Errors in Shareholder Voting

Patrick Blonien

Jones Graduate School of Business
Rice University, Houston, TX 77005, U.S.A.

Alan Crane

Jones Graduate School of Business
Rice University, Houston, TX 77005, U.S.A.

Kevin Crotty

Jones Graduate School of Business
Rice University, Houston, TX 77005, U.S.A.

David De Angelis

C.T. Bauer College of Business
University of Houston, Houston, TX 77204, U.S.A.

Abstract

Voting errors occur when bad proposals pass (false positives) and good proposals fail (false negatives). We develop a structural empirical framework to study voting errors for shareholder proposals. Over one-quarter of vote outcomes are mistakes, with 6% (21%) as false positives (negatives). Prices respond negatively to false positives. Sophisticated owners are generally associated with fewer false positives and more false negatives, but high passive ownership is associated with worse overall outcomes and activists with better. Our evidence contributes to policy debates on proxy access and advisors and investor communication by showing voting errors are common and passing bad proposals is costly.

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Email addresses: `Patrick.J.Blonien@rice.edu` (Patrick Blonien), `Alan.D.Crane@rice.edu` (Alan Crane), `Kevin.P.Crotty@rice.edu` (Kevin Crotty), `deangelis@bauer.uh.edu` (David De Angelis)

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1. Introduction

Shareholder voting is a fundamental aspect of corporate governance (Yermack, 2010). When shareholders exercise their right to vote, they can influence corporate policies and improve governance. On the other hand, shareholder "democracy" is argued to be a largely ineffectual form of governance because of dispersed ownership (Denes et al., 2017) or worse, value-destroying due to misinformed shareholders influencing management to adopt sub-optimal policies (Karpoff and Rice, 1989; Aghion and Tirole, 1997; Burkart et al., 1997). Not surprisingly, shareholder voting has also attracted a substantial amount of attention among policymakers, who have proposed regulations to different areas of the voting process, such as shareholder proxy access, voter communication, and proxy advisors' services. There have been debates accompanying each regulation about whether they would ultimately improve or harm governance.[1] At the core of these academic and policy debates lies the question: are shareholders informed?

This is a challenging question to answer since whether or not shareholders' votes are informed is inherently unobservable. To address this, we propose a simple structural empirical framework that characterizes the voting process. First, we assume that proposal quality is either "good" or "bad" (in the sense that they will either create or destroy equity value if passed), and that quality is either obvious or contentious. Second, shareholders are either informed or uninformed about the quality of a proposal, and uninformed shareholders vote by flipping a (weighted) coin. Informed votes are "correct"–voting in favor of good proposals and against bad ones. Thus, our framework implicitly assumes that good proposals, on average, receive more voting support than bad proposals due to informed voting.[2] This simple

[1] For example, see the debate around proxy access (i.e., whether shareholders should be allowed to nominate a candidate for election to the board of directors) and the conflicting evidence about its potential impact (Becker et al., 2012; Cohn et al., 2016; Larcker et al., 2011; Akyol et al., 2012; Stratmann and Verret, 2015).

[2] Under our framework, voters aim to maximize equity value (since they own that stock) and vote accordingly. However, we acknowledge that voters may have other objectives, such as societal considerations, that may not necessarily coincide with equity value maximization (Matsusaka and Shu, 2021). We discuss our assumptions in Section 2.1.

foundation yields an entirely new empirical framework that we show fits the data remarkably well; we cannot reject that the true data came from our model. This framework allows us to characterize the quality of proposals, the fraction of informed votes, and ultimately, the fraction of voting errors. For the first time, this paper quantifies how often shareholders pass bad proposals (false positive) and how often they fail to pass good proposals (false negative).

We address two broad questions using our new framework: (i) In general, what are the voting error rates for shareholder proposals as described above, and (ii) How do predicted costs and benefits of collecting information by shareholders impact these rates? To answer this second question, we run three sets of tests. First, we test differences across ownership structures, as prior work predicts variation in the percent of informed votes as a function of these characteristics (e.g., Shleifer and Vishny, 1986; Gordon and Pound, 1993; Burkart et al., 1997). Second, the ability of shareholders to access proxies and the presence of proxy advisors may impact voting outcomes (Pound, 1991; Alexander et al., 2010). We test how errors vary across intermediaries' recommendations and periods with differential costs associated with accessing proxy information. Third, we examine situations where prior research predicts returns to activism to be higher, such as in small firms (Cremers and Nair, 2005) and when the manager is more likely to be entrenched (Bebchuk et al., 2009).

Our main estimates indicate that 6% of shareholder proposals pass when they are bad (false positive), and 21% of shareholder proposals fail even though they are good (false negative). To put these error rates into perspective, we compare them to those estimated from management proposals.[3] Only 0.8% of all management proposals pass despite being bad and virtually no good management proposals fail (false negative errors are only 0.5% of management proposals). Overall, the fraction of "mistakes" made for shareholder proposals is much larger than for management proposals (26% vs. 1%, respectively). Interestingly, part of the policy debate around proxy access for shareholders centers around whether shareholders

[3]The focus of our analysis is on shareholder proposals. From a policy standpoint, these types of proposals inform the debate about owners' ability to impact firm decisions directly.

are sufficiently informed to discriminate appropriately against bad shareholder proposals. Our estimates support the view that shareholders struggle to correctly identify the quality of shareholder proposals, but not those sponsored by management.

The stock market responds to voting errors. However, the market reactions differ depending on the type of shareholder error. The stock market responds negatively to both errors, but only the response to the probability of a false-positive result is statistically significant. These results are consistent with the first-order concerns behind the proxy-access regulation and the possibility of passing frivolous shareholder proposals that harm firm value. The estimated economic impact of a false positive is economically meaningful. For example, our results indicate that a one standard deviation increase in the probability of a false positive corresponds to a decline of about 45 to 51 basis points in the stock price over the three days around the voting results' publication.

Next, we study how these voting error rates in shareholder proposals change when prior research predicts shareholders' costs and benefits to collect information to differ. Our first set of tests focuses on ownership characteristics. Theoretical arguments predict that ownership structure should influence the percent of votes that are informed. For example, in firms with concentrated ownership, investors with large equity stakes may have more incentives to collect information, predicting that voting would be more informed. Yet, at the same time, other shareholders may free-ride on the perception that large investors are already informed and thus forgo collecting information, which may induce voting errors (Pound, 1991). Prior literature has also argued that institutional investors are likely to be more informed in proxy voting (Iliev and Lowry, 2015; Malenko and Shen, 2016; McCahery et al., 2016; Gantchev and Giannetti, 2020). Examining standard empirical proxies for institutional ownership level and concentration, we find that high institutional ownership levels or concentration are not unconditionally good; high institutional ownership is associated with smaller false positive errors (6% vs. 8% for low ownership levels) but significantly larger false-negative errors (26% vs. 15%). Therefore, the net effect of high ownership by sophisticated investors is not unambiguously good. This evidence is consistent with the ambiguity in the theoretical predictions since the perception of more informed owners may deter small minority shareholders from collecting information.

We also study institutional ownership types. Appel et al. (2016) suggests passive investors improve firm governance via monitoring, while others suggest passive institutions, such as index funds, are less effective monitors (see, e.g., Heath et al., 2020). We estimate large differences in errors as a function of Quasi-Index ownership (defined as in Bushee (1998)). High passive ownership is associated with much worse outcomes in terms of false negatives when compared to low levels of passive ownership (32.5% vs. 16.7%), and no significant difference in false positives, suggesting worse voting outcomes when passive ownership is high. In contrast, we draw the opposite conclusions when hedge fund activists (HFAs) are involved. In the presence of an HFA, defined as in Brav et al. (2008), there is no significant difference in false negatives, but significant improvements in false positives for HFA firms (2%), which is 85% lower than the non-HFA sample (14%). The evidence suggests lower overall errors in the presence of an activist compared to firms with high levels of passive ownership.

Our second set of tests study variation across information technology and intermediaries' recommendations. Prior research has proposed that proxy advisors are a solution to the free-riding problem of information collection (Alexander et al., 2010). However, recent debates have focused on advisors' potential conflicts of interest. Moreover, Malenko and Malenko (2019) shows that incentives to collect information about proposal quality depend on proxy advisors' information precision. Ultimately, their impact on voting outcomes is an open empirical question. We find that error rates depend considerably on the proxy advisors' recommendations. Specifically, when proxy advisor ISS supports the shareholder proposal, the false positive and false negative errors are 2% and 53%, respectively. When ISS is against a proposal, shareholders always get it right. We can also calculate whether ISS gets it right. Fewer than 2% of proposals they recommend voting against turn out to be good. On the other hand, ISS recommendations in favor of an item coincide with good proposals 83% of the time.

Pound (1988) points out that inefficiencies in the proxy process can lead to incorrect voting (generally in management's favor). To study changes in the information technology environment, we estimate the model before and after the 2007 SEC regulation that mandated proxies to be available electronically over the internet (implemented 2008-2009). After that regulation, false-positive errors remained unchanged, but false-negative errors increased dramatically: from 9% of all proposals to 24%. Our results indicate that when voter information became more readily available, the percent of good proposals increased drastically. However, good proposals were less likely to succeed, suggesting that voters were less likely to collect information. These tests are time-series based, and therefore only suggestive (it is possible that other effects, such as the rise in passive ownership, may explain this result). Nonetheless, there is a sharp decline in voters getting it right after 2007.

Finally, our third set of tests examine situations where prior research predicts the return to activism to be higher. We study voting outcomes as a function of firm size, age, and a proxy for a firm's internal governance, the E-index, which aims to capture the extent of managerial entrenchment (Bebchuk et al., 2009). We expect the return to governance via voting, and thus the incentives to collect information, to be greater in small and younger firms and when the manager is more likely to be entrenched. Firms with more entrenched managers see fewer bad proposals pass than low E-index firms (false-positive errors of 5% vs. 9%), but are much more likely to see good proposals fail (31% vs. 11%). Therefore, shareholder proposals are less likely to affect change in these arguably more poorly governed firms. We see very similar patterns across size and age. These results suggest heterogeneous governance impacts to voting as a function of existing governance.

This paper contributes to the corporate governance literature in two ways. First, it proposes a new methodology to study an important issue in the literature: are shareholders informed? Our methodology allows us to estimate the fraction of informed votes directly, and in particular, false positive and false negative error rates in voting, which are at the core of the debate in recent governance-related policy issues. Previous research focuses on ex-ante classifications of informed investors. For example, recent literature argues that certain institutional investors are likely to be informed. Thus, more ownership by such institutions correlates with more informed shareholders. Other recent work defines informed shareholders based as those that deviate from ISS recommendations (Iliev and Lowry, 2015; Gantchev and Giannetti, 2020) or whose votes agree with the direction of announcement returns (Gao and Huang, 2021). Our results complement this work by looking at aggregate voting outcomes and showing that the presence of such informed investors does not necessarily lead to better voting outcomes. We view our structural estimation as a complement to the methods employed in past studies and believe that the collection of results combine to inform academics and policymakers. Similar statistical methods are applied in other studies.[4] Maug and Rydqvist (2009) also develop a structural model to study shareholder voting. However, their focus is on detecting strategic voting, while ours is on estimating informed voting and gauging voting error rates.

Second, our estimates shed light on the role of shareholder voting in corporate governance and reveal a novel interaction with the ownership structure. For example, we identify a tradeoff between errors in voting. Ownership structure characteristics related to fewer false-positive errors (i.e., passing bad proposals) are generally related to more false-negative errors (i.e., failing to pass good proposals) and vice versa.

The rest of the paper continues as follows. In Section 2, we explain our methodology and describe the data. Section 3 analyzes the full sample results. Section 4 contains our three sets of tests relating error rates to ownership, proxy access, and advisor recommendations, and returns to activism. Section 5 concludes.

[4]For example, in the mutual funds literature to infer fund managers' performance (e.g., Barras et al., 2010; Harvey and Liu, 2016), in the market microstructure literature to estimate the probability of informed trading (e.g., Easley et al., 1996, 2002), and in the political science literature to detect fraudulent elections (e.g., Klimek et al., 2012; Mebane Jr et al., 2014).

2. Methodology and Data

2.1. Methodology

We impose structure on the voting data to characterize the voting process and estimate unobservable quantities, such as voting errors. This structure comes from three underlying assumptions we make about proposals and voting behavior. First, we assume that proposal quality is either obvious or contentious. The probability that a proposal's quality is obvious is δ, and the probability that a proposal's quality is contentious is $1-\delta$. Our second assumption is that proposals are either good or bad proposals where good proposals generate shareholder value and bad proposals destroy shareholder value. We allow the probability that a proposal is good to vary across obvious and contentious proposals. A contentious proposal is good with probability α_c and bad with probability $1-\alpha_c$. Similarly, an obvious quality proposal is good with probability α_o and bad with probability $1-\alpha_o$. Finally, we assume informed votes are "correct" – voting in favor of good proposals and against bad proposals. Thus, our framework implicitly assumes that good proposals, on average, receive more voting support than bad proposals due to informed voting.

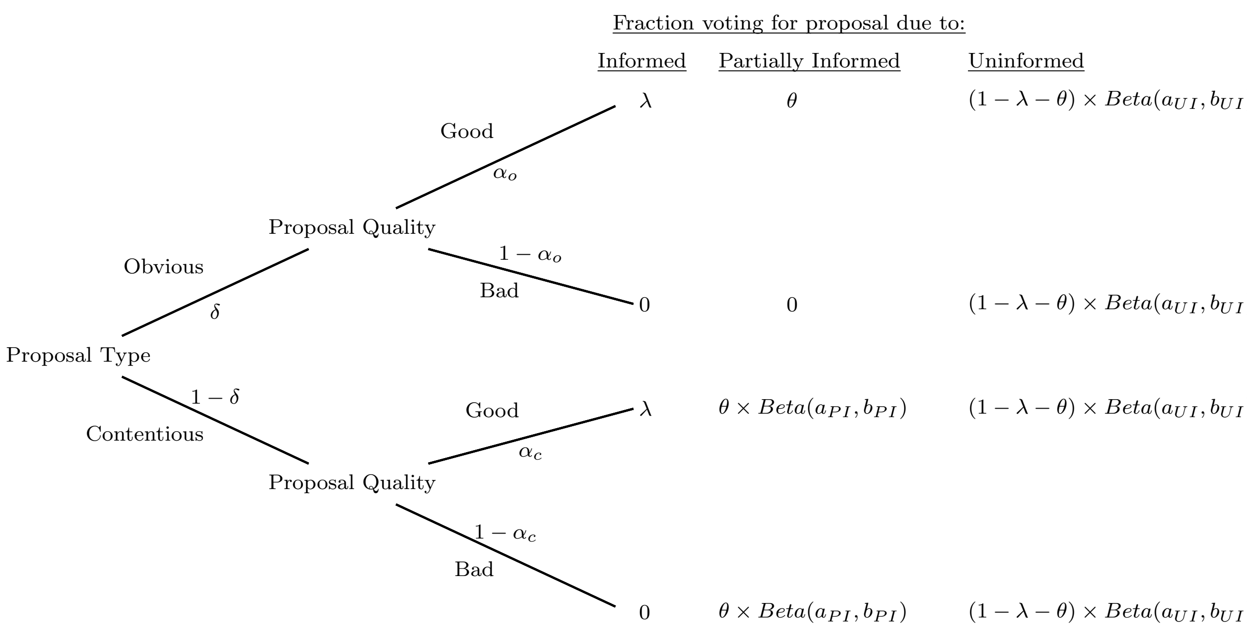
Shareholders are assumed to be either always informed, sometimes informed (hereafter partially-informed investors), or always uninformed. Informed investors always vote "correctly". Uninformed investors vote randomly. These investors flip a weighted coin to decide to vote either in favor of or against the proposals. For a given proposal, each uninformed investor flips the same coin with some probability p_{UI} of voting yes. However, this probability is unknown. We therefore assume the coin's probability is itself random and is drawn from a beta distribution, $p_{UI} \sim \text{Beta}(a_{UI}, b_{UI})$. Thus, the unconditional expected fraction of uninformed investors voting in favor of a proposal will be $a_{UI}/(a_{UI}+b_{UI})$. Partially-informed investors are informed for obvious proposals but uninformed for contentious ones. So they vote in favor of (against) obviously good (bad) proposals and flip their own coin to determine their votes for contentious proposals. As with the fully uninformed investors, we assume this coin's probability is random for a given proposal and beta-distributed: $p_{PI} \sim \text{Beta}(a_{PI}, b_{PI})$.

The fraction of informed investors is denoted by λ, partially informed by θ, and uninformed by $(1 - \lambda - \theta)$.

The beta distribution assumption for uninformed voting is motivated by three reasons. First, there is precedent for using the beta distribution to model uncertainty over the probability parameter p in models of voting (Chamberlain and Rothschild, 1981; Berg, 1990). Second, the beta distribution is the conjugate prior for the probability parameter, p, when the likelihood is a binomial random variable in Bayesian statistics.[5] Third, and more practically, the property that the beta distribution is bounded on the unit interval naturally fits the domain of possible probabilities while being parsimoniously parameterized by two shape parameters. The distribution is flexible, allowing the data to dominate the fit while keeping the model fully parametric for simplicity.

Figure 1: Data Structure

This figure describes the data structure of informed, partially informed, and uninformed voting underlying the mixture distribution of voting. $Beta(a_i, b_i)$ denotes a beta distributed variable with shape parameters a_i and b_i.



[5]This model is equivalent to a fully Bayesian hierarchical model with a beta distribution prior for a binomial likelihood, commonly known as the Beta-Binomial model, where we maximize the marginal likelihood function. An empirical Bayes method can approximate this hierarchical model to estimate the prior distribution parameters from the data, ex-ante unknown to the econometrician, and what is done in this paper is equivalent.

Our structural assumptions are presented graphically in Figure 1. This structure implies that the unconditional voting distribution is a mixture of beta distributions. Let Θ denote the set of parameters $\{\delta, \alpha_o, \alpha_c, \lambda, \theta, a_{PI}, b_{PI}, a_{UI}, b_{UI}\}$.

The data used in our estimation is a sample of vote share outcomes, $\{v_i\}_{i=1}^N$. It is important to note that there is variation across proposals regarding the base used for calculating passage. Some proposals use the fraction v^A = For/(For + Against + Abstentions) while others use v^B = For/(For + Against). The structural framework described above abstracts from abstentions, but a simple re-scaling of v^A allows the framework to apply to proposals using the v^A vote-share base. Let π denote the fraction of voters not abstaining. In our empirical work, we define the vote share v_i as:

$$v_i = \begin{cases} v_i^A/\pi_i & \text{if vote share base is For + Against + Abstentions} \\ v_i^B & \text{if vote share base is For + Against}\,. \end{cases} \tag{1}$$

Thus, the parameters λ and θ are the fractions of non-abstaining shareholders that are informed and partially informed. Empirically, this distinction should be of little concern as the median number of shares that abstain from voting on shareholder proposals is only 1.5%.

The negative log-likelihood function for a sample of voting outcomes $\{v_i\}_{i=1}^N$ is given by:

$$\begin{aligned} -L(\{v_i\}_{i=1}^N; \Theta) = -\sum_{i=1}^{N} log \Big[& \delta\alpha_o \cdot \Pr(v_i; \text{Obvious \& Good, } \Theta) \\ & + \delta(1-\alpha_o) \cdot \Pr(v_i; \text{Obvious \& Bad, } \Theta) \\ & + (1-\delta)\alpha_c \cdot \Pr(v_i; \text{Contentious \& Good, } \Theta) \\ & + (1-\delta)(1-\alpha_c) \cdot \Pr(v_i; \text{Contentious \& Bad, } \Theta) \Big], \end{aligned} \tag{2}$$

where $(\delta, \alpha_o, \alpha_c, \lambda, \theta) \in [0,1]^5$, $\lambda + \theta \in [0,1]$, and $(a_{PI}, b_{PI}, a_{UI}, b_{UI}) \in (0, \infty)^4$. The probabilities of observing a vote v_i conditional on each type of proposal are:

$$\Pr(v_i; \text{Obvious \& Good}, \Theta) = \frac{(v_i - \lambda - \theta)^{a_{UI}-1}(1-v_i)^{b_{UI}-1}}{(1-\lambda-\theta)^{a_{UI}+b_{UI}-1}B(a_{UI}, b_{UI})}\mathbb{1}(\lambda + \theta < v_i < 1)\,, \tag{3}$$

$$\Pr(v_i; \text{Obvious \& Bad}, \Theta) = \frac{v_i^{a_{UI}-1}(1-\lambda-\theta-v_i)^{b_{UI}-1}}{(1-\lambda-\theta)^{a_{UI}+b_{UI}-1}B(a_{UI}, b_{UI})}\mathbb{1}(0 < v_i < 1-\lambda-\theta)\,, \tag{4}$$

$$\begin{aligned}\Pr(v_i; \text{Contentious \& Good}, \Theta) = \int_{-\infty}^{\infty} \Bigg(&\frac{(z-\lambda)^{a_{PI}-1}(\lambda+\theta-z)^{b_{PI}-1}}{\theta^{a_{PI}+b_{PI}-1}B(a_{PI}, b_{PI})}\mathbb{1}(\lambda < z < \lambda+\theta) \\ &\frac{(v_i - z)^{a_{UI}-1}(1-\lambda-\theta-v_i+z)^{b_{UI}-1}}{(1-\lambda-\theta)^{a_{UI}+b_{UI}-1}B(a_{UI}, b_{UI})}\mathbb{1}(0 < v_i - z < 1-\lambda-\theta)\Bigg)dz\,,\end{aligned} \tag{5}$$

$$\begin{aligned}\Pr(v_i; \text{Contentious \& Bad}, \Theta) = \int_{-\infty}^{\infty} \Bigg(&\frac{z^{a_{PI}-1}(\theta-z)^{b_{PI}-1}}{\theta^{a_{PI}+b_{PI}-1}B(a_{PI}, b_{PI})}\mathbb{1}(0 < z < \theta) \\ &\frac{(v_i - z)^{a_{UI}-1}(1-\lambda-\theta-v_i+z)^{b_{UI}-1}}{(1-\lambda-\theta)^{a_{UI}+b_{UI}-1}B(a_{UI}, b_{UI})}\mathbb{1}(0 < v_i - z < 1-\lambda-\theta)\Bigg)dz\,.\end{aligned} \tag{6}$$

To estimate the parameters Θ, we minimize (2) in these parameters subject to the constraints noted above.

2.1.1. Statistics of Interest

An advantage of our structural model is that we can examine economically interesting statistics that the literature has previously been unable to estimate. First, we can characterize the proportion of proposals based on their quality and whether or not they are contentious. These proportions correspond to the probabilities of arriving at each branch of the tree in Figure 1. The probabilities of each type of proposal are:

$$\Pr(\text{Obvious \& Good}) = \delta \times \alpha_o\,, \tag{7}$$

$$\Pr(\text{Obvious \& Bad}) = \delta \times (1 - \alpha_o)\,, \tag{8}$$

$$\Pr(\text{Contentious \& Good}) = (1 - \delta) \times \alpha_c\,, \tag{9}$$

$$\Pr(\text{Contentious \& Bad}) = (1 - \delta) \times (1 - \alpha_c)\,. \tag{10}$$

It is trivial to calculate the percentage of good proposals from these, regardless of whether they were obvious or contentious. This quantity is simply the sum of the probabilities of a proposal being (1) obvious and good and (2) contentious and good:

$$\mathbb{E}(\text{Percent Good Proposals}) = \delta \times \alpha_o + (1 - \delta) \times \alpha_c\,. \tag{11}$$

Note that if voting was perfectly efficient and all voters were informed, this would be the percent of proposals that would pass.

We can also calculate the unconditional expected fraction of informed votes (Percent Informed), which is the sum of the fraction of votes that are from always informed investors (λ) plus the fraction of votes from partially informed voters (θ) times the probability those votes are informed (δ):

$$\mathbb{E}(\text{Percent Informed}) = \lambda + \delta \times \theta\,. \tag{12}$$

Finally, given estimates of the parameters Θ, we can characterize error rates associated with voting, which is the main focus of this paper. In particular, we can estimate the percent of proposals that (1) pass but are bad (false positives) or (2) fail but are good (false negatives). Using equations (4) and (6), we calculate the fraction of proposals that pass but are bad as:

$$\Pr(\text{Pass, but Bad}) = \int_{.5}^{1} \Big[\delta(1-\alpha_o)\Pr(v;\text{Obvious \& Bad}, \Theta) \\ + (1-\delta)(1-\alpha_c)\Pr(v;\text{Contentious \& Bad}, \Theta) \Big] dv \,. \tag{13}$$

Similarly, the fraction of proposals that fail but are good is calculated in conjunction with equations (3) and (5) as:

$$\Pr(\text{Fail, but Good}) = \int_{0}^{.5} \Big[\delta\alpha_o\Pr(v;\text{Obvious \& Good}, \Theta) \\ + (1-\delta)\alpha_c\Pr(v;\text{Contentious \& Good}, \Theta) \Big] dv \,. \tag{14}$$

Though these formulas are more complicated than the previous statistics, both are easily interpreted. We calculate the probability that a bad proposal passes as the likelihood that a bad proposal, either obvious or contentious, receives at least 50% of votes and therefore passes. Likewise, the probability that a good proposal fails is the likelihood that a good proposal, either obvious or contentious, receives less than 50% of votes and therefore does not pass.[6]

2.1.2. A Visualization of the Model

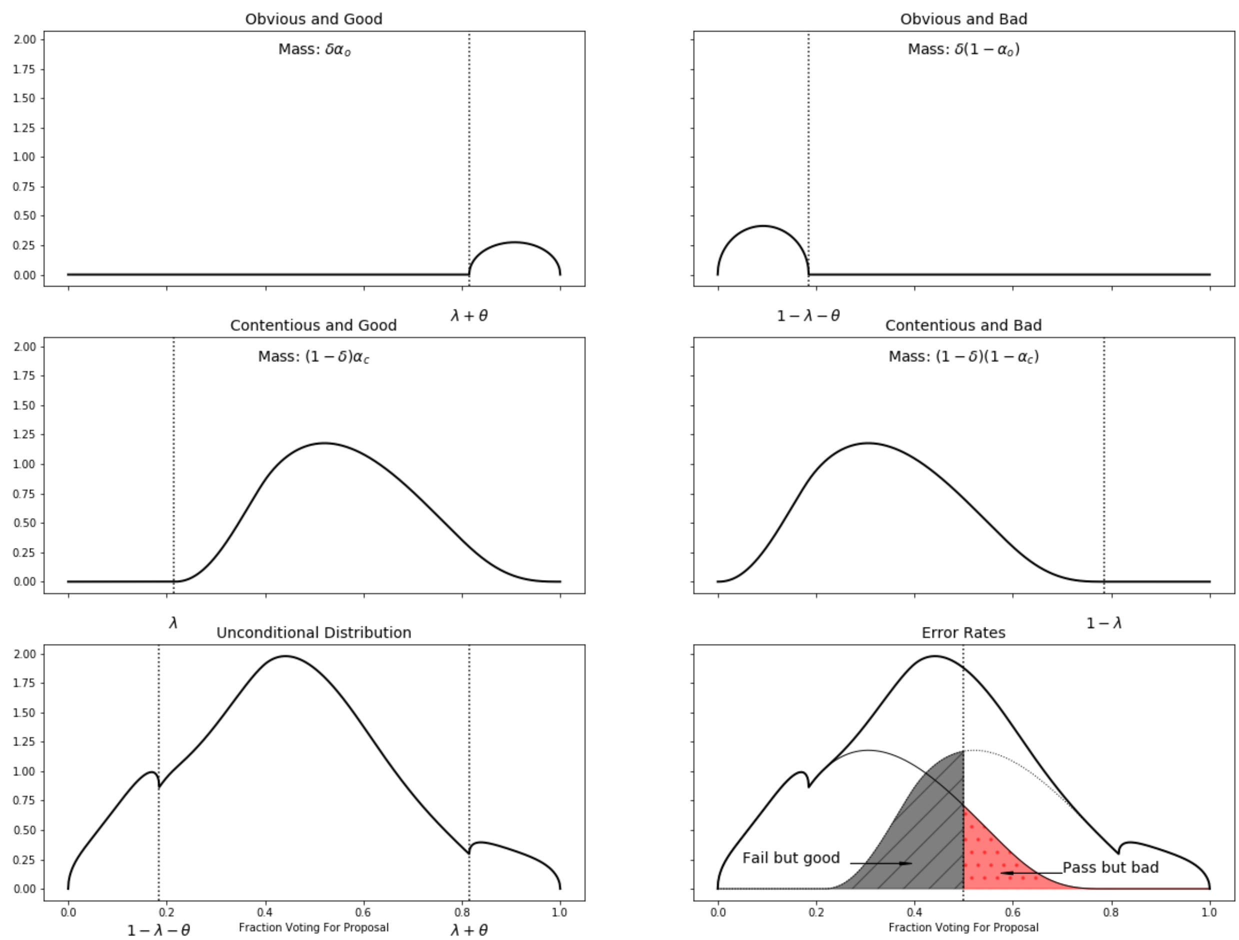
For intuition, we present an example of the mixture model described above. Figure 2 plots distributions of the fraction of votes in favor of a proposal for a sample model. In the first two rows, we separately plot the probabilities of observing voting results *conditional* on each of the four latent states of proposal characteristic: obvious and good, obvious and bad, contentious and good, and contentious and bad.

For obvious proposals (top row of Figure 2), the distribution's shape is the same across

[6] In our empirical analyses, we also report summary statistics of the unconditional distribution of voting outcomes (mean, standard deviation) given the set of estimated parameters and the likelihood functions defined in equations (2)-(6).

Figure 2: Probabilities of Fractional Voting Outcomes: A Sample Model

This figure plots a sample distribution of the fraction of votes in favor of a proposal. The top two rows show the conditional distributions of votes corresponding to the four terminal nodes in Figure 1. The bottom left plot shows the unconditional distribution of votes. The shaded regions in the bottom right plot represent error rates: good proposals that fail to pass and bad proposals that do pass. The parameters used for the plot are $\delta = 0.1$, $\alpha_o = 0.4$, $\alpha_c = 0.5$, $\lambda = 0.22$, $\theta = 0.6$, $a_{PI} = 1.8$, $b_{PI} = 2.5$, $a_{UI} = 1.5$, and $b_{UI} = 1.5$.



good and bad proposals, but their locations differ. Both informed and partially informed investors vote in favor of obviously good proposals, so the lower end of the distribution with positive mass starts at $\lambda + \theta$. On the other hand, for obviously bad proposals, these same investors vote against, so the distribution has zero mass above the fraction $1 - \lambda - \theta$. The uninformed investors' voting governs the shape of the distribution.

For contentious proposals (middle row of Figure 2), only informed investors vote correctly with certainty. Thus, the voting distribution has a positive mass starting at λ for good proposals and has zero mass starting at $1 - \lambda$ for bad proposals. There are two sets of uninformed investors for contentious proposals: the partially informed and always uninformed investors. The shape of the distribution is thus based on the convolution of the voting behavior of these two groups' distributions.

The conditional distributions are multiplied by the likelihood that each proposal quality state occurs. That is, the mass for the obvious and good distribution is $\delta\alpha_o$. Since $\alpha_o < 0.5$ in the example, the mass of Obvious and Bad is larger than Obvious and Good. Thus α_o and α_c, the probabilities of a good proposal in the obvious or contentious state, respectively, govern the relative mass across good and bad proposals. The relative mass between obvious and contentious proposals is governed by the parameter δ. Lower levels of δ put less mass on the obvious proposal states. In the example, $\delta = 0.1$; this is reflected in the smaller likelihood the example model places on voting outcomes identified as obvious.

The bottom left plot of Figure 2 shows the unconditional distribution of voting outcomes, which is the sum of the four probabilities of the four proposal quality states. As can be seen, the model is capable of capturing asymmetric and multimodal voting outcomes.

Finally, Figure 2's bottom right plot illustrates the mass of voting errors defined in Equations (13) and (14). The area of the grey hatched region represents the fraction of proposals that fail but were good (false negatives), while the red dotted region represents bad proposals that pass (false positives), which are the main statistics of interests of this study.

2.2. Discussion of the Empirical Framework

As noted above, our framework implicitly assumes that value-enhancing proposals will, on average, receive more votes in favor relative to value-destroying proposals. In essence, we assume that investors are maximizing share price when they vote (since these investors own the firm's stock) and that differences in information sets drive the variation in voting choice.

We, therefore, abstract away from the possibility that some voters have different private valuations for shareholder proposals that vary systematically with the underlying proposal quality.

The theoretical literature on voting generally assumes that variation in voting stems from either differences in voters' information sets or private valuations. Our empirical structure focuses on the former for several reasons. First, in our view, the ongoing policy debates focus primarily on whether shareholders are informed, which maps more closely to the idea of different information sets. Second, while there is evidence of conflicts of interest that arise in voting due to, for example, business ties between firms and investors (Davis and Kim, 2007) or social connections between CEOs and fund managers (Butler and Gurun, 2012), these are almost certainly a small minority of shareholders. Our view is that the vast majority of shareholders' primary interest is in maximizing the share price. Finally, even if some investors have different objectives, as long as those different objectives do not vary systematically with the value implications of the proposals, then our estimates will still be unbiased, as such behavior will be accounted for with our distribution of uniformed voters (i.e., it is absorbed in the "error" term). For example, socially responsible investors (which, over our sample period, also will make up a trivial fraction of voters) may vote for reasons other than value maximization. However, as long as the environmental and social (E&S) proposals they support are not systematically value-destroying, our basic framework is still reasonable. Given that there is still ongoing debate about the value of E&S initiatives, and if anything, the literature seems to support the view that those initiatives are value-enhancing (e.g., Flammer, 2015; He, Kahraman, and Lowry, 2020), we think our assumption here is reasonable.

Nevertheless, we examine the validity of our underlying assumptions throughout the text. For example, our assumptions have predictions about the relation between voting outcomes and valuations that we test directly. We also show evidence inconsistent with the view that shareholders are voting systematically in favor of E&S proposals for reasons other than value maximization over our sample period.[7]

2.3. Data

Our data consists of proxy voting data from ISS for the years 2003–2019. We use both shareholder and management proposals.[8] For the latter category, we drop proposals related to board elections since these are required to be filled. We merge the data with Compustat firm characteristics from the annual reporting data that immediately precede the meeting date. Data from CRSP is merged to the immediately preceding month of the vote. We include institutional ownership data from the holdings reported in the fourth quarter that precedes the meeting date. These data are from Thomson-Reuters's 13f database. Institutional ownership classifications are obtained from Brian Bushee and follow Bushee (2001). We obtain hedge fund activism data from Alon Brav. We compute the E-index using the Risk Metrics database for the year 2007-2013 following the methodology proposed in Bebchuk, Cohen, and Ferrell (2009).

Overall, we have 548,301 agenda items over 17 years. These include 10,164 shareholder-sponsored agenda items. To deal with the log-likelihood being unbounded at 0 and 1, as is common in the literature, Hautus (1995), we shift those data points by $\frac{1}{2N}$, where N is the sample size. For tests requiring data on institutional holdings, we have 9,380 shareholder-sponsored agenda items that match the 13f data. Table 1 presents the summary statistics for the shareholder proposal sample.

3. Results

3.1. Baseline estimates

Our first main question concerns the overall error rates in voting for shareholder proposals. We report our estimates in Table 2. We find that about 27% of vote outcomes are

[7] Throughout the paper, we use the term "good" and "bad" for proposal quality which reflects our underlying assumption about value and voting outcomes. However, we recognize many proposals may be "good" proposals from, for example, an employee or societal viewpoint, irrespective of their value impact.

[8] Data for shareholder proposals runs through 2018, and for management proposals runs through 2019.

mistakes. Decomposing these errors, about 6% of shareholder proposals are passed when they are bad (false positives), and about 21% of all proposals are rejected even though they are good (false negatives).

The focus of recent policy debates has centered around shareholder proposals rather than management proposals. It is therefore natural to compare our estimates from the shareholder proposal sample to those from management proposals. Column 2 of Table 2 presents the estimates for the management proposed items. We find that the fraction of mistakes is 1%. In particular, both false positive and negative-errors are substantially lower (0.8% and 0.5% respectively) for management than shareholder proposals. This suggests that shareholders only struggle to vote correctly on shareholder proposals.

Our model estimates also provide some other interesting statistics about shareholder proposals that help to interpret our main results. For example, we estimate that roughly 32% of votes are expected to be informed, and 38% of shareholder proposals are good. Only 12% of the proposals are either obviously good or bad, with the remaining 88% being contentious. This is consistent with what is discussed in McCahery et al. (2016). Proposals typically are discussed with management and the fact that it appears on the proxy signals that the sponsor and management couldn't agree. Therefore, the proposal is likely to be contentious. The fraction of informed votes is slightly higher for management proposals at 38%. The average proposal quality is also far higher for management proposals, with 99% of proposals estimated to be good, albeit mostly contentious (64%).

The estimated voting behavior of the uninformed voters is particularly informative for understanding our estimated error rates. For management proposals, p_{un} is drawn from a $\text{Beta}(0.92, 0.30)$, which implies that 79% of votes by uninformed investors are in favor of the proposal.[9] For shareholder proposals, p_{un} is drawn from a $\text{Beta}(0.60, 0.42)$, which implies

[9] We allow for uninformed votes to be drawn from different distributions across management and shareholder proposals for several reasons. First, the types of proposals are generally different across these two samples. Second, the actual voting rules, including the chosen voting base, differ dramatically between the two samples. Finally, unvoted shares generally default to votes for management's recommendation, which also differs dramatically across the two samples. Economically, our assumption allows for the possibility that

that 60% of votes by uninformed investors are in favor of the proposal. This has the nice interpretation as a Beta$(0.5, 0.5)$ is the Jeffreys prior, non-informative prior, for a binomial likelihood. There is a more substantial difference for partially informed investors, who vote randomly only for contentious items. 99% of votes by these investors are likely to support management proposals, but only 21% support shareholder proposals. Because such a large fraction of shareholder proposals are contentious, these partially informed voters drive down the passage rates dramatically for shareholder proposals compared to management proposals.

Overall, these results suggest that shareholder proposals are of lower quality relative to those sponsored by management. However, mistakes occur for both good and bad shareholder proposals where mistakes rarely occur for management proposals. Indeed, part of the policy debate around proxy access for shareholders centers around whether shareholders are sufficiently informed to discriminate appropriately against bad shareholder proposals. Our main estimates inform this policy debate since they indicate that they fail to correctly discriminate between good and bad proposals at a much higher rate for shareholder than management proposals, thereby providing some evidence against the adoption of proxy access.

3.1.1. Model Fit

The top left panel of Figure 3 displays the density histogram of the underlying voting outcomes for the shareholder proposals used in Table 2. The top right panel shows the model-implied distribution from our estimation. Visual inspection of these two histograms suggests that our model does quite well in fitting the data and helps validate the use of our model-implied statistics for inference on voting behavior and outcomes. We statistically test the model fit below and find that it is statistically plausible that the data was generated from our model. The additional plots in Figure 3 show the decomposition of the model, with the density of each branch of the model plotted separately. It is immediately clear that

uninformed investors may vote differently for shareholder and management proposals.

the vast majority of shareholder proposals are contentious (as reported in Table 2). These plots also make clear the proportion of voting mistakes made, as a substantial portion of "Contentious and Good" proposals receive fewer than 50% votes in favor (as illustrated by the mass to the left of 0.50), and a smaller but still important fraction of "Contentious and Bad" proposals have outcomes that fall to the right of 0.50.

We plot the same set of graphs for management proposals in Figure 4. It is obvious from the data plot that management proposals are fundamentally different from shareholder proposals, with the vast majority of proposals receiving support of greater than 95%. Importantly, the model-implied distribution matches the data extremely well in this case too. We also find that it is statistically plausible that the data was generated from our model. This further validates the underlying model assumptions; the model matches two entirely different underlying distributions with the same relatively simple identifying assumptions. We conclude that virtually all management proposals are good. The small fraction of proposals estimated to be bad are mostly contentious, but they are essentially all false positives because they ultimately pass.

We assess our model fit formally by testing whether we can reject that the data are generated by the model-implied distribution. To do this, we run a bootstrapped version of the Kolmogorov-Smirnov test to account for the estimation error caused by sampling noise in the MLE estimates in our model's CDF fit. We generate a null distribution by bootstrapping the maximum distance between (a) an empirical CDF of a data set simulated from our model (using the estimated parameters from Table 2 and the same number of observations as in the actual data) and (b) the estimated model distribution obtained when the model is fit to the simulated data. The procedure thus provides a distribution of maximum deviations of a CDF due to sampling and estimation error if the data were generated by our model. We calculate the maximum distance between the empirical CDF of the actual data and the estimated model reported in Table 2, and we compare this statistic with the bootstrapped distribution. For both the shareholder and management proposal data sets, we fail to reject the null at the 10% level.[10] We, therefore, conclude that our model could have generated the observed data, and any differences between our model and the data can be attributed to sampling noise. This is a high threshold we pass for model validation, given our large sample sizes. This can be visualized in Figure 5. In this figure, we plot the empirical CDF of the data, the CDF of our model, and confidence bounds of the 90^{th} percentile of the null distribution from the Kolmogorov-Smirnov test around our model's CDF. A failure to reject the null is equivalent to the data's empirical CDF being completely contained within the confidence bounds at all points of the distribution. For both the shareholder and management proposal data sets, the empirical CDF of the data is completely contained within the confidence bounds. This plot and test validate that the way we characterize the voting process fits the true data generating process up to sampling error.

As an additional test of our model fit, we compare the fit of the structural estimates to the fit of reduced form linear probability models (LPM) of voting outcomes. Specifically, we run reduced-form regressions of voting outcomes on ISS and management recommendations, firm and year fixed-effects, and other various controls. Table 3 presents the regression outputs. We plot the CDFs from the LPMs along with the empirical CDF and our model's CDF in Figure 6 for shareholder and management proposals. It is clear from the plots that our model has a better fit than the fitted LPMs. This once again speaks to the quality of fit of our model. To statistically test this, we calculate the RMSE between the empirical CDF of the data and each model's CDF. We use a bootstrap of the RMSE to determine statistical significance.[11] Table 3 reports the results for shareholder proposals in columns 1-3. Our model's fit is economically and statistically better at the 1% confidence level than a reduced-form regression with firm and year fixed effects that has an adjusted R^2 of 0.89, and our model allows us to measure variables a reduced-form regression cannot measure. The model

[10] It is worth noting that given we fail to reject at the 10% level, we would also fail to reject at any confidence level less than 10%, such as 5% or 1% levels which are commonly used in the literature.

[11] An LPM generates predicted values outside of $[0, 1]$, so we censor the predicted values to $[0, 1]$ to put the LPM on a more level footing to our model.

for management proposals is statistically a better fit at the 1% confidence level than any of the tested reduced form model specifications (shown in columns 4-6 of Table 3).

3.1.2. Market Reaction to Estimated Errors in Voting

In this subsection, we examine whether our estimates of voting errors have economic content. If our model estimates capture errors in voting outcomes, then, all else equal, we would expect errors to be associated with decreases in firm value.[12] To test this, we calculate the conditional probability that a given shareholder proposal outcome is an error. We separately consider the probabilities that the voting outcome is a false positive or false negative. For example, a proposal that passes has zero probability of being a false-negative, but a potentially non-zero probability of being a false positive. We calculate the probability of a false positive (negative) error conditional on the percent of votes for each proposal by using Bayes' Theorem, where t_i is the threshold for the item to pass:

$$\Pr(\text{False Positive}|v_i) = \frac{\mathbb{1}(v_i > t_i)\sum_{j\in\{Obv.,Cont.\}}\Pr(v_i|j \ \&\ \text{Bad})\Pr(\text{Bad}|j)\Pr(j)}{\sum_{j\in\{Obv.,Cont.\}}\sum_{k\in\{Good,Bad\}}\Pr(v_i|j \ \&\ k)\Pr(k|j)\Pr(j)}\,, \tag{15}$$

$$\Pr(\text{False Negative}|v_i) = \frac{\mathbb{1}(v_i < t_i)\sum_{j\in\{Obv.,Cont.\}}\Pr(v_i|j \ \&\ \text{Good})\Pr(\text{Good}|j)\Pr(j)}{\sum_{j\in\{Obv.,Cont.\}}\sum_{k\in\{Good,Bad\}}\Pr(v_i|j \ \&\ k)\Pr(k|j)\Pr(j)}\,. \tag{16}$$

A significant challenge to using announcement returns to infer the market's response to a given proposal is that there are often multiple proposals from a given shareholder meeting, including management- and shareholder-sponsored agenda items, with results announced on the same day. Therefore, we aggregate the individual proposal conditional probabilities to the firm-date level by taking an equal-weighted average of each probability across all proposals for a given firm-year. We average separately within both shareholder and management proposals. Such aggregation may bias any relation between returns and mistakes toward zero, as we are averaging across some proposals with a high conditional mistake probability

[12]If the model estimates contain economically meaningful content in tests outside of the model, this helps provide some level of comfort that the model is not "overfit."

and others with low conditional mistake probabilities. We also aggregate the overall vote outcomes by averaging the percent votes in favor of each proposal. We control for the average vote outcome to ensure that any relation between market returns and mistakes is not just capturing the overall vote outcome.

Table 4 presents regression of CARs around the voting outcome announcement on the average probability of mistakes in voting outcomes. CARs are calculated over the (-1,1) window following Gantchev and Giannetti (2020). We include the average vote outcome for shareholder proposals as a covariate of interest. Across columns, we present results for CARs based on four different risk models: market adjusted, CAPM adjusted, Fama-French 3-factor adjusted, and Fama-French 4-factor adjusted. In addition to the covariates of interest, each regression includes firm fixed effects, fixed effects for the year and month of the vote, and controls for the coincident management proposal mistake probabilities and vote outcomes.

The results indicate that the market reacts negatively to voting errors. Specifically, we observe a strong negative reaction to false positives (bad proposals that mistakenly pass). A one-standard-deviation increase in the average probability of a false positive for a firm is associated with a 45 to 51 (sd=.215) bps drop in value over the three-day window. To put this differently, if a firm's average probability of an error goes from 0 to 50% (the largest we observe in the data for a false-positive error), we would expect a decrease in the equity value of just over 1% over the 3-day window. Interestingly, the effect is not symmetric. While the point estimate on the average probability of a false negative is negative, the economic magnitude is small and statistically indistinguishable from zero. This is consistent with the view that false negatives are less costly than false positives. However, it is worth noting that we would not expect a price reaction if the "mistakes" were expected. Empirically, the average votes in favor of a proposal corresponding to a high probability of being a false negative are farther away from the passing threshold than a false positive. Therefore, it also possible that the false negatives are less surprising, and the effects are therefore priced before the vote announcement.

Our model implicitly assumes expected vote share conditional on being good is higher than the expected vote share conditional on being bad. In our regressions, we control for the average vote share across all proposals. We find that the CARs are positively related to the votes in favor. These estimates are borderline statistically significant at conventional thresholds (e.g., p-value=0.103, and t-stat=1.63 in column 4) and economically meaningful. Given that our assumption has a directional prediction, a one-tailed test will reject that the relation is negative in all four specifications at the 10% level. Economically, a one standard deviation increase in the fraction of votes in favor is associated with a 18-21 bps increase in market value over the three-day window. Overall, this result is consistent with our underlying structural assumptions. Note that it is not surprising that the statistical power of this test is low, given that most proposals pass or fail by wide margins. It is likely that the market has a relatively clear expectation of vote outcomes for most proposals prior to the vote, and we, therefore, expect little price reaction over this window.

Overall, our structural estimates fit the data remarkably well and have economic content consistent with our underlying assumptions. In the following section, we use this framework to examine cross-sectional variation in our estimates as a function of firm and proposal characteristics that are motivated by theory and prior empirical findings. As noted above, we focus on shareholder proposals going forward. When we do these conditional analyses, we fix the shape parameters from the uninformed investors' Beta distributions, (a_{UI}, b_{UI}) and (a_{PI}, b_{PI}), at the values estimated from the overall sample of shareholder proposals. This ensures that the prior for uninformed investor behavior does not change relative to the baseline estimates. This means that the "coin" flipped by the uninformed investors is the same, regardless of the sub-sample characteristics we examine. We believe this is consistent with the notion of an uninformed investor.

4. Model Estimates and Variation in Costs and Benefits of Information Collection

4.1. Cross-Sectional Estimates: Ownership Characteristics

Policy debates around proxy voting, such as the regulation of proxy advisors and proxy access initiatives, revolve around the ability and incentives of the owners to collect information and vote in an informed way. Given this, it is natural to examine how voting outcomes relate to the types of owners in the firm. We focus on variation in ownership structure related to institutional investors. There is increasing evidence that institutional investors serve a monitoring role in firms. These investors are frequently identified as those investors most likely to be informed about proxy items (e.g., Iliev and Lowry, 2015; Malenko and Shen, 2016; Gantchev and Giannetti, 2020). However, we also know that institutions differ with respect to investment objectives, position size, and even the governance role they play. Therefore, in this section, we examine variation in our parameter estimates as a function of the level, the concentration, and type of institutional ownership.

4.1.1. Institutional Ownership and Concentration

We first sort firms based on aggregate institutional ownership characteristics. We compare estimates for firms above and below the median on institutional ownership, institutional ownership concentration, and the concentration of the Top 5 institutional owners (as in Hartzell and Starks, 2003). The classifications are similar to the measures of informed voters used in, for example, Gantchev and Giannetti (2020), as these voters are, ex-ante, likely to be more sophisticated and have more substantial incentives to be informed due to both fiduciary duties and position sizes. As noted above, we fix the beta distribution parameters for each sub-sample at the values estimated from the full sample model so that the uninformed investors' "coin" is drawn from the same distribution across all models.

The estimates from the aggregate institutional ownership sub-samples are presented in Table 5. Firms with a large fraction of institutional ownership see higher quality proposals on average. Surprisingly though, we find little evidence to support the view that firms with more institutional ownership or higher levels of ownership concentration have higher fractions of informed votes. The estimated fraction of informed votes for high levels of institutional ownership (30.2%) is not economically meaningfully different from the estimated fraction of informed investors in low institutional ownership firms (30.9%). The fraction of informed votes is slightly higher when ownership concentration is high, but slightly lower when the concentration of the top 5 owners is low, although again the differences are small (33% vs. 27% and 32% vs. 34%, respectively). Thus, while it may be true that some institutional investors themselves are more informed, that does not appear to translate to a statistically or economically significant higher fraction of informed voters overall.

Turning to the false positive and false negative errors in voting, we see that higher levels and concentrations of institutional owners are associated with much higher false-negative errors. That is, good proposals fail more frequently, suggesting such investors are biased against shareholder proposals. High institutional ownership (IO) firms are estimated to have 26% of proposals that are good but ultimately fail compared to only 15% for low IO firms, a statistically significant difference. Results are similar for ownership concentration. There does seem to be a tradeoff; high institutional ownership levels and concentration correspond to lower false-positive errors. Bad proposals are less likely to pass, but the differences across groups are smaller than those for false-negative errors. For example, high IO firms are estimated to have 6% of proposals that are bad but still pass compared to 8% for low IO firms. If false positive and false negative errors were equally costly to investors, then we would conclude that higher institutional ownership levels and concentration are actually bad for voting outcomes in that it is associated with 32% of all votes being in error, compared to 23% for low IO firms. However, our return analysis presented in Table 4 suggests that institutional owners' tilt toward fewer false positives at the expense of more false negatives may be value increasing, as the negative stock price response to false positives is much larger. These results suggest that the ownership environment plays a more nuanced role in voting outcomes. It does not appear that higher levels of concentration of institutional ownership relate to unconditionally better voting outcomes but may improve outcomes where they matter most.[13]

4.1.2. Active vs. Passive Ownership

Our final ownership-related analysis examines the extent to which our estimates vary in the presence of high levels of passive owners or in the presence of a hedge fund activist (HFA), defined as in Brav et al. (2008). There is debate in the literature as to the governance impact of passive investors. For example, results in Appel et al. (2016) suggest better monitoring by passive owners, in particular index investors, as a result of their large ownership stakes and inability to exit positions. On the other hand, Heath et al. (2020) suggests that governance outcomes are worse in the presence of such investors as they lack the underlying incentives to monitor. With respect to activist investors, there is relatively consistent evidence that hedge fund activists improve firm value. However, there is debate as to how those value increases manifest and there is little evidence as to their effect on value through their impact on voting outcomes.

We estimate our empirical model as a function of both passive ownership and hedge fund activist ownership. Passive ownership is proxied for by Quasi-Indexer ownership as defined in Bushee (1998). Specifically, we split the sample into above- and below-median levels of ownership. Similar, we split our sample based on the presence of a hedge fund activist as defined in Brav et al. (2008). The results of these estimations are presented in Table 6.

Columns 1 and 2 of Table 6 present the results of our estimation for high- and low- passive ownership, respectively. Turning first to the error rates, it is immediately clear that overall voting outcomes are worse in the presence of high levels of passive ownership. The fraction of voting outcomes classified as false negatives is nearly double when passive ownership is high compared to when it is low (32.5% vs. 16.7%). This difference is highly statistically

[13]This is perhaps not surprising given there is uncertainty about the impact of any given voter and who actually has rights to vote (Kalay et al., 2014; Fos and Holderness, 2021).

significant as well. The point estimates for false positives suggest a slight improvement when passive ownership is high, but the economic magnitude is small and the difference is insignificant. Overall, we estimate that 37% of all proposal outcomes are mistakes when passive ownership is high compared to 23% when it is low. Overall, these results suggest that passive investors are not improving monitoring through better voting outcomes consistent with the findings of Heath et al. (2020).

We draw very different conclusions when we look at activist investors (columns 3 and 4 of Table 6). While we estimate significantly less informed voting when a high fraction of ownership is passive, we estimate significantly more informed voting when there is an activist present. This translates to better voting outcomes. The presence of a hedge fund activist is associated with economically meaningful improvements in false positives - down to 2.5% from 14.3% when there is no activist present. This difference is also statistically significant at the 10% level. On the other hand, there is not statistical difference in false negatives across the two groups, and while the point estimates suggest they are marginally worse in the presence of an activist, the difference is small. Given we show that false positive outcomes are particularly costly, the dramatic improvement on this dimension suggest that part of the value benefits associated with hedge fund activists (documented in, e.g., Brav et al., 2008) stem from preventing the passage of value destroying proposals.

4.2. Cross-Sectional Estimates: Availability of Information

4.2.1. Proxy Advisory and Management Recommendations

Malenko and Malenko (2019) show that incentives to collect information about proposal quality depend on proxy advisors' information. Proxy advisors are also an integral part of the regulatory and policy debates surrounding governance generally and corporate voting in particular. Therefore, we test whether the voting environment is conditional on proxy advisor recommendations. Our proxy advisor recommendations are from ISS, and we estimate the model for proposals conditional on whether ISS recommends in favor of the proposal or whether they recommend against.

The results from this analysis are presented in Table 7. We estimate that 83% of the shareholder proposals supported by ISS are good, so ISS gets these proposals "right" far more often than not. When ISS recommends against, we estimate that virtually all of those proposals are, in fact, bad. Overall, these estimates show that ISS is more accurate in terms of proposal quality when they fail to support a recommendation, but that overall they do quite well in identifying "good" proposals.

Interestingly, when ISS recommends in favor of shareholder proposals, we estimate that only 22% of votes are informed. However, when ISS recommends against, over 56% of votes are informed, suggesting that investors collect more information in response to (the less common) ISS recommendations against proposals. This finding would be largely consistent with Malenko and Malenko (2019) if investors view negative recommendations as less precise. However, this is somewhat inconsistent because ISS appears to be less accurate for the proposals they recommend voting for.

If all investors blindly follow ISS, then based on our structural framework, we should observe ISS getting it "right" all the time. However, this is not what we observe in the data. Almost all of those proposals that ISS recommends supporting are contentious (95%). Investors do not blindly follow these recommendations. As a result, 53% of the proposals that ISS supports are, in fact, good proposals that still ultimately fail (false-negative errors). As documented by, for example, Iliev and Lowry (2015) and Malenko and Shen (2016), many institutions do not rely on ISS and vote in the opposite direction. Surprisingly, our evidence suggests that, for shareholder proposals, this is frequently a mistake. When ISS recommends against the proposal, both ISS and voters seem to get it right; the false positive and false negative errors are essentially zero. As noted above, when ISS is in favor, the fraction of mistakes is nontrivial, suggesting that deviations from ISS might be more a more relevant measure of informed voting when ISS is in favor of the proposals.[14]

[14]Consistent with variation in the informativeness of ISS recommendations, Albuquerque et al. (2020) find mixed evidence of ISS recommendations being informative about the quality of the firm's compensation policies.

A natural benchmark for ISS recommendations is the recommendations by management on the shareholders' proposals. Management is rarely in favor of shareholder proposals, with such favorable recommendations making up only 10% of the sample.[15] When management is in favor of a proposal, we estimate that 84% of these proposals are, in fact, good. In these cases, close to 73% of voters are expected to be informed, and ultimately, the investors get it right. There are virtually no bad proposals passed, and only 1% of good proposals fail. In other words, the false positive and false negative errors are tiny. Even though most proposals are good when managers are in favor, we estimate that 16% of the proposals are bad. Yet, investors can discriminate almost perfectly, consistent with the high estimated fraction of informed votes. On the other hand, when management recommends against a proposal, they get it wrong roughly a quarter of the time, with 26% of the proposals estimated as good. Interestingly, when management recommends against a proposal, all proposals are classified as contentious. We also see a much lower fraction of expected informed votes. As a result, many good proposals fail to pass (17%) when management comes out against them. We also observe that 8% of proposals are bad but pass nonetheless. Overall, when management is against proposals, shareholders get it wrong 25% of the time.

Management's positive recommendations appear far more conservative relative to ISS. As a result, there is a tradeoff in their recommendation errors. Management is much more likely to be correct than ISS when they come out in favor. However, they are more likely to make mistakes in classification when they come out against a proposal. Interestingly, when management is in favor of a proposal, ISS almost always agrees. The disagreement between the two recommendations is almost exclusively confined to proposals that ISS recommends in favor and management recommends against.

[15] Matsusaka et al. (2020) show that managers often actively fight against such proposals. The fact that the proposal is on the proxy statement is a signal that the sponsor and management could not reach an agreement beforehand (McCahery et al. (2016)). Therefore, it is not surprising management recommends against a large fraction of proposals.

4.2.2. Before and After e-Proxy Requirements

We next turn to variation in estimates over the time series. Over our sample, there was one major SEC mandate that changed the proxy information environment. In 2007, the SEC mandated that proxies be available electronically over the internet, with accelerated filers required to comply by January 1st, 2008, and all filers complying by January 1st, 2009. We test whether our parameter estimates differ before 2008 compared to 2008 onward.

The point estimate for the fraction of informed votes is higher in the early period (38% compared to 31%), but the difference is not statistically indistinguishable from zero. There is, however, a dramatic increase in the quality of proposals in the later time period, consistent with the view that easier access to proxies overall improves proposal quality. However, we also see that the investors do not adjust perfectly for this increase in quality; a much larger fraction of good proposals fail to pass in the latter half of the sample. While broadly consistent with better governance through voting in the later period, there are again tradeoffs present: better proposals overall, but more mistakes.

It is necessary to note that we cannot say conclusively that these differences result from the 2007 e-proxy rules. While 2007 to 2008 is the only obvious structural change we observe in the data, we cannot say for sure that this change is due to the rule change and not merely coincident in time, especially given the rise in passive ownership over time.

4.3. Cross-Sectional Estimates: Firm and Proposal Characteristics

In this subsection, we estimate our model as a function of firm and proposal characteristics. Governance via voting likely has differential effects depending on firm characteristics, such as size (Cremers and Nair, 2005) or the existing governance structure of the firm Bebchuk et al. (2009). It is also likely that such impacts are also a function of the costs and benefits of the proposals themselves, as certain proposals, such as those focused on governance, are likely to be more effective tools for increasing shareholder value (Davis and Kim, 2007).

4.3.1. Firm Characteristics

The first firm characteristics we explore are firm size, age, profitability, and the dividend-paying status of the firm. Such firm characteristics have been shown to relate to governance outcomes.[16] We sort firms based on the characteristic and split firms into above and below the median for characteristics other than dividend-paying status. The model is estimated for each group separately, and the results are presented in Table 9.

The fraction of investors' good proposals is significantly higher for small firms, young firms, low profitability firms, and firms that do not pay dividends. These results are consistent with shareholders taking a more proactive role in the governance of firms that would be traditionally associated with more governance-related issues. These relations are consistent with endogenous monitoring by some shareholders in firms that would be targeted for improvement. However, some of this may be offset by the voting outcomes. Small, non-dividend paying, and young firms also see a substantially higher level of good proposals fail despite the higher quality proposals.

This may be explained by the fact that investors are only slightly more informed in these firms even though proposal quality is higher. In fact, the difference in the fraction of informed investors is only statistically different from zero for the firm size and dividend payer splits. Non-dividend paying and small firms have point estimates on the fraction of informed investors that are smaller, but the estimates are quite noisy.

Finally, we examine whether our estimates relate to firms' governance. We proxy for the firm's internal governance with the E-index measure proposed by Bebchuk et al. (2009). The E-index is a proxy for managerial entrenchment. It is based on six anti-takeover provisions: staggered boards, limits to shareholder bylaw amendments, poison pills, golden parachutes, and supermajority requirements for mergers and charter amendments. The results are reported in Table 10.

Good shareholder proposals are more likely to be put forth in firms with high E-index.

[16]For example, see Jensen (1986) and Cremers and Nair (2005).

This result is consistent with other results on firm characteristics and suggests that shareholders make more value-enhancing proposals when firms are managed in what some would argue is a sub-optimal way.

Overall, our results indicate that firm characteristics matter. For example, firms with more entrenched managers see fewer bad proposals pass compared to low E-index firms (false positive errors of 5% vs. 9%), but are much more likely to see good proposals fail (31% vs. 11%). Therefore, shareholder proposals are less likely to affect change in these arguably more poorly governed firms. We see very similar patterns across firm size and age. Again, because of the asymmetry we observe in stock price reactions, it is not obvious that the firms with 'worse' governance are worse when it comes to voting errors since they have fewer false positives at the expense of the less costly false negatives. Overall, these results suggest heterogeneous governance impacts to voting as a function of existing governance.

4.3.2. Proposal Characteristics

Prior work has classified shareholder proposal quality based on the subject of the proposal itself. For example, Davis and Kim (2007) generally classify governance-related proposals as good proposals. We test whether proposal quality, expected fraction informed, and voting errors are a function of proposal type. We examine proposals that fall into one of four broad categories: corporate governance, director-related proposals, compensation proposals, and social and environmental (E&S) proposals. Model estimates for each category are presented in Table 11.

The results show significant variation in model estimates as a function of the proposal type. The vast majority of governance-related shareholder proposals are estimated to be good (79%). Governance proposals are almost all controversial, with only 1% of proposals estimated to be of obvious quality. On the other hand, 45% of director-related proposals are obviously good, suggesting that, overall, director-related shareholder proposals are expected to be of the highest quality when considering the overall investor consensus. In terms of true latent quality, compensation- and director-related proposals are slightly more likely to be bad than good (44% and 46% are estimated to be good, respectively). E&S proposals are essentially all "bad" (i.e., would destroy shareholder value), with only 0.6% estimated to be good.[17]

Interestingly, we see the highest fraction of informed votes for the E&S proposals (43%). Most E&S proposals are contentious (90%), as the higher uncertainty around the value of these proposals leads to a higher likelihood the proposal is contentious, as highlighted in He et al. (2020). Consistent with this, there are almost no voting mistakes made on these proposals. As noted in Section 2.1, our underlying identifying assumptions would be counterfactual if a large fraction of investors vote for E&S proposals and those E&S proposals were systematically value-destroying. Overall, our results suggest that is not an issue, as no significant fraction of investors votes for E&S proposals over our sample period.

Director-related proposals also have a relatively high fraction of informed votes at 41%, followed by governance and compensation proposals at 32% and 23%, respectively. Relatively large fractions of good proposals fail for governance and compensation proposals, suggesting that voters systematically under-appreciate the value of these proposals. Only compensation and director related proposals see an economically meaningful fraction of bad proposals pass at 7% and 9%, respectively.

Overall, governance proposals are overwhelmingly good but fail at relatively high rates. The stark quality difference of E&S proposals suggests that such proposals, while potentially socially beneficial, are detrimental to firms' values over our time period. Such differences also highlight the endogenous nature of information acquisition. Firm-level proxies for the degree of informed investors (such as levels of institutional ownership) will not provide variation across proposal types.

[17] Our definition of "bad" is based on the revealed voting by shareholders under the assumption that informed shareholders vote correctly. Here "bad" does not necessarily imply a bad objective, merely that shareholders do not view this as beneficial for the firm. Importantly, our data stops at the end of 2018. Anecdotal evidence suggests increasing support in the most recent years for certain E&S proposals, suggesting these results may change going forward.

5. Conclusion

This paper studies voting error rates for shareholder proposals. We estimate false positive and negative errors in voting outcomes by developing a structural empirical framework that characterizes the voting process. Our estimates indicate that mistakes in vote outcomes are not trivial; more than one-quarter of vote outcomes are mistakes, with 6% as false positives and 21% as false negatives. In general, we find that sophisticated owners are associated with fewer false positives but more false-negative outcomes. Moreover, voting errors seem to be strictly worse in total in the presence of large passive ownership, but better in the presence of an activist hedge fund. Finally, we find that error rates are higher when proxy advisors are in favor of the proposal and after electronic proxies are mandated.

Our findings contribute to the corporate governance literature. Overall, our evidence highlights the importance of information collection incentives in voting outcomes and informs the policy debate on regulating the shareholder voting process. In particular, our results imply that voting outcomes are not necessarily better in instances where it has been argued that the shareholder base is likely to be more informed. Our results also add to the recent literature on the implications of passive ownership and the presence of hedge fund activists on corporate outcomes. Finally, they also shed light on the informational role of proxy advisor recommendations.

Our paper proposes a novel structural framework to assess the extent to which votes are informed. In particular, our approach allows us to directly estimate false positive and negative error rates in voting, which can help inform academic and policy debates around the implications of corporate democracy and the voting process. For example, we show that stock prices respond negatively to the probability of a false positive shareholder proposal, consistent with the first-order concerns behind the proxy-access regulation and the possibility of passing frivolous shareholder proposals that would harm firm value. Echoing the arguments in Strebulaev and Whited (2011), we view our structural estimation as a complement to the reduced-form methods and natural experiments employed in past studies.

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Table 1:
Shareholder Proposals Summary Statistics

This table reports summary statistics for the data used for shareholder proposals tables. The data covers from mid 2003 through the end of 2018. Percent For is calculated as the percentage of votes for a proposed item divided by the number of votes for and against. The indicator variable ISS Recommended For takes the value of one when ISS recommends for a proposed item and zero when ISS recommends against a proposed item. The indicator variable Mgmt. Recommended For takes the value of one when management recommends to vote for a proposed item and zero when management recommends against a proposed item. Inst. Own. % is the percentage of a firm owned by institutional investors as defined by Thomson-Reuters's 13f database. Inst. Own. Concentration is the sum of the squared percentages of a firm owned by institutional investors as defined by Thomson-Reuters's 13f database. Top Five Inst. Own. is the percent of a firm owned by the five largest blockholders. Transient, Dedicated, and Quasi-Indexer Own. % is the percent of a firm owned by each type of institutional investor, respectively, as defined by Bushee (2001). Market Capitalization is the CRSP market capitalization. Age of Firm is calculated as the difference in years from when an item was voted on and that firm's listed beginning date from CRSP. Profitability is calculated as the operating income before depreciation minus interest minus taxes, divided by lagged assets, where interest and taxes are replaced by zero if missing. The dummy variable for Dividend Payer takes the value of one if a firm payed a dividend that year and zero otherwise. E-Index is calculated following Bebchuk et al. (2009). The indicator variable HFA Present takes the value if an HFA is present and zero otherwise.

Statistic	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Percent For	10,164	0.343	0.270	0.097	0.301	0.476
$\mathbb{1}$(ISS Rec. For)	9,490	0.657	0.475	0.000	1.000	1.000
$\mathbb{1}$(Mgmt. Rec. For)	10,042	0.104	0.306	0.000	0.000	0.000
Inst. Own. %	9,380	0.705	0.214	0.610	0.731	0.843
Inst. Own. Concentration	9,380	0.023	0.021	0.012	0.019	0.030
Top Five Inst. Own.	9,380	0.261	0.100	0.198	0.252	0.318
Transient Own. %	9,380	0.117	0.081	0.059	0.099	0.157
Dedicated Own. %	9,380	0.059	0.067	0.0003	0.044	0.094
Quasi-Index Own. %	9,380	0.488	0.168	0.407	0.502	0.593
Market Capitalization	9,340	53,975,335	83,639,295	4,634,342	18,754,828	64,421,340
Age of Firm	9,326	39.518	25.339	19.000	35.000	56.000
Profitability	6,510	−0.058	4.791	0.062	0.104	0.144
$\mathbb{1}$(Dividend Payer)	8,493	0.787	0.409	1.000	1.000	1.000
E-Index	5,898	3.636	0.965	3.000	4.000	4.000
$\mathbb{1}$(HFA Present)	6,169	0.042	0.201	0.000	0.000	0.000

Table 2:
Shareholder and Management Proposals Estimates

This table reports the maximum likelihood estimates of (2) and derived statistics from the model over the data sets of all proposed items from mid 2003 through the end of 2018 categorized by whether they were shareholder or management proposals. Model implied voting errors are calculated according to (13) and (14). Other model implied statistics are calculated according to (11) and (10). Percent of proposals by type are calculated from equations (6) – (9). The mean, standard deviation, and quantiles are numerically calculated from the fitted density. N is the sample size of proposed items.

	Shareholder Proposals	Management Proposals
Model Implied Voting Errors:		
Passed, but Bad	0.062	0.008
Failed, but Good	0.206	0.005
Other Model Implied Statistics:		
Expected Informed	0.320	0.376
Percent Good Proposals	0.383	0.990
Percent of Proposals by Type:		
Obvious and Good	0.058	0.360
Obvious and Bad	0.066	0.002
Contentious and Good	0.325	0.630
Contentious and Bad	0.552	0.008
Model Implied Moments:		
Mean	0.342	0.941
SD	0.262	0.100
Fit Parameters:		
α_o	0.466	0.995
α_c	0.371	0.988
δ	0.124	0.362
λ	0.233	0.044
θ	0.699	0.917
Beta_{PI}	(0.60,1.52)	(4.26,0.37)
Beta_{UI}	(0.60,0.42)	(0.92,0.30)
N	10,164	548,301
Negative Log-likelihood	−2,791	−1,285,150

Table 3:
LPM Model Comparison

This table calculates the root-mean-square error (RMSE) between the empirical CDF of the percent of votes for an item in our sample, and the CDF implied by the model used. The model numbers refer to the LPM used for comparison from Panel B. The Our Model column refers to the fit model from Table 2. Models (1) – (3) are fit for shareholder proposals, and models (4) – (6) are fit for management proposals. The RMSE is bootstrapped 100 times to asses statistical significance between the two estimates. Panel B runs six linear probability models (LPM) to try and fit the percent of votes for a proposal, which we then use for model fit comparisons in Panel A, and Figures 6. Other controls used in columns (3) and (6) are: indicator for dividend payer status, size of the firm, percent of the firm that is dedicated, transient and quasi-indexers, both measures of concentrated institutional ownership, and the base of the vote. Standard errors are clustered by date and firm. t-statistics reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10% respectively.

Panel A: RMSE between Data's Empirical CDF and Model's CDF

	(1)	(2)	(3)	(4)	(5)	(6)
Our Model	0.0109	0.0109	0.0109	0.0067	0.0067	0.0067
LPM	0.0396	0.0344	0.0257	0.0678	0.0632	0.0459
Difference	-0.0288***	-0.0235***	-0.0148***	-0.0610***	-0.0565***	-0.0392***
Percent Difference	-72.6%***	-68.4%***	-57.7%***	-90.1%***	-89.4%***	-85.4%***

Panel B: LPM Regressions Used in Panel A

	(1) Pct. For	(2) Pct. For	(3) Pct. For	(4) Pct. For	(5) Pct. For	(6) Pct. For
$\mathbb{1}$(ISS Rec. For)	-0.020	-0.131	-0.277***	0.040***	0.055***	0.017
	(-0.33)	(-0.94)	(-12.58)	(5.85)	(3.91)	(1.46)
$\mathbb{1}$(ISS Rec. Against)	-0.328***	-0.431***	-0.521***	-0.161***	-0.152***	-0.182***
	(-5.45)	(-3.14)	(-21.07)	(-22.64)	(-8.95)	(-14.66)
$\mathbb{1}$(MGMT Rec. For)	0.095***	0.139***	0.128***	0.123***	0.121**	0.007
	(2.69)	(2.95)	(3.32)	(3.40)	(2.75)	(0.54)
$\mathbb{1}$(MGMT Rec. Against)	-0.353***	-0.227***	-0.105***	-0.261***	-0.230***	-0.159***
	(-11.66)	(-5.89)	(-3.38)	(-4.22)	(-3.39)	(-7.94)
$\mathbb{1}$(ISS Rec. Withhold)	-0.209***	-0.372**	-0.520***	-0.057***	-0.055***	-0.116***
	(-3.02)	(-2.44)	(-11.22)	(-8.27)	(-3.02)	(-6.72)
$\mathbb{1}$(ISS Rec. Do Not Vote)	-0.067	-0.197	-0.290***	-0.062***	-0.030	0.009
	(-1.02)	(-1.37)	(-6.75)	(-4.14)	(-1.63)	(0.60)
Vote Result			0.282***			0.345***
			(23.93)			(26.70)
Vote Requirement			-0.263**			0.007
			(-2.60)			(1.60)
Firm FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Other Controls	No	No	Yes	No	No	Yes
Adjusted R^2	0.62	0.78	0.89	0.20	0.38	0.51
Observations	10,164	9,840	7,893	548,291	548,010	405,294

Table 4:
Market Reaction to Voting Errors

This table reports regression of 3-day CARs around the publication of voting results on firm-level average error probabilities for shareholder proposals. CARs are calculated over the window (-1,1) under the following risk-adjustments: market adjusted (MM), CAPM adjusted (CAPM), Fama-French 3-factor adjusted (FF3) and Fama-French 4-factor adjusted (FF4). Factor loadings are calculated over a 250-day estimation window and stopping 60 days prior to the event. Standard errors are clustered by date and firm. t-statistics reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10% respectively.

	MM	CAPM	FF3	FF4
	(1)	(2)	(3)	(4)
Pr(False Positive Error)	-0.0236***	-0.0238***	-0.0220***	-0.0210***
	(-3.74)	(-3.77)	(-3.58)	(-3.47)
Pr(False Negative Error)	-0.0035	-0.0030	-0.0035	-0.0037
	(-1.03)	(-0.91)	(-1.06)	(-1.13)
Per. Votes For (Shareholder)	0.0068	0.0068	0.0067	0.0077
	(1.40)	(1.43)	(1.41)	(1.63)
Firm FE	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes
Mgmt. Proposal Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.09	0.09	0.08	0.09
Number Firms	698	698	698	698
Observations	3,699	3,699	3,699	3,699

Table 5:
Shareholder Proposals by Institutional Ownership Characteristics

This table reports the maximum likelihood estimates of (2) and derived statistics from the model over the data sets of all proposed items from mid 2003 through the end of 2018 parameterized by institutional ownership characteristics. Specifically, we modify (2) by replacing each mixing probability by the logistic function with a dummy variable for being in the first column per variable of interest. We parameterize λ and θ by an affine function of the dummy variable for being in the first column per variable of interest. Inst. Own. % is the percentage of a firm owned by institutional investors as defined by Thomson-Reuters's 13f database. Inst. Own. Conc. (HHI) is the sum of the squared percentages of a firm owned by institutional investors as defined by Thomson-Reuters's 13f database. Inst. Own. Conc. (Top 5) is the percent of a firm owned by the five largest blockholders. Model implied voting errors are calculated according to (13) and (14). Other model implied statistics are calculated according to (11) and (10). Percent of proposals by type are calculated from equations (6) – (9). The mean, standard deviation, and quantiles are numerically calculated from the fitted density. N is the sample size of proposed items. ***, **, * represent significance levels at 1%, 5%, and 10% respectively of the null that the estimated parameter is equal across splits (always listed on the right column.).

	Shareholder Sponsored Proposals					
	Inst. Own. %		Inst. Own. Conc. (HHI)		Inst. Own. Conc. (Top 5)	
	Above	Below	Above	Below	Above	Below
Model Implied Voting Errors:						
Passed, but Bad	0.057	0.075*	0.053	0.083	0.053	0.056
Failed, but Good	0.260	0.152***	0.255	0.144***	0.262	0.101***
Other Model Implied Statistics:						
Expected Informed	0.302	0.309	0.326	0.272	0.324	0.345
Percent Good Proposals	0.464	0.303***	0.483	0.256***	0.481	0.229***
Percent of Proposals by Type:						
Obvious and Good	0.058	0.066*	0.0823	0.032***	0.072	0.043**
Obvious and Bad	0.044	0.048	0.043	0.036	0.065	0.009
Contentious and Good	0.406	0.237***	0.400	0.224***	0.409	0.186***
Contentious and Bad	0.492	0.649**	0.474	0.708***	0.455	0.762***
Model Implied Moments:						
Mean	0.364	0.329***	0.379	0.308***	0.370	0.301***
SD	0.261	0.267	0.278	0.236***	0.271	0.246**
Fit Parameters:						
α_o	0.567	0.577	0.654	0.468	0.526	0.823
α_c	0.453	0.267***	0.458	0.241***	0.473	0.196***
δ	0.102	0.114	0.126	0.068	0.136	0.052*
λ	0.230	0.227	0.237	0.225	0.227	0.312
θ	0.706	0.714	0.708	0.703	0.709	0.630
Beta_{PI}	(0.60,1.52)		(0.60,1.52)		(0.60,1.52)	
Beta_{UI}	(0.60,0.42)		(0.60,0.42)		(0.60,0.42)	
Fraction of Data	0.504	0.496	0.497	0.503	0.502	0.498
N	9,380		9,380		9,380	
Negative Log-likelihood	−2,646		−2,822		−2,637	

Table 6:
Shareholder Sponsored Proposals by Types of Institutional Ownership

This table reports the maximum likelihood estimates of (2) and derived statistics from the model over the data sets of all proposed items from mid 2003 through the end of 2018 parameterized by types of institutional owners or HFA presence. Specifically, we modify (2) by replacing each mixing probability by the logistic function with a dummy variable for being in the first column per variable of interest. We parameterize λ and θ by an affine function of the dummy variable for being in the first column per variable of interest. Quasi-Indexer Own. % is the percent of a firm owned by quasi-indexers, as defined by Bushee (2001). The indicator variable HFA Present takes the value if an HFA is present and zero otherwise. Model implied voting errors are calculated according to (13) and (14). Other model implied statistics are calculated according to (11) and (10). Percent of proposals by type are calculated from equations (6) – (9). The mean, standard deviation, and quantiles are numerically calculated from the fitted density. N is the sample size of proposed items. ***, **, * represent significance levels at 1%, 5%, and 10% respectively of the null that the estimated parameter is equal across splits (always listed on the right column).

	Shareholder Sponsored Proposals			
	Quasi-Indexers		HFA Present	
	Above	Below	Yes	No
Model Implied Voting Errors:				
Passed, but Bad	0.044	0.065	0.024	0.143*
Failed, but Good	0.325	0.167***	0.275	0.232
Other Model Implied Statistics:				
Expected Informed	0.311	0.350**	0.457	0.038***
Percent Good Proposals	0.551	0.345***	0.717	0.319**
Percent of Proposals by Type:				
Obvious and Good	0.052	0.083***	0.301	0.020*
Obvious and Bad	0.094	0.093	0.116	0.006***
Contentious and Good	0.500	0.262***	0.416	0.299
Contentious and Bad	0.354	0.562	0.167	0.676**
Model Implied Moments:				
Mean	0.372	0.342	0.526	0.311***
SD	0.255	0.279***	0.328	0.254***
Fit Parameters:				
α_o	0.354	0.472	0.722	0.773
α_c	0.585	0.318***	0.713	0.307
δ	0.146	0.176*	0.417	0.026***
λ	0.209	0.227	0.170	0.014
θ	0.704	0.700	0.686	0.929*
Beta_{PI}	(0.60,1.52)		(0.60,1.52)	
Beta_{UI}	(0.60,0.42)		(0.60,0.42)	
Fraction of Data	0.497	0.503	0.042	0.958
N	9,380		6,169	
Negative Log-likelihood	−2,813		−1,842	

Table 7:
ISS and Management Recommendations

This table reports the maximum likelihood estimates of (2) and derived statistics from the model over the data sets of all proposed items from mid 2003 through the end of 2018 parameterized by ISS and management recommendations. Specifically, we modify (2) by replacing each mixing probability by the logistic function with a dummy variable for being in the first column per variable of interest. We parameterize λ and θ by an affine function of the dummy variable for being in the first column per variable of interest. The dummy variable ISS Recommended For takes the value of one when ISS recommends for a proposed item and zero when ISS recommends against a proposed item. The dummy variable Mgmt. Recommended For takes the value of one when management recommends to vote for a proposed item and zero when management recommends against a proposed item. Model implied voting errors are calculated according to (13) and (14). Other model implied statistics are calculated according to (11) and (10). Percent of proposals by type are calculated from equations (6) – (9). The mean, standard deviation, and quantiles are numerically calculated from the fitted density. N is the sample size of proposed items. ***, **, * represent significance levels at 1%, 5%, and 10% respectively of the null that the estimated parameter is equal across splits (always listed on the right column)..

	Shareholder Sponsored Proposals			
	ISS Recommendation		Mgmt. Recommendation	
	For	Against	For	Against
Model Implied Voting Errors:				
Passed, but Bad	0.022	0.000***	0.001	0.084***
Failed, but Good	0.525	0.000***	0.014	0.166***
Other Model Implied Statistics:				
Expected Informed	0.222	0.555***	0.731	0.235***
Percent Good Proposals	0.832	0.013***	0.844	0.260***
Percent of Proposals by Type:				
Obvious and Good	0.039	0.001***	0.677	0.000***
Obvious and Bad	0.007	0.130***	0.102	0.000***
Contentious and Good	0.793	0.012***	0.167	0.260
Contentious and Bad	0.161	0.857***	0.054	0.740***
Model Implied Moments:				
Mean	0.435	0.149***	0.759	0.294***
SD	0.222	0.130***	0.291	0.209***
Fit Parameters:				
α_o	0.846	0.004***	0.869	1.000**
α_c	0.831	0.014***	0.756	0.260***
δ	0.046	0.131***	0.779	0.000***
λ	0.189	0.497***	0.444	0.235**
θ	0.710	0.456***	0.369	0.709***
Beta_{PI}	(0.60,1.52)		(0.60,1.52)	
Beta_{UI}	(0.60,0.42)		(0.60,0.42)	
Fraction of Data	0.657	0.343	0.104	0.896
N	9,490		10,042	
Negative Log-likelihood	−6,067		−4,771	

Table 8:
Time Series of Voting

This table reports the maximum likelihood estimates of (2) and derived statistics from the model over the data sets of all proposed items from mid 2003 through the end of 2018 split by time period. Specifically, we modify (2) by replacing each mixing probability by the logistic function with a dummy variable for being in the first column per variable of interest. We parameterize λ and θ by an affine function of the dummy variable for being in the first column per variable of interest. Model implied voting errors are calculated according to (13) and (14). Other model implied statistics are calculated according to (11) and (10). Percent of proposals by type are calculated from equations (6) – (9). The mean, standard deviation, and quantiles are numerically calculated from the fitted density. N is the sample size of proposed items. ***, **, * represent significance levels at 1%, 5%, and 10% respectively of the null that the estimated parameter is equal across splits (always listed on the right column)..

	Shareholder Sponsored Proposals		
	Time Series Split		
	2003 – 2007		2008 – 2018
Model Implied Voting Errors:			
Passed, but Bad	0.036		0.058
Failed, but Good	0.085		0.243***
Other Model Implied Statistics:			
Expected Informed	0.379		0.311
Percent Good Proposals	0.191		0.459***
Percent of Proposals by Type:			
Obvious and Good	0.003		0.080***
Obvious and Bad	0.027		0.033
Contentious and Good	0.189		0.379 ***
Contentious and Bad	0.782		0.509***
Model Implied Moments:			
Mean	0.265		0.374***
SD	0.210		0.274***
Fit Parameters:			
α_o	0.093		0.708***
α_c	0.194		0.427***
δ	0.029		0.112***
λ	0.363		0.231
θ	0.576		0.711
Beta_{PI}		(0.60,1.52)	
Beta_{UI}		(0.60,0.42)	
Fraction of Data	0.320		0.680
N		10,164	
Negative Log-likelihood		−3,238	

Table 9:
Shareholder Sponsored Proposals by Firm Characteristics

This table reports the maximum likelihood estimates of (2) and derived statistics from the model over the data sets of all proposed items from mid 2003 through the end of 2018 parameterized by cross-sectional firm characteristics. Specifically, we modify (2) by replacing each mixing probability by the logistic function with a dummy variable for being in the first column per variable of interest. We parameterize λ and θ by an affine function of the dummy variable for being in the first column per variable of interest. Market Capitalization is the CRSP market capitalization. Age of Firm is calculated as the difference in years from when an item was voted on and that firm's listed beginning date from CRSP. Profitability is calculated as the operating income before depreciation minus interest minus taxes, divided by lagged assets, where interest and taxes are replaced by zero if missing. The dummy variable for Dividend Payer takes the value of one if a firm payed a dividend that year and zero otherwise. Model implied voting errors are calculated according to (13) and (14). Other model implied statistics are calculated according to (11) and (10). Percent of proposals by type are calculated from equations (6) – (9). The mean, standard deviation, and quantiles are numerically calculated from the fitted density. N is the sample size of proposed items. ***, **, * represent significance levels at 1%, 5%, and 10% respectively of the null that the estimated parameter is equal across splits (always listed on the right column)..

	Shareholder Sponsored Proposals							
	Firm Size		Firm Age		Profitability		Dividend Payer?	
	Above	Below	Above	Below	Above	Below	Yes	No
Model Implied Voting Errors:								
Passed, but Bad	0.090	0.050***	0.084	0.056*	0.075	0.058	0.076	0.045**
Failed, but Good	0.103	0.285***	0.132	0.244***	0.178	0.214	0.183	0.250***
Other Model Implied Statistics:								
Expected Informed	0.249	0.326*	0.263	0.329	0.279	0.303	0.263	0.379**
Percent Good Proposals	0.166	0.534***	0.238	0.453***	0.316	0.405	0.320	0.528***
Percent of Proposals by Type:								
Obvious and Good	0.003	0.096***	0.028	0.075***	0.038	0.063***	0.033	0.134***
Obvious and Bad	0.003	0.057***	0.005	0.086***	0.031	0.039	0.005	0.057***
Contentious and Good	0.163	0.437***	0.210	0.378***	0.278	0.342	0.288	0.394***
Contentious and Bad	0.831	0.410***	0.757	0.462***	0.653	0.555	0.674	0.415***
Model Implied Moments:								
Mean	0.269	0.394***	0.303	0.365***	0.322	0.350***	0.324	0.413***
SD	0.205	0.283***	0.233	0.271***	0.244	0.270***	0.240	0.307***
Fit Parameters:								
α_o	0.434	0.629	0.857	0.466*	0.545	0.616	0.863	0.703
α_c	0.164	0.516***	0.217	0.450***	0.299	0.381	0.299	0.487***
δ	0.006	0.153***	0.033	0.160***	0.069	0.103	0.038	0.191***
λ	0.245	0.216*	0.240	0.217	0.230	0.253	0.236	0.243
θ	0.706	0.720	0.702	0.701	0.706	0.706	0.707	0.712
Beta_{PI}	(0.60,1.52)		(0.60,1.52)		(0.60,1.52)		(0.60,1.52)	
Beta_{UI}	(0.60,0.42)		(0.60,0.42)		(0.60,0.42)		(0.60,0.42)	
Fraction of Data	0.504	0.496	0.517	0.483	0.497	0.503	0.787	0.213
N	9,340		9,326		6,510		8,493	
Negative Log-likelihood	−3,062		−1817.3		−1,826		−2,536	

Table 10:
Shareholder Sponsored Proposals by E-Index

This table reports the maximum likelihood estimates of (2) and derived statistics from the model over the data sets of all proposed items from mid 2003 through the end of 2018 parameterized by the E-Index. Specifically, we modify (2) by replacing each mixing probability by the logistic function with a dummy variable for being in the first column per variable of interest. We parameterize λ and θ by an affine function of the dummy variable for being in the first column per variable of interest. E-Index is calculated following Bebchuk et al. (2009). Model implied voting errors are calculated according to (13) and (14). Other model implied statistics are calculated according to (11) and (10). Percent of proposals by type are calculated from equations (6) – (9). The mean, standard deviation, and quantiles are numerically calculated from the fitted density. N is the sample size of proposed items. ***, **, * represent significance levels at 1%, 5%, and 10% respectively of the null that the estimated parameter is equal across splits (always listed on the right column)..

	Shareholder Sponsored Proposals		
	E-Index		
	Above		Below
Model Implied Voting Errors:			
Passed, but Bad	0.053		0.087
Failed, but Good	0.313		0.113***
Other Model Implied Statistics:			
Expected Informed	0.272		0.254
Percent Good Proposals	0.516		0.190***
Percent of Proposals by Type:			
Obvious and Good	0.030		0.010***
Obvious and Bad	0.033		0.000**
Contentious and Good	0.486		0.180***
Contentious and Bad	0.451		0.810***
Model Implied Moments:			
Mean	0.361		0.278***
SD	0.242		0.215***
Fit Parameters:			
α_o	0.478		1.000**
α_c	0.519		0.182***
δ	0.062		0.010**
λ	0.227		0.247
θ	0.715		0.706
Beta_{PI}		(0.60,1.52)	
Beta_{UI}		(0.60,0.42)	
Fraction of Data	0.672		0.328
N		5,898	
Negative Log-likelihood		−1,864	

Table 11:
Shareholder Sponsored Proposals by Proposal Types

This table reports the maximum likelihood estimates of (2) and derived statistics from the model over the data sets of all proposed items from mid 2003 through the end of 2018 parameterized by proposal types. Specifically, we modify (2) by replacing each mixing probability by the logistic function with a dummy variable for being in the first column per variable of interest. We parameterize λ and θ by an affine function of the dummy variable for being in each column. Each column has a dummy variable taking the value of one if the shareholder proposal is classified by ISS in that category, and zero otherwise. Model implied voting errors are calculated according to (13) and (14). Other model implied statistics are calculated according to (11) and (10). Percent of proposals by type are calculated from equations (6) – (9). The mean, standard deviation, and quantiles are numerically calculated from the fitted density. N is the sample size of proposed items.

	Shareholder Sponsored Proposals			
	Corporate Governance	Director Related	Compensation	Social or Environmental
Model Implied Voting Errors:				
Passed, but Bad	0.015	0.090	0.067	0.038
Failed, but Good	0.411	0.001	0.281	0.001
Other Model Implied Statistics:				
Expected Informed	0.322	0.406	0.226	0.425
Percent Good Proposals	0.790	0.455	0.437	0.006
Percent of Proposals by Type:				
Obvious and Good	0.009	0.454	0.004	0.004
Obvious and Bad	0.002	0.253	0.005	0.098
Contentious and Good	0.781	0.001	0.434	0.003
Contentious and Bad	0.208	0.292	0.557	0.896
Model Implied Moments:				
Mean	0.469	0.554	0.337	0.189
SD	0.209	0.294	0.217	0.154
Fit Parameters:				
α_o	0.821	0.642	0.410	0.035
α_c	0.790	0.002	0.438	0.003
δ	0.011	0.707	0.010	0.101
λ	0.315	0.087	0.220	0.368
θ	0.610	0.451	0.714	0.559
Beta_{PI}	(0.60,1.52)			
Beta_{UI}	(0.60,0.42)			
Fraction of Data	0.149	0.257	0.185	0.409
N	9,075			
Negative Log-likelihood	−5,058			

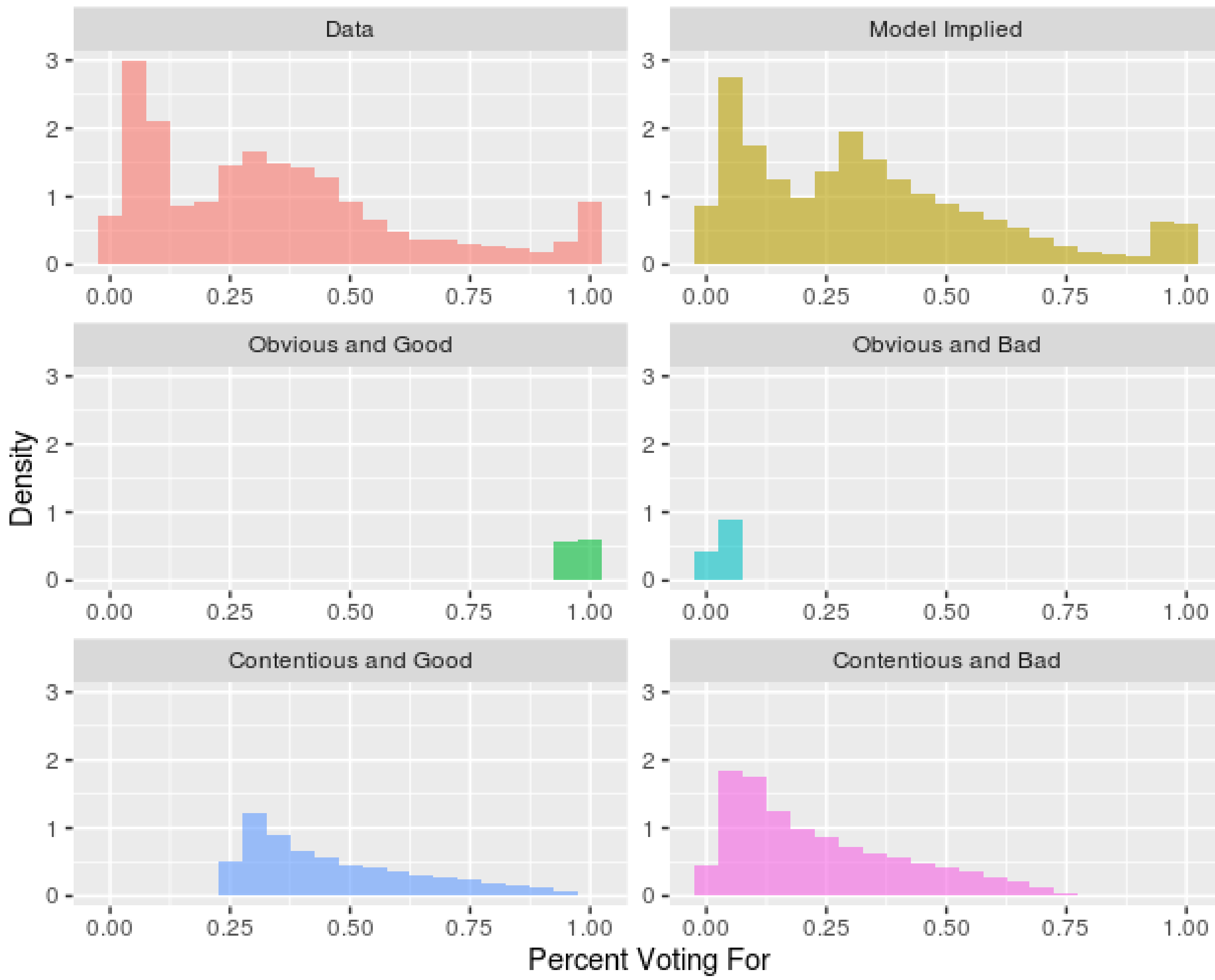


Figure 3: **Shareholder Proposals** The plots above relate to the column shareholder proposals from Table 2. All plots are on the same scale for comparability and use the Freedman-Diaconis rule applied to the underlying data to determine the optimal bin width for the histogram. All subsequent plots use this bin width for comparability, but are simulated from a larger sample size. The top left plot is of a density histogram of the data that (2) is fit. The top-right plot is the model implied density function. The bottom four plots are the relative density histograms of each branch of our model. Therefore, the sum of the bottom four plots will produce the top right plot. The bottom four plots have a total density of that listed in Table 2's section Percent of Proposals by Type.

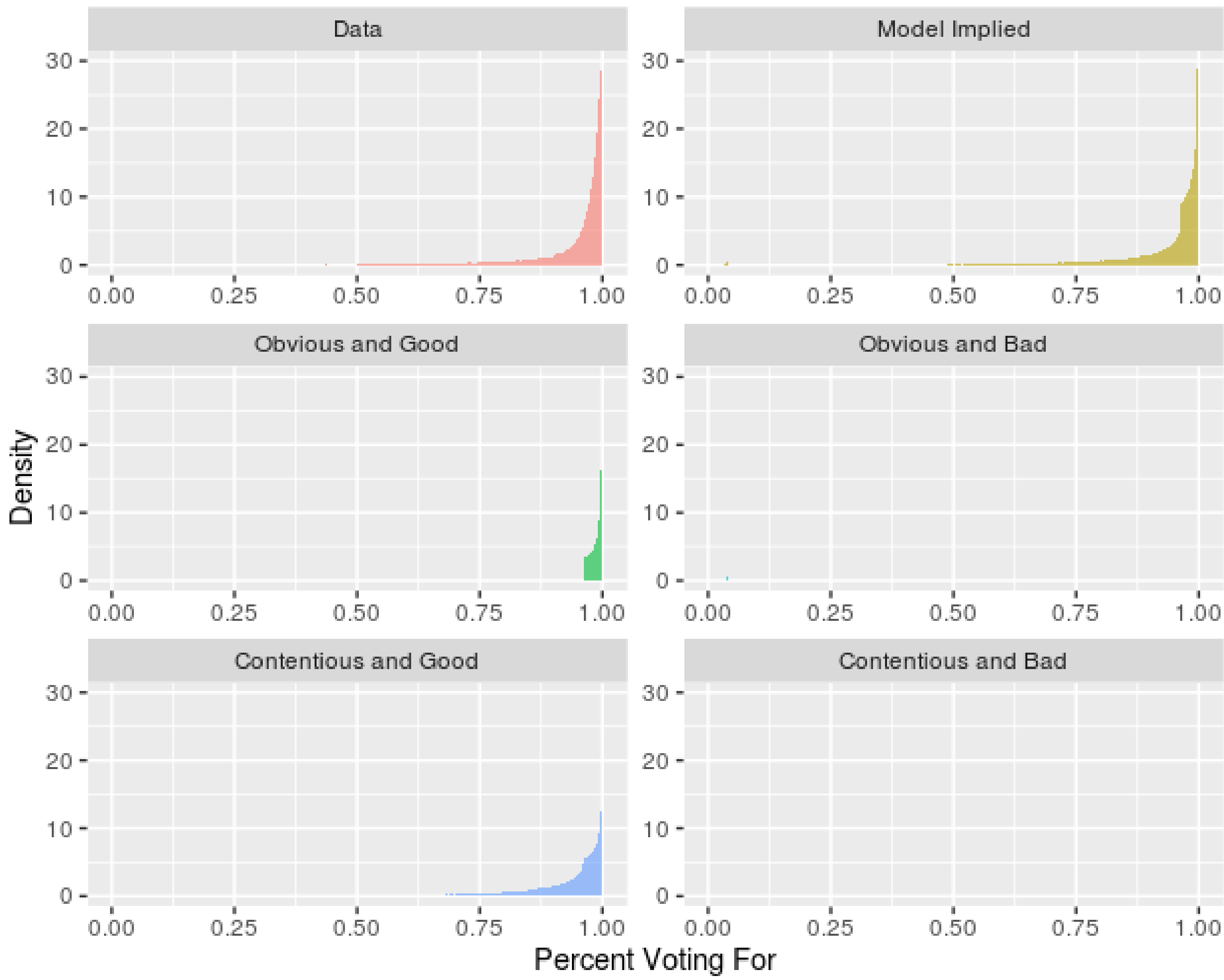
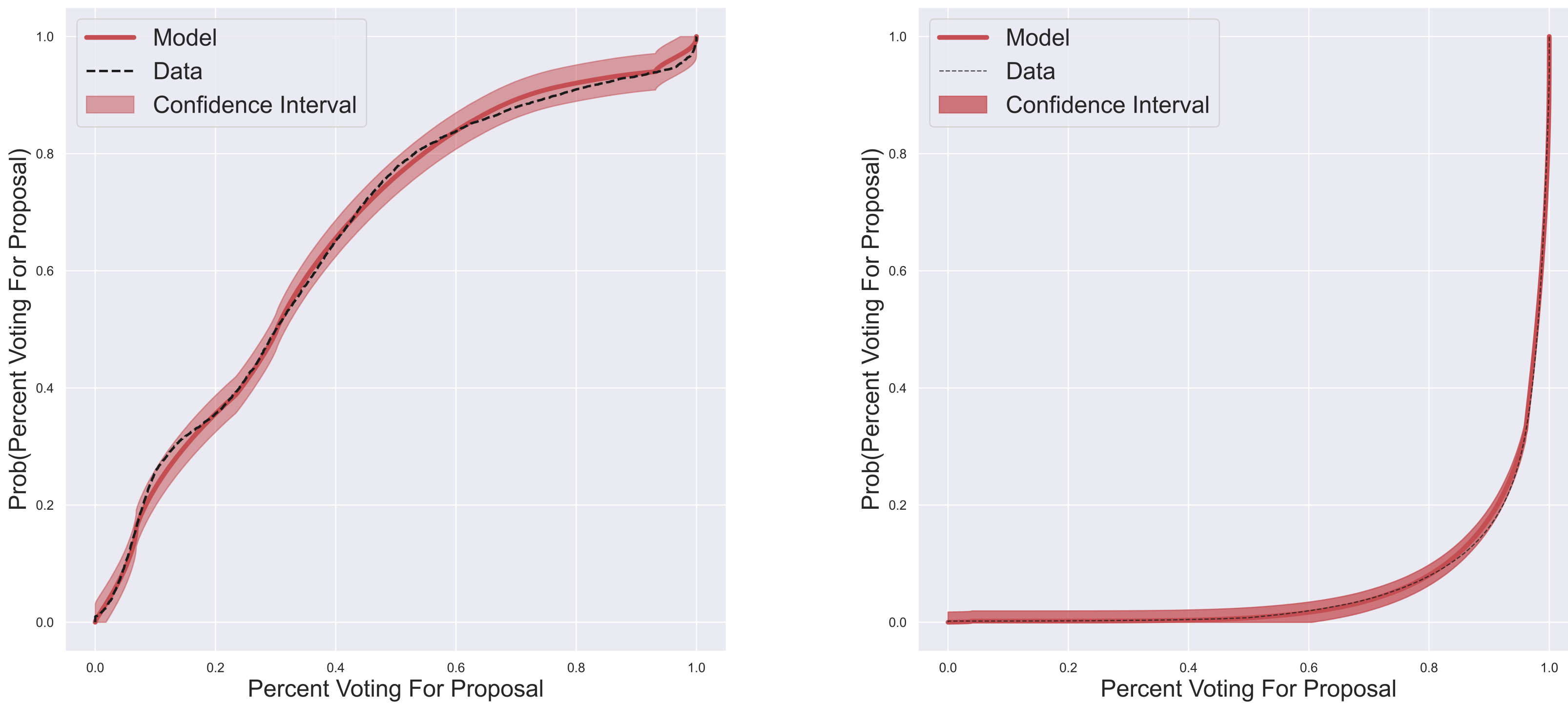


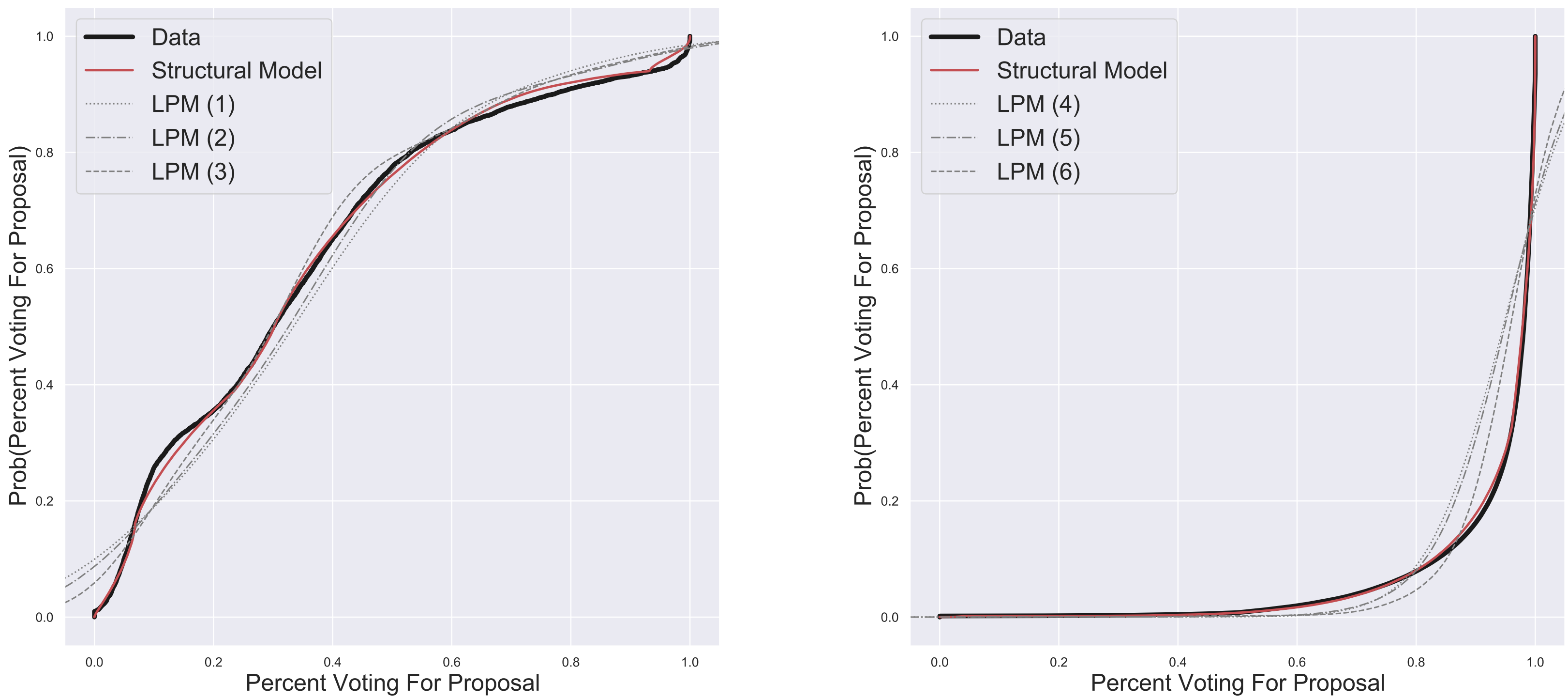
Figure 4: **Management Proposals** The plots above relate to the column management proposals from Table 2. All plots are on the same scale for comparability and use the Freedman-Diaconis rule applied to the underlying data to determine the optimal bin width for the histogram. All subsequent plots use this bin width for comparability, but are simulated from a larger sample size. The top left plot is of a density histogram of the data that (2) is fit. The top-right plot is the model implied density function. The bottom four plots are the relative density histograms of each branch of our model. Therefore, the sum of the bottom four plots will produce the top right plot. The bottom four plots have a total density of that listed in Table 2's section Percent of Proposals by Type.



(a) Shareholder

(b) Management

Figure 5: **Empirical CDF versus Model-implied CDF with Sampling & Estimation Error**
The figure plots the model-implied CDF, 90% confidence bounds due to sampling & estimation error for the model-implied CDF, and the empirical CDF of the actual data. The left panel shows the results for shareholder proposals, and the right panel shows the results for management proposals. This plot is of the empirical CDF, our model's CDF, with 90% confidence bounds. The model-implied CDF is based on parameters from Table 2. The confidence bounds come from an inversion of a bootstrapped Kolmogorov-Smirnov test at the 90% confidence level where the null is that the empirical CDF is drawn for our model's CDF, and therefore the empirical CDF from the data would be entirely contained within the bounds. The bootstrapped p-value for the Kolmogorov-Smirnov test is 0.16 (0.13), and we can therefore fail to reject the null at any confidence level less than 16% (13%) for shareholder (management) proposals. The red line is the structural model CDF, the dashed black line is the empirical CDF and the shaded red region is the 90% confidence interval.



(a) Shareholder

(b) Management

Figure 6: **Fits of Structural and Linear Probability Models**
The figure plots the empirical CDF, our model-implied CDF, and CDFs based on the linear probability models (LPMs) labeled relative to their column number from Table 3. The left panel shows the results for shareholder proposals, and the right panel shows the results for management proposals.