$

with

$$\alpha(t) = \frac{\xi - \mu_{s|T}(t)}{\sigma_{s|T}}, \quad \lambda_1(\alpha) = \frac{\phi(\alpha)}{1 - \Phi(\alpha)}, \quad \lambda_0(\alpha) = \frac{\phi(\alpha)}{\Phi(\alpha)},$$

and

$$\delta_1(\alpha) = \lambda_1(\alpha)\big(\lambda_1(\alpha) - \alpha\big), \qquad \delta_0(\alpha) = \lambda_0(\alpha)\big(\lambda_0(\alpha) + \alpha\big).$$

Replacing t with $\Phi^{-1}(\tau_j)$ yields (B.4)–(B.7) and completes the proof. ■

Lemma 4 (Identification of blockholder parameters)**.** *Suppose the primitives of the model in Section 2 hold and that the dispersed side of the information structure has already been identified as in Lemma 2. In particular:*

- *the state satisfies* $x_j \sim N(0,1)$*;*
- *dispersed shareholders observe a reduced-form public signal*

$$\eta_{Dj} = x_j + u_{Dj}, \qquad u_{Dj} \sim N(0, \sigma^2_{u_D}),$$

  and private signals $z_{ij} = x_j + \varepsilon_{ij}$ *with* $\varepsilon_{ij} \sim N(0, \sigma^2_{\varepsilon_D})$*;*
- *a proxy advisor forms a latent Gaussian assessment* s_j *of* x_j *and issues the binary recommendation*

$$S_j = \mathbf{1}\{s_j > \xi\};$$

- *from the joint distribution of* (τ_j, S_j) *the econometrician has already identified* $(\xi, \sigma^2_{u_D}, \sigma^2_{\varepsilon_D}, k_D)$*, and hence knows the posterior law of* x_j *conditional on* (τ_j, S_j)*:*

$$x_j \mid (\tau_j, S_j) \sim N\big(\mu_{x|\tau,S}(\tau_j, S_j), \sigma^2_{x|\tau,S}(\tau_j, S_j)\big),$$

  as implied by the Gaussian structure and the mapping between (x_j, η_{Dj}) *and* (τ_j, S_j) *characterized in Lemma 2.*

On the blockholder side, suppose that for each blockholder $b = 1, \dots, N_B$*:*

- *the blockholder-specific public signal is*

$$\eta_{Bj} = x_j + u_{Bj}, \qquad u_{Bj} \sim N(0, \sigma^2_{uB}),$$

  independent of (x_j, u_{Dj})*;*
- *the private signal is*

$$z_{bj} = x_j + \varepsilon_{bj}, \qquad \varepsilon_{bj} \sim N(0, \sigma^2_{\varepsilon_b}),$$

  independent across b *and of* (x_j, u_{Dj}, u_{Bj})*;*
- *blockholder* b *uses the cutoff strategy induced by the voting rule (13):*

$$V_{bj} = 1 \quad \iff \quad m_{bj} \equiv \mathbb{E}[x_j \mid \eta_{Bj}, z_{bj}] \geq k_b,$$

with type $(\sigma^2_{uB}, \sigma^2_{\varepsilon_b}, k_b)$*.*

Let $s_{Bj} = \sum_{b=1}^{N_B} \psi_b V_{bj}$ *denote aggregate blockholder support as in* (??)*. Assume the econometrician observes, for each proposal* j*, the triple*

$$\big(\tau_j, S_j, s_{Bj}\big),$$

and, in addition, each individual blockholder vote V_{bj} *and ownership weight* ψ_b*.*

Then, under the Gaussian structure and the monotone index form of the voting rule (13)*, the joint cross-sectional distribution of*

$$\Big\{\big(\tau_j, S_j, s_{Bj}, \{V_{bj}\}_{b=1}^{N_B}\big)\Big\}_j$$

identifies:

(i) the blockholder public-signal variance σ^2_{uB}*; and*

(ii) for each blockholder b*, the private-signal variance* $\sigma^2_{\varepsilon_b}$ *and cutoff* k_b*.*

Given these objects and the identified information structure on the dispersed side, each blockholder's preference parameter δ_b *is then identified from the best-response condition*

$$\mathbb{E}\left[x_j \,\middle|\, z_{bj} = k_b,\ \mathrm{piv}_{bj}\right] = -\delta_b$$

in (15)*.*

Sketch of proof. Step 1: posterior of x_j *and* η_{Bj} *given* (τ_j, S_j)*.* By Lemma 2, the parameters $(\xi, \sigma^2_{u_D}, \sigma^2_{\varepsilon_D}, k_D)$ are identified from the joint distribution of (τ_j, S_j), and the Gaussian structure implies a closed-form posterior

$$x_j \mid (\tau_j, S_j) \sim N\big(\mu_{x|\tau,S}(\tau_j, S_j), \sigma^2_{x|\tau,S}(\tau_j, S_j)\big).$$

Given $\eta_{Bj} = x_j + u_{Bj}$ with $u_{Bj} \sim N(0, \sigma^2_{uB})$ independent of x_j, we obtain

$$\eta_{Bj} \mid (\tau_j, S_j) \sim N\Big(\mu_{x|\tau,S}(\tau_j, S_j),\ \sigma^2_{x|\tau,S}(\tau_j, S_j) + \sigma^2_{uB}\Big), \tag{B.8}$$

which is the blockholder analogue of the conditional law of the dispersed public signal, with σ_{uB}^2 entering only through the variance term.

Step 2: identification of σ_{uB}^2 from $s_{Bj} \mid (\tau_j, S_j)$. Using (13), blockholder b's voting probability conditional on (x_j, η_{Bj}) is

$$p_b(x_j, \eta_{Bj}) = \Pr(V_{bj} = 1 \mid x_j, \eta_{Bj}) = \Phi\left(\sigma_{\varepsilon_b}\left[\frac{\eta_{Bj}}{\sigma_{uB}^2} + \frac{x_j}{\sigma_{\varepsilon_b}^2} - k_b\Lambda_b\right]\right),$$

with $\Lambda_b = 1 + 1/\sigma_{uB}^2 + 1/\sigma_{\varepsilon_b}^2$. Aggregate blockholder support is

$$s_{Bj} = \sum_{b=1}^{N_B} \psi_b V_{bj},$$

so conditional on (x_j, η_{Bj}) it has mean $\sum_b \psi_b p_b(x_j, \eta_{Bj})$ and variance depending on $p_b(x_j, \eta_{Bj})$.

Given (τ_j, S_j), the law of (x_j, η_{Bj}) is fully determined except for σ_{uB}^2, via (B.8). Hence the conditional distribution

$$s_{Bj} \mid (\tau_j, S_j)$$

depends on σ_{uB}^2 only through the variance term $\sigma_{x|\tau,S}^2(\tau_j, S_j) + \sigma_{uB}^2$ in (B.8). Variation in (τ_j, S_j) across proposals generates variation in both $\mu_{x|\tau,S}$ and $\sigma_{x|\tau,S}^2$, which in turn shifts the mean and dispersion of $s_{Bj} \mid (\tau_j, S_j)$ in a way that is strictly monotone in σ_{uB}^2 under the Gaussian index structure. Therefore the mapping

$$\sigma_{uB}^2 \longmapsto F_{s_B|\tau,S}(\cdot \mid t, \ell; \sigma_{uB}^2, \{\sigma_{\varepsilon_b}^2, k_b\}_b)$$

is one-to-one for all (t, ℓ) in the support of (τ_j, S_j), and the joint distribution of s_{Bj} given (τ_j, S_j) identifies σ_{uB}^2.

Step 3: identification of $(\sigma_{\varepsilon_b}^2, k_b)$ from $V_{bj} \mid (\tau_j, S_j)$. Fix blockholder b and treat (τ_j, S_j) as observable covariates. Conditional on (τ_j, S_j), we know:

- the distribution of x_j;
- the distribution of η_{Bj} via (B.8), with σ_{uB}^2 now identified from Step 2;
- the law of $z_{bj} = x_j + \varepsilon_{bj}$ with variance $\sigma_{\varepsilon_b}^2$.

By linear-Gaussian updating, the posterior mean $m_{bj} = \mathbb{E}[x_j \mid \eta_{Bj}, z_{bj}]$ is a linear index in (x_j, η_{Bj}), and conditional on (τ_j, S_j) it is normally distributed with mean and variance that are known functions of $(\sigma^2_{\varepsilon_b}, k_b)$ and the known quantities $\mu_{x|\tau,S}(\tau_j, S_j)$ and $\sigma^2_{x|\tau,S}(\tau_j, S_j)$. Thus

$$\Pr\left(V_{bj} = 1 \mid \tau_j, S_j\right) = \Pr\left(m_{bj} \geq k_b \mid \tau_j, S_j\right) = \Phi\left(a_b(\tau_j, S_j; \sigma^2_{\varepsilon_b}, k_b)\right),$$

for some smooth function $a_b(\cdot)$ that is strictly monotone in the underlying index. Observing the conditional choice probabilities (equivalently, the distribution of V_{bj}) over a rich support of (τ_j, S_j) therefore yields a standard probit-type identification problem in which the slope and intercept of the index are pinned down by cross-sectional variation in $\mu_{x|\tau,S}(\tau_j, S_j)$ and $\sigma^2_{x|\tau,S}(\tau_j, S_j)$. Under the normalization $x_j \sim N(0, 1)$, this uniquely identifies $(\sigma^2_{\varepsilon_b}, k_b)$.

Step 4: identification of δ_b. Given $(\sigma^2_{uB}, \sigma^2_{\varepsilon_b}, k_b)$ and the already identified dispersed-side parameters, the equilibrium probability of being pivotal piv_{bj} as a function of the state x_j is known, and so is the posterior density $f(x_j \mid z_{bj} = k_b, \mathrm{piv}_{bj})$ in (16). The best-response condition (15),

$$\mathbb{E}\left[x_j \,\middle|\, z_{bj} = k_b,\ \mathrm{piv}_{bj}\right] = -\delta_b,$$

therefore uniquely determines δ_b.

These steps yield identification of σ^2_{uB} and $(\sigma^2_{\varepsilon_b}, k_b, \delta_b)$ for each blockholder b. ■

Lemma 5 (Identification of preference parameters)**.** *Suppose the primitives of the information environment and equilibrium cutoffs are identified as in Lemmas 1 to 4. In particular, assume that the econometrician knows:*

- *the dispersed information parameters $(\sigma^2_{uD}, \sigma^2_{\varepsilon D})$ and cutoff k_D;*
- *for each blockholder b, the public and private information parameters $(\sigma^2_{uB}, \sigma^2_{\varepsilon_b})$ and cutoff k_b;*
- *the proxy–advisor alignment parameter ρ and threshold ξ;*
- *the voting weights and pass threshold $(\{\psi_b\}_b, \Psi_D, \lambda^*)$ that determine pivotality.*

Then the dispersed preference parameter δ_D and each blockholder preference parameter δ_b are *identified from the equilibrium best-response (indifference) conditions at the cutoffs:*

$$\mathrm{E}\left[x_j \mid m_{Dj} = k_D,\ \mathrm{piv}_{Dj}\right] = -\,\delta_D, \tag{B.9}$$

$$\mathrm{E}\left[x_j \mid m_{bj} = k_b,\ \mathrm{piv}_{bj}\right] = -\,\delta_b, \qquad b = 1, \dots, N_B, \tag{B.10}$$

where m_{Dj} and m_{bj} denote the dispersed and blockholder posterior means defined in Section 2, and $\mathrm{piv}_{Dj}, \mathrm{piv}_{bj}$ are the corresponding pivotality events.

Proof. We give the argument for δ_D; the blockholder case is analogous.

Step 1: Posterior mean distribution at the cutoff. Under the Gaussian information structure, the dispersed posterior mean $m_{Dj} = \mathrm{E}[x_j \mid \eta_{Dj}, z_{Dj}]$ is a linear function of $(x_j, u_{Dj}, \varepsilon_{Dj})$. In particular, conditional on $x_j = x$ it is normal:

$$m_{Dj} \mid x_j = x \sim N\left(\mu_{m_D}(x), \sigma^2_{m_D}\right),$$

where the mean $\mu_{m_D}(x)$ and variance $\sigma^2_{m_D}$ are explicit functions of $(\sigma^2_{uD}, \sigma^2_{\varepsilon D})$:

$$\mu_{m_D}(x) = \frac{\frac{1}{\sigma^2_{uD}} + \frac{1}{\sigma^2_{\varepsilon D}}}{\Lambda_D}\, x, \qquad \sigma^2_{m_D} = \frac{\Lambda_D - 1}{\Lambda_D^2}, \qquad \Lambda_D = 1 + \frac{1}{\sigma^2_{uD}} + \frac{1}{\sigma^2_{\varepsilon D}}.$$

Thus the conditional density of m_{Dj} at the cutoff k_D is known:

$$f_{m_D|x}(k_D \mid x) = \frac{1}{\sigma_{m_D}}\, \phi\left(\frac{k_D - \mu_{m_D}(x)}{\sigma_{m_D}}\right),$$

where ϕ is the standard normal PDF and all parameters are identified from the first-step information estimates.

Step 2: Pivotality as a function of the state. Given the identified information environment and cutoffs $(k_D, \{k_b\}_b)$, the voting strategies of all other shareholders are known. For any state realization x, this pins down the distribution of the total vote from all other dispersed shareholders and blockholders, and therefore the probability that a representative dispersed shareholder is pivotal at the cutoff. Let

$$\pi_D(x) \equiv \Pr\left(\mathrm{piv}_{Dj} = 1 \mid x_j = x,\ m_{Dj} = k_D\right)$$

denote this pivotality kernel. It is a known function of the identified primitives and can be computed (analytically or numerically) from the equilibrium voting game.

Step 3: Bayes rule at the cutoff. With the prior $x_j \sim N(0,1)$ (density $\phi(x)$), Bayes rule implies that the density of x_j conditional on $(m_{Dj} = k_D, \mathrm{piv}_{Dj})$ is proportional to

$$\phi(x)\, f_{m_D|x}(k_D \mid x)\, \pi_D(x).$$

Hence

$$\mathrm{E}\left[x_j \mid m_{Dj} = k_D, \mathrm{piv}_{Dj}\right] = \frac{\displaystyle\int_{-\infty}^{\infty} x\ \phi(x)\, f_{m_D|x}(k_D \mid x)\, \pi_D(x)\, dx}{\displaystyle\int_{-\infty}^{\infty} \phi(x)\, f_{m_D|x}(k_D \mid x)\, \pi_D(x)\, dx}.$$

Every object under the integrals is an explicit function of the identified parameters $(\sigma^2_{uD}, \sigma^2_{\varepsilon D}, k_D)$ and the equilibrium pivotality kernel $\pi_D(x)$, itself determined by $(\sigma^2_{uB}, \{\sigma^2_{\varepsilon_b}, k_b\}_b, \rho, \xi, \{\psi_b\}_b, \Psi_D, \lambda^*)$.

Combining this with the best-response condition (B.9) gives the identification formula

$$\delta_D = -\frac{\displaystyle\int_{-\infty}^{\infty} x\ \phi(x)\, f_{m_D|x}(k_D \mid x)\, \pi_D(x)\, dx}{\displaystyle\int_{-\infty}^{\infty} \phi(x)\, f_{m_D|x}(k_D \mid x)\, \pi_D(x)\, dx},$$

which is a known scalar function of the previously identified primitives. Thus δ_D is identified.

Step 4: Blockholder preferences. For each blockholder b, the same logic applies. Given $(\sigma^2_{uB}, \sigma^2_{\varepsilon_b}, k_b)$, the posterior mean m_{bj} satisfies

$$m_{bj} \mid x_j = x \sim N\left(\mu_{m_b}(x), \sigma^2_{m_b}\right),$$

with coefficients determined by $(\sigma^2_{uB}, \sigma^2_{\varepsilon_b})$. Let $f_{m_b|x}(k_b \mid x)$ denote the corresponding density at the cutoff. Define

$$\pi_b(x) \equiv \Pr\left(\mathrm{piv}_{bj} = 1 \mid x_j = x,\ m_{bj} = k_b\right),$$

the equilibrium pivotality probability for blockholder b, which is known from the identified information environment, cutoffs, and voting weights. Bayes rule then yields

$$\mathrm{E}\left[x_j \mid m_{bj} = k_b, \mathrm{piv}_{bj}\right] = \frac{\displaystyle\int x\ \phi(x)\, f_{m_b|x}(k_b \mid x)\, \pi_b(x)\, dx}{\displaystyle\int \phi(x)\, f_{m_b|x}(k_b \mid x)\, \pi_b(x)\, dx},$$

and the indifference condition (B.10) implies

$$\delta_b = -\frac{\displaystyle\int x\ \phi(x)\, f_{m_b|x}(k_b \mid x)\, \pi_b(x)\, dx}{\displaystyle\int \phi(x)\, f_{m_b|x}(k_b \mid x)\, \pi_b(x)\, dx}.$$

Therefore each δ_b is uniquely determined by the identified primitives.

Thus, given the identified information and cutoff parameters and the proxy-advisor alignment (ρ, ξ), the preference parameters $(\delta_D, \{\delta_b\}_b)$ are identified. ∎

B.2. Estimation Strategy

This section formalizes the estimation routine.

- **Analytic moments.** We derive closed-form expressions for all model-implied moments used in estimation (including ISS–dispersed moments and blockholder voting moments), so the moment mapping $g(\theta)$ is computed analytically and is fully consistent with the model's equilibrium voting rules.

- **Single GMM objective** Although it is helpful to describe the parameters as belonging to distinct components of the model (e.g., ISS/dispersed information, blockholder behavior, and preference parameters), we estimate the full parameter vector jointly in a single GMM objective. All moments enter one stacked moment vector $\hat{g}(\theta)$,

$$\hat{\theta} = \arg\min_{\theta}\ \hat{g}(\theta)^{\top} \hat{W}\, \hat{g}(\theta),$$

  is our GMM objective.

- **Two-step GMM.** We implement a standard two-step routine: a first step using an initial weighting matrix (e.g., identity) to obtain $\hat{\theta}^{(1)}$, followed by a second step using the efficient weighting matrix $\hat{W} = \widehat{\Omega}(\hat{\theta}^{(1)})^{-1}$, where $\widehat{\Omega}$ is the estimated covariance matrix of the sample moments.

- **Blockholder probit moments as GMM restrictions.** Blockholder probit-style moments are implemented as equivalent GMM moment restrictions: we include the orthogonality conditions implied by the probit specification.

- **Inference.** Standard errors follow conventional GMM asymptotics, using the estimated Jacobian of moments and the estimated moment covariance matrix (sandwich form) evaluated at $\hat{\theta}$.