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When Shareholders Disagree: Trading after Shareholder Meetings

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This paper analyzes how trading after shareholder meetings changes the composition of the shareholder base. Analyzing daily trades, we find that mutual funds reduce their holdings if their votes are opposed to the voting outcome. Trading volume is high even when stock prices do not change, peaks on the meeting date, and remains high up to four weeks after shareholder meetings. The results support models based on differences of opinion that predict that shareholders' beliefs may diverge more after observing voting outcomes. Hence, trading after meetings creates a more homogeneous shareholder base, which has important implications for corporate governance. (*JEL* G11, G12, G14, G30, G40)

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A large empirical literature on shareholder voting in corporate finance analyzes why shareholders vote the way they do, and whether voting affects governance.[1]

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[1] See, for example, Iliev and Lowry (2015) and Malenko and Shen (2016) for recent papers on how shareholders vote, and Karpoff, Malatesta, and Walkling (1996) and Ertimur, Ferri, and Stubben (2010) for contributions on how voting affects governance.

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This literature takes its cues from agency theory and is based on the premise that the main conflict governance arrangements need to address is that between shareholders and management.[2] In this framework, shareholders and management may have different interests, for example, when management has the opportunity to appropriate private benefits or when voting constrains managerial discretion. Shareholders are mostly assumed to be homogeneous, and they vote differently only if they have access to different information, which is then aggregated in the voting process.

In this paper, we analyze trading after shareholder meetings and ask two main research questions. First, we ask whether shareholder votes are sufficiently meaningful to affect trades, and second, whether trading after shareholder meetings creates a shift in the shareholder base. To the best of our knowledge, no empirical study has investigated how shareholders trade after voting. We find that voting significantly affects trades, that abnormal trading volume after shareholder meetings is high, and that shareholders in our sample reduce their holdings if their vote at the meeting was contradicted by the voting outcome.

Within the framework described above, these findings are puzzling. We would not expect a systematic relationship between voting and post-meeting trades if voting only aggregates private signals.[3] Similarly, disclosures of meeting results and other news released at shareholder meetings should lead shareholders' beliefs to converge, thus reducing the need for trading.[4] Hence, we start from a different perspective and emphasize disagreement as a source of friction to explain trading after shareholder meetings. Disagreement arises in differences-of-opinion models, which assume that individuals have heterogeneous beliefs even though they are equally well-informed.[5] Disagreement may also arise from differences in preferences, but preference-based models have not been used to generate predictions about trading volume.[6]

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2 This literature is too vast to survey here. See Yermack (2010) for a survey of shareholder voting; Cuñat, Giné, and Guadalupe (2016) and Schwartz-Ziv and Wermers (2020) for contributions to the say-on-pay debate; Malenko and Shen (2016) on the role of proxy advisory firms; Brav et al. (2021) and Calluzzo and Kedia (2019) on mutual fund voting; and Fos, Li, and Tsoutsoura (2017) on director elections. All these papers contain extensive discussions of the prior literature. Relatedly, a theoretical literature builds on informational frictions, which we will discuss below, but this approach has been less influential in the empirical debate.

3 See Maug and Rydqvist (2009), Levit and Malenko (2011), and Bar-Isaac and Shapiro (2019) for models of information aggregation in shareholder voting. In a model without pre-meeting opportunities to trade (Meirowitz and Pi 2020), some information may not be aggregated and inspire trade after shareholder meetings.

4 In their discussion of the prior literature, Hong and Stein (2007) generally associate high trading volume with disagreement. Some models predict trading even if beliefs converge. We discuss these models and how to distinguish them from one another empirically in Section 1.

5 This approach has been used to explain trading volume going back to Karpoff (1986), Varian (1989), and Harris and Raviv (1993). The only application of this approach to governance that we are aware of is Kakhbod et al. (2020).

6 Several contributions have developed explanations of shareholder voting based on heterogeneous preferences, often in the context of takeovers (Matvos and Ostrovsky 2010; Van Wesep 2014; Bernhardt, Liu, and Marquez 2018; Cvijanovic, Groen-Xu, and Zachariadis 2020; Levit, Malenko, and Maug 2020). However, none of these papers provides predictions for trading volume.

In this paper, we build on theories in which individuals have different opinions because they interpret the same information differently (Harris and Raviv 1993; Kandel and Pearson 1995; Boot, Gopalan, and Thakor 2006). Commonly observed signals are ambiguous and require models to interpret them, such as models of the economy or valuation models of the firm, which reflect investors' assumptions about "how the world works." Disagreement among investors arises from differences in these models and can motivate trading decisions. Such disagreement is rational and cannot be resolved by processing more information (see Kurz 1994b and the discussion in Section 1.1.1). This aspect distinguishes differences-of-opinion models from Bayesian-learning models, which attribute differences in beliefs to differential access to information.[7]

If we look at trading decisions after shareholder meetings through the lens of differences-of-opinion models, then our empirical findings can be interpreted more easily. If shareholders have different opinions, then they trade rather than change their beliefs. Consider the example of a vote on a merger and a shareholder who believes that the synergies are too small to justify an acquisition premium, whereas the majority believes the opposite. If these beliefs are based on diverging models, for example, valuation models, then the dissenting shareholder will conclude that the company is overvalued if the merger goes through, and sell, rather than updating her beliefs based on the voting decisions of the majority.

We perform analyses at two levels. To begin, we analyze trading and voting at the fund level and ask whether there is a systematic relationship between voting and trading after the meeting. The theoretical foundation is based on Boot, Gopalan, and Thakor (2008), who analyze the public-private trade-off in a difference-of-opinion model in which the composition of the shareholder base can change. If the firm is public, then in equilibrium the shares are held by those investors whose beliefs are most closely aligned with those of the main decision-maker, in our case the majority that prevails at the shareholder meeting. In a second step, we analyze the relationship between trading volume and volatility at the meeting level, which allows us to gauge the relative importance of differences of opinions and Bayesian learning. We rely on the methodology of Bollerslev, Li, and Xue (2018) and construct measures of disagreement using proposal-level information from shareholder meetings.

We merge data on funds' daily trades from ANcerno, voting data from ISS Voting Analytics, and fund characteristics from Thomson Reuters and CRSP, resulting in a sample of 243 unique active US mutual funds and 12,794 unique fund-meeting combinations during the period from February 28, 2010 to September 30, 2011. We find that the funds in our sample are significantly more likely to reduce their holdings if their voting decision was opposed by the majority of other shareholders for at least one proposal that was voted

7 Heterogeneous-preference models can also explain how shareholders trade after voting. To the best of our knowledge, only Levit, Malenko, and Maug (2020) formulate such a model in one of their extensions.

on at the shareholder meeting. They reduce their holdings, independently of whether the fund supports management and the majority of other shareholders opposes management, or the reverse. We conclude that the fund's decision to trade after the meeting is not based on whether it supports or opposes management, but whether its view of the decision the firm should take is shared by the majority of other shareholders. We repeat this analysis for subsamples in which we distinguish several categories of routine proposals (director elections, say-on-pay proposals, auditor appointments) and nonroutine proposals, and show that the effect we document prevails for all categories of proposals. Similarly, it prevails for close as well as nonclose votes. This finding shows that models in which shareholders vote differently only if they observe different pieces of information cannot fully explain how shareholders vote and trade. In these models, shareholders update their beliefs as soon as they observe the voting result, which eliminates differences in their assessments of the value of the firm, and of their preferred decision the shareholder meeting should take. Hence, based on these models, there should be little scope for trading after shareholder meetings. By contrast, in differences-of-opinion models, shareholders rebalance their portfolios instead of updating their beliefs if their views are opposed by the majority of other shareholders.

We complement the fund-level analysis with a meeting-level analysis of trading volume around shareholder meetings. The average daily volume starting from the meeting date to 10 trading days after the meeting date is 16.5% higher than the average daily volume during the pre-voting period. We believe we are the first to document the high abnormal volume after shareholder meetings and view it as an important finding because it demonstrates a substantial reshuffling of the shareholder base after shareholder meetings. Moreover, we find significant trading volume even if price changes are small. Differences-of-opinion models are ideally suited to explain high trading volume, especially if high volume is not associated with large price changes (e.g., Harris and Raviv 1993; Kandel and Pearson 1995). Disagreement generates trading volume without price changes since shareholders with more optimistic beliefs buy from shareholders with more pessimistic beliefs without necessarily changing the valuation of the marginal investor. By contrast, symmetric-information and rational expectations models cannot generate predictions for the high abnormal trading volume we observe around shareholder votes (Milgrom and Stokey 1982), and models with asymmetric information can predict a high trading volume only if it is associated with proportionately large price changes (e.g., Kyle 1985; Kim, and Verrecchia 1991b).

We adapt the methodology of Bollerslev, Li, and Xue (2018), who build on these theoretical models. This methodology nests differences-of-opinion models and Bayesian learning models in one framework and allows us to assess their relative importance by looking at the extent to which increases in volatility and increases in trading volume are proportional to each other. We find that the trading volume and volatility are related, but much less than proportional, and that the proportionality declines significantly around shareholder meetings compared to placebo dates, which indicates more disagreement around meetings. Moreover, the degree of disagreement among shareholders can be related to six different proxies for disagreement constructed from the voting results, for example, whether ISS opposes management, whether shareholders oppose management, whether shareholders oppose ISS, or whether a meeting is a special meeting. These findings suggest that differences of opinions increase after shareholder meetings and can be related to meeting characteristics. However, while the association between volatility and trading volume declines after shareholder meetings, it does remain significant, which shows that shareholders not only disagree but also learn from each other, and Bayesian learning retains explanatory power. Furthermore, we check whether disagreement may arise from limited attention by testing whether our measure of disagreement is higher for those meetings with many other shareholder meetings on the same date, which may distract shareholders. We find no evidence that disagreement is related to limited attention.

We conclude from our analyses that a framework based on a combination of differences of opinions and Bayesian learning provides a parsimonious and coherent interpretation of the evidence: shareholder meetings may increase disagreement about firm values, and shareholders who disagree with the majority sell after shareholder meetings. We further conclude that trading after shareholder meetings aligns the shareholder base so that shareholders buy if their views are close to those of the majority of the other shareholders, whereas those whose beliefs are less aligned with the majority tend to sell. Our findings suggest that trading after meetings results in a more homogeneous shareholder base.

The shift of emphasis from an agency perspective of corporate governance to one based on divergent views between shareholders has important consequences for corporate governance, which we explore in greater detail in a separate section. The literature on disagreement argues persuasively that the cohesion between decision-makers is important for effective decision-making and that trading between decision-makers may be uniquely suited to reach efficient outcomes. The best achievable outcome may be one in which those shareholders who favor a certain decision can buy the shares from other shareholders who disagree with them. Hence, trading after shareholder meetings, and the creation of a more homogeneous shareholder base may be important for efficient decision-making inside the firm. Understanding the source of frictions is also important to make accurate prescriptions for improving governance. Whereas governance frictions attributable to agency issues usually prescribe some form of incentive alignment, and informational frictions often prescribe disclosure requirements, frictions from disagreement cannot be resolved through these strategies. Hence, creating a more homogeneous shareholder base may be critical and relevant for firm value.

Our paper contributes to the voting literature by providing novel evidence and by developing a new conceptual perspective on shareholder voting. To begin, we are first to match daily trading data with voting data, which allows us to show how funds' views, proxied by their voting stance, relate to their trading decisions. Our results indicate that funds reduce their holdings after the meeting when they observe that their vote contradicts the voting outcome. Based on quarterly holdings data, prior research shows that mutual funds reduce their holdings if they disagree with ISS's recommendation (Iliev and Lowry 2015) or when ISS's recommendation is inconsistent with management's recommendation (Duan and Jiao 2016). Based on daily data, we find that funds sell more after meetings if they agree with ISS, but the majority of other shareholders does not. Neither of these studies addresses disagreement among shareholders and Duan and Jiao (2016) treat trading ("exit") as an alternative to voting, whereas we interpret exit as a decision by shareholders to leave companies with a shareholder base that does not match their own beliefs or preferences. Further, we are also first to document high abnormal volume and volatility around shareholder meetings for extended periods after the meeting. By contrast, prior literature has focused on stock returns, with inconclusive results.[8] We show that, even when abnormal returns are virtually zero, abnormal volume and volatility around shareholder meeting are high, implying a significant shift in the shareholder base around shareholder meetings.

Our analysis also contributes to the literature on the composition of the shareholder base. Several papers relate the characteristics of the shareholder base, and notably its cohesiveness, to firm valuation. Kandel, Massa, and Simonov (2011) show that Swedish companies with a more homogenous shareholder base in terms of investors' size, age, wealth, and location have higher profitability and returns. Schwartz-Ziv and Volkova (2020) find that heterogeneity among blockholders is systematically related to lower firm valuations and suggests that the effect is causal. Brav et al. (2021) show that blockholders are more likely to target companies with a more pro-dissident shareholder base, suggesting that the composition of the shareholder base influences the likelihood of value-enhancing activism.[9] Hence, if trading after meeting creates a more homogeneous shareholder base, then it may also improve firm valuation, an implication on which we follow up when we discuss the governance implications of our findings at the end of this paper.

We document selling by shareholders who disagree with other shareholders and emphasize that these trades are very different from those suggested by the

[8] Some studies find no or negligible price effects around shareholder meetings (see Karpoff, Malatesta, and Walkling 1996; Gillan and Starks 2000; Karpoff 2001 for a survey). Other studies document significant abnormal returns around shareholder meeting dates (e.g., Cuñat, Giné, and Guadalupe 2012). Recent research indicates that management may influence close voting outcomes (Bach and Metzger 2017; Babenko, Choi, and Sen 2019).

[9] In a related context, Adams, Akyol, and Verwijmeren (2018) show that commonalities among directors improve firm performance.

literature on "exit" (Admati and Pfleiderer 2009; Edmans 2009). This literature argues that shareholders who believe managers have made suboptimal decisions may sell their shares in the company. Their trades then decrease prices and have a disciplinary impact. However, our argument emphasizes differences in beliefs between shareholders, whose disagreement-induced trades may have no price impact.

We place our paper in the context of the larger literature on disagreement models in finance. This literature originated to explain the high trading volume observed in financial markets, which is difficult to reconcile with rational expectations models.[10] The part of this literature closest to ours discusses earnings announcements (for a survey, see Bamber, Barron, and Stevens 2011) and relates differences of opinion to measures based on analyst forecasts, news releases, or social media.[11] Compared to this literature, our setup is unique in that, we can observe not only trading decisions but also voting decisions for the shareholders in our sample, which can provide, at least to some extent, a proxy for investors' priors and allow us to construct proxies for disagreement from the content of shareholder meetings.

1. Hypothesis Development

We develop hypotheses based on two different theoretical foundations: disagreement models, in which investors have differences of opinion about firm value and about which decisions are optimal for the firm even if they have access to the same information, and Bayesian learning models, in which investors share the same understanding of how to interpret publicly available information. We derive hypotheses from both frameworks. Section 1.1 derives predictions about the relationship between trading and voting at the individual fund level and Section 1.2 derives predictions at the meeting level.

1.1 Voting and trading at the individual shareholder level

In this section, we develop hypotheses about the relationship between trading and voting at the individual shareholder level to provide a theoretical framework for our analysis at the fund level for disagreement models (Section 1.1.1) and for Bayesian learning models (Section 1.1.2).

1.1.1 Voting and trading with disagreement. Boot, Gopalan, and Thakor (2008) develop a model of how the shareholder base may change endogenously

[10] Early examples include Varian (1985, 1989, 1992) and Karpoff (1986). Later contributions build on this (e.g., Harris and Raviv 1993; Kandel and Pearson 1995; Kandel and Zilberfarb 1999; Hong and Stein 2003). Hong and Stein (2007) provide a survey of this literature, and Xiong (2013) discusses the literature that explains speculative bubbles with heterogeneous beliefs.

[11] On analyst forecasts and recommendations, see Diether, Malloy, and Scherbina (2002) and Bamber, Barron, and Stevens (2011), among others. On internet news, see Fedyk (2018). On social media, see Cookson and Niessner (2020) and Giannini, Irvine, and Shu (2018).

through trading to increase agreement among shareholders and we extend their reasoning to the voting context. Consider a firm in which shareholders have to decide on anything from electing new directors to approving a merger or a change in the governance structure. They differ in their beliefs about whether or not a particular choice is value-maximizing. Shareholders first vote and then trade after voting results have been publicly disclosed. For our purposes, the key insight of Boot, Gopalan, and Thakor (2008) is that in a liquid public market with negligible search costs for finding a buyer, the firm will always be held by those shareholders who value the firm most, that is, those whose beliefs are most closely aligned with those of the main decision-maker in the firm; this is management in the model of Boot, Gopalan, and Thakor (2008), and the majority of other shareholders in the context of shareholder voting. When the current shareholders realize that the firm will adopt policies they do not endorse, whereas other investors do, the former will sell to the latter. Hence, shareholders learn two facts from the meeting: first, the decision about the proposal, which affects firm value, and second, how other shareholders voted on the same proposal, which helps them predict how they will vote in the future. Those shareholders who disagree with the majority will value the firm less than the majority of other shareholders and thus sell their shares.

Hypothesis 1 (Alignment of the shareholder base). *If shareholders disagree, then those whose vote is contradicted by the majority of shareholders at the meeting are more likely to sell after the meeting, whereas those who voted with the majority of other shareholders are more likely to buy additional shares.*

Hypothesis 1 builds on three assumptions. First, it requires that shareholders were not perfectly aligned before the meeting, for example, from trading after previous shareholder meetings. This assumption seems to be innocuous, since shareholders may change their beliefs, and the shareholder base turns over continuously because of liquidity trading so that any alignment of the shareholder base is probably temporary and easily disrupted. Second, we need to assume that shareholders do not fully know each other's beliefs, so that the extent of their disagreement comes to shareholders as a surprise; otherwise, they would have traded already ahead of learning the meeting result. This assumption is also not strong, since it is probably difficult for shareholders to predict other shareholders' opinions. Third, Hypothesis 1 is based on a notion of disagreement in which shareholders interpret the same information differently because they use different models. For example, investors may gather valuation-relevant information about different dimensions of the firm and its economic environment, for example, its product-market strategy, corporate governance, or technology. Aggregating these pieces of information requires complex models, such as a valuation model of the firm or an equilibrium model of the macroeconomy. Investors may differ with respect to the models they use, that is, their assumptions about the data-generating process. An example would be whether an observed shock to earnings is transitory or permanent.

Accordingly, investors do not update their beliefs if they learn that other economic agents have different beliefs, because they do not attribute these differences in beliefs to information they should incorporate. Note that deriving different conclusions from the same information is not irrational and consistent with assuming rational beliefs.[12]

An alternative approach to modeling disagreement assumes that agents are exogenously endowed with different beliefs, which then become a part of the description of the economy (e.g., Varian 1985; Morris 1995; Allen and Gale 1999). Models in this "heterogeneous priors" category usually assume that agents give commonly observed signals the same interpretation and update their different priors accordingly. For our purposes, this approach is less useful, since it implies that agents' beliefs converge after observing voting outcomes, whereas we need a framework that accommodates increased differences of opinions to explain trading after meetings.[13]

1.1.2 Voting and trading with Bayesian learning. In this section, we contrast the disagreement approach with models in which shareholders agree on the interpretation of publicly available information, such as the disclosure of the voting results at shareholder meetings, and we will refer to these models comprehensively as Bayesian learning models.

If all shareholders update their priors consistently with Bayes' rule after observing public information, then their beliefs will converge. This is clearly the case if shareholders have symmetric information and start out with common priors and then update their beliefs. However, if shareholders possess private information before the meeting and they agree on how new information should be interpreted, voting would aggregate private information and the disclosure of voting outcomes would reveal this commonly understood information to all shareholders.[14] Then, if shareholders' beliefs were different before the shareholder meeting because of asymmetric information, these differences in beliefs would be reduced, if not eliminated, with the disclosure of the voting results.[15] Finally, even if investors have heterogeneous priors, but

12 Kurz (1994b) defines rational beliefs as those that are not contradicted by the data, and Kurz (1994a) shows that rational beliefs do not necessarily converge to rational expectations. Acemoglu, Chernozhukov, and Yildiz (2016) show that with Bayesian learning a convergence of beliefs may not occur even if agents have access to infinitely many common observations.

13 As such, the heterogeneous-priors approach is closer to the Bayesian learning approach discussed in Section 1.1.2. Note that we deviate from Boot, Gopalan, and Thakor (2008), whose primary interest is not in modeling trading. Our argument also relaxes the assumption that shareholders have common knowledge about disagreement among themselves.

14 Maug and Rydqvist (2009), Levit and Malenko (2011), and Bar-Isaac and Shapiro (2019) all use similar settings to study information aggregation through voting. Beliefs after disclosing the voting outcome in these models always converge and are identical unless at least some shareholders do not vote according to their signals.

15 If voting at shareholder meetings is "sincere" in the sense of the literature cited in the previous footnotes, asymmetries of information are eliminated completely; otherwise, some information may remain private. See, for example, Meirowitz and Pi (2020) for a model in which shareholders strategically vote on less information, so they can trade more after meetings.

interpret new information in the same way, Bayesian updating implies that their beliefs converge after learning more information, because the weight of their heterogeneous priors will decline, so incorporating the new information from meeting results would lead to a convergence of beliefs. Hence, a robust feature of all three scenarios, (1) common priors with common information, (2) asymmetric information, and (3) heterogeneous priors, is that beliefs after the meeting will be either identical, or at least converge, as long as investors agree on how to interpret new information. In information-based models of trading, shareholders trade only if they have information other shareholders do not (yet) have. Hence, if beliefs converge and information is aggregated, the incentives to trade decline. Shareholders whose votes were contradicted by most other shareholders only learn that others had information they did not have. Consequently, while shareholders may still trade for liquidity reasons after the meeting, they would not trade on their interpretation of the voting outcome. In particular, the beliefs that made a shareholder vote for or against a particular proposal at the meeting would not be informative about trading behavior after the meeting.

Hypothesis 2 (Trading and voting with common models). *If shareholders agree on the interpretation of commonly observed information, such as voting results, then their direction of trade after the meeting is independent of their voting stance at the meeting.*

Hence, if shareholders use the same models of the world to interpret voting results, they will tend to hold on to their portfolio and revise their beliefs after shareholder meetings.[16] By contrast, disagreement models predict that shareholders hold on to their beliefs and revise their portfolio holdings.

The discussion above and Hypothesis 2 rely on the assumption, standard in most Bayesian learning models, that shareholders not only interpret the commonly observed signal in the same way but also give the new information the same weight relative to their prior. However, consider a situation in which shareholders observe signals of different precisions before they vote such that some shareholders are better informed than others. After observing the voting results, the shareholders with more precise information will change their beliefs less compared to those with less precise information. In this case, shareholders with more precise information at the voting stage who find themselves in the minority may conclude that the other shareholders were less informed. We do not formulate hypotheses on the direction of trades based on such a model because the predictions of such a model would depend on important details. For example, in such models, the less-informed shareholders should abstain from voting (see, e.g., Feddersen and Pesendorfer 1996; Bar-Isaac and Shapiro 2019). Moreover,

[16] The next section provides a more detailed discussion about models that predict trading even after beliefs converge because of Bayesian updating, for example, if investors have different levels of risk aversion.

management should choose not to implement a proposal passed by less-informed shareholders (Levit and Malenko 2011). However, models with differently precise signals can be tested based on observations of volume and volatility at the meeting level, which we explore in the next section.

1.2 Voting, trading, and volatility at the meeting level

This section shows how Bayesian learning models, in which shareholders differ regarding the precision of their information can be distinguished from disagreement models by analyzing meeting-level information. The meeting-level analysis builds on the model of Kandel and Pearson (1995) (henceforth KP), which is attractive because it combines aspects of Bayesian learning and disagreement and can be used to nest models with different assumptions on how shareholders form beliefs. We provide a brief outline of the model here, with as many details as necessary to develop empirical implications and defer the more technical details to the Appendix.

Let V_{it} denote trading volume in some period t for some stock i and let ΔP_{it} denote price changes at time t for the same stock. All investors observe a public signal of the asset payoff (e.g., an earnings announcement), but they disagree on its interpretation. In particular, some investors are endowed with optimistic priors and some with pessimistic priors of the signal (i.e., earnings forecasts). Then the same signal value provides a negative (positive) surprise for investors with optimistic (pessimistic) priors about the signal. In addition, the two types of investors differ with respect to the precision of their priors. Suppress the index i and let all symbols refer to some representative stock. Then the KP model predicts that

$$V_t = |\beta_0 + \beta_1 \Delta P_t|. \tag{1}$$

According to KP, $|\beta_0|$ increases with disagreement and equals zero if investors share the same *interpretation* of the signal, whereas $|\beta_1|$ increases with the difference in the precision of their signals and equals zero if shareholders have the same *precision* of the signal (see Equation (A1) in the Appendix). Interestingly, whether investors have common priors or heterogeneous priors about firms' future cash flows, as opposed to priors about the signal, does not matter for the parameters β_0 and β_1, that is, for the relationship between price changes and trading volume.[17]

1.2.1 Volume and volatility in different models. The KP model nests three other models that have implications for the relation between volume and volatility.

[17] Note that we use the term "heterogeneous priors" only to refer to those differences-of-opinion models that model disagreement as differences of priors about the outcome variable (e.g., earnings, firm value). By contrast, we use the terminology "models" or "interpretations" of commonly observed information to refer to different theories, such as Kandel and Pearson (1995), in which investors have different priors about the *signals* that help them predict this outcome variable.

Symmetric information. Both types of investors share the same interpretation of the signal and give the same weight to the signal when they update their beliefs. Then $\beta_0 = 0$, $\beta_1 = 0$, and trading volume is zero. This reflects the classic no-trade result for rational expectation models, because rational traders cannot agree on a trade that is mutually beneficial if both sides have rational expectations and make correct inferences from fully revealing stock prices (Milgrom and Stokey 1982; Tirole 1982).[18] Such a model forms a natural theoretical benchmark, even though it has no explanatory power in our context.

Bayesian learning only. Both types of investors agree on the interpretation of the signal and $\beta_0 = 0$, but they have different qualities of prior information, so that some investors have more precise priors and give less weight to the common signal than others. Then $\beta_1 \neq 0$ and $V_t = |\beta_1 \Delta P_t|$ so volume is proportional to price changes.[19] The motivation to trade arises because shareholders give different weights to the new information, even if they interpret it in the same way. Such a model implies that higher trading volume is associated with correspondingly larger price changes. Note that the same prediction can be obtained from a model in which investors are asymmetrically informed (e.g., Kyle 1985), in which trading volume and price changes are also proportional.

Disagreement only. If both types of investors are symmetrically informed and attribute the same precision to the public signal and their priors, but disagree on the interpretation of public signals, then $\beta_1 = 0$ and $\beta_0 \neq 0$: trading volume is positive, but unrelated to price changes ($V = |\beta_0|$). With disagreement, investors with lower valuations sell to those with higher valuations, which generates trades but may not be associated with price changes. In the KP model, stock prices are a weighted average of investors' valuations, and these averages may remain unchanged even if the individual valuations of all investors change.[20]

General model with disagreement and Bayesian learning. The KP model itself allows for differential prior information ($\beta_1 \neq 0$) and disagreement ($\beta_0 \neq 0$) and nests all the three other models above as special cases.

1.2.2 Testing the Kandel-Pearson model.

Bollerslev, Li, and Xue (2018) derive testable implications from the KP model. Let m denote expected volume and let σ denote volatility. Then define the elasticity of volume with respect to

18 These models are slightly different in that investors have asymmetric information before trading and can infer information only from the price. It takes a considerable modeling effort to generate trading volume in rational models with common priors, for example, by introducing frictions in the trading process and different preferences (see Karpoff 1986; Kyle and Wang 1997).

19 This proportionality obtains also in the model of Kim, and Verrecchia (1991a, 1991b). Their model builds on the same assumptions. In their model, market participants differ in their risk aversion and prior information but interpret new information identically.

20 Söderlind (2009) extends this result to a consumption-based asset-pricing model. Hence, we obtain a robust implication of disagreement models.

volatility and denote it by $\epsilon \equiv \frac{\partial ln(m(\sigma))}{\partial ln(\sigma)}$. (See Equation (A2) in Appendix A and the explanations there for more details.) Based on the discussion above, we can distinguish the general KP model with disagreement and Bayesian learning and the three special cases discussed in the previous section with respect to their assumptions and predictions about this elasticity:

	Assumptions		Predictions			
Model	Precision signal	Interpretation signal	**V**	β_0	β_1	ϵ
Symmetric information	=	=	0	0	0	Not defined
Disagreement only	=	≠	>0	≠0	0	0
Bayesian learning only	≠	=	>0	0	≠0	1
Disagreement with Bayesian learning (KP)	≠	≠	>0	≠0	≠0	$0<\epsilon<1$

Hence, we can think of pure disagreement as an extreme case, in which investors trade as they update their valuation of the firm in the light of new signals, but without learning from each other. Then there is no relationship between trading volume and price changes ($\epsilon=0$). By contrast, a model with only Bayesian learning is at the other end of the spectrum, since it implies a strict proportionality between trading volume and price changes ($\epsilon=1$). The general, and likely the most realistic case, combines disagreement with Bayesian learning, so that shareholders disagree to some extent on the interpretation of new information, but to some extent, they also learn from each other. This is the general KP model in which $0<\epsilon<1$, and ϵ decreases with disagreement and increases with the degree to which investors learn from each other, so that ϵ can be regarded as a measure that expresses the relative importance of disagreement and Bayesian learning. Models with symmetric information are included as a theoretical benchmark, but for them the volume-volatility elasticity ϵ is undefined since trading volume is zero.

1.2.3 Heterogeneous preferences. We have derived Hypothesis 1 from a framework in which disagreement is created by differences of opinions. However, similar predictions may also emerge from differences in preferences. Shareholders may have heterogeneous preferences for a variety of reasons, such as differences in attitudes to social, political, and environmental issues ("investor ideology"), risk, tendency to support management, tendency to follow ISS recommendations, human-capital investments in the firm, investment time horizon, cross-ownership with other firms, or tax status.[21] Levit, Malenko, and Maug (2020) develop a model of shareholder voting and

[21] Many studies document the importance of several dimensions of shareholder preferences for how shareholders value firms and evaluate firms' strategies. A nonexhaustive list includes the following aspects: tax status, Bagwell (1991) and Desai and Jin (2011); investors' time horizon, Bushee (1998) and Gaspar, Massa, and Matos (2005); human capital investments, Fos and Jiang (2016); associations

trading, in which shareholders are distributed along a continuum that ranges from "conservative" shareholders, who prefer the status quo, to "activist" shareholders, who prefer adoption of the proposal. In one of their extensions, they show that shareholders trade before and after the vote, and that those shareholders who are more likely to support the proposal are also more likely to sell (buy) if the majority votes against it (in favor). Such a preference-based model is probably isomorphic to a model based on differences of opinion regarding the predictions on the directions of trade (Hypothesis 1) derived in Section 1.2.1. However, we are not aware of a preference-based model of voting and trading that also has predictions on trading volume corresponding to those of the KP model. Therefore, we rely on differences-of-opinion models to guide our discussion in the remaining part of this paper, keeping in mind the potential isomorphism between preferences and beliefs discussed above.

2. Data and Institutional Context

This section describes how we collect the data and construct the sample (Section 2.1) and the institutional context (Section 2.2).

2.1 Data and sample selection

In this section, we describe the data sets used in the paper. The data set we use is defined by the intersection of mutual fund data for which we have trading records and data on voting. Table B1 in Appendix B defines the variables.

Mutual fund daily trading data. ANcerno Ltd. provides institutional trading data with fund identification for the period between January 1, 1999, and September 30, 2011. ANcerno (also known as Abel Noser) is a consulting firm working with institutional investors to monitor execution costs. The ANcerno database captures clients' complete transaction histories, including the date of execution, execution price, number of shares traded, and whether the transaction is a buy or sell. The database does not disclose the names of the funds but anonymizes them by assigning its own unique fund identifier to each trade. Hence, we employ the matching procedures of Busse et al. (2021) to match the mutual funds in ANcerno to the quarterly holdings data of mutual funds in Thomson Reuters Mutual Fund Holdings (formerly CDA/Spectrum S12) over the period from January 1999 to September 2011. After September 30, 2011, ANcerno does not provide the fund identifier anymore, so we cannot match later trades to funds and their votes. Hu et al. (2018) describe the ANcerno data and the studies that have used these data. Puckett and Yan (2011) estimate that, while the institutions included in ANcerno are larger than the average 13F

with labor interests, Agrawal (2012) and Kim and Ouimet (2014); investor ideology and social preferences, Bolton et al. (2020) and Bubb and Catan (2020); private benefits from managing firms' pension funds, Cvijanovic, Dasgupta, and Zachariadis (2016) and Davis and Kim (2007); and cross-ownership, Cvijanovic, Dasgupta, and Zachariadis (2016) and He, Huang, and Zhao (2019).

institution, they are similar to 13F institutions with respect to stock holdings, stock trades, and return characteristics. We further match the S12 funds to the CRSP mutual fund data and CRSP-Compustat merged database. Our final sample includes only funds for which we can observe at least one trade from 15 months before to 9 months after a meeting date.

Voting data. Voting outcomes are obtained from the ISS Voting Analytics database. This data set documents the aggregate voting outcomes for each proposal that came up for a vote at a shareholder meeting. These outcomes are reported in 8-K, 10-Q, and 10-K filings. In addition, the ISS Voting Analytics database includes funds' votes, ISS's recommendations, management recommendations, proxy filing dates, outcome filing dates, and data on the votes cast by mutual funds reported on SEC form N-PX. For meetings held before February 28, 2010, companies were required to report voting outcomes in 10-K or 10-Q filings. This practice resulted in long reporting lags, 51 days on average, that make these data unusable for our purposes, which require daily price responses. Therefore, we do not use data for the period before February 28, 2010. For meetings held on or after February 28, 2010, companies were required to report the voting outcome on form 8-K within 4 days of the meeting. We limit the analysis to firms that file form 8-K within 4 days of the meeting date, as required by law.

Mutual fund holding data. We match the funds to the CRSP mutual fund data through the MFLINK data provided by WRDS (see Wermers 2000). Data on mutual fund holdings are obtained from the CRSP mutual fund holding files. We match these data to ISS Voting Analytics using the approach of Schwartz-Ziv and Wermers (2020).

Daily trading measures. The Trade and Quote (TAQ) database provides the trades for all individual securities listed on the NYSE, NASDAQ, and AMEX stock exchanges. We use TAQ to estimate daily volatility and number of trades and use CRSP to obtain data on daily volume and returns.

Company data. Data on stock and accounting performance at the company level are obtained from CRSP and Compustat, respectively.

Event dates. We obtain shareholder meeting dates from ISS Voting Analytics. We manually collect the dates on which voting outcomes are filed, the proxy filing dates, and the 8-K, 10-Q, and 10-K filing dates by using Seek Edgar to search through SEC filings. We search within 8-K, 10-K and 10-Q filings for the phrases "vote for," "votes for," or "voted for," or for tables that include the words "against" and "abstain"; "against" and "withheld"; or "against" and "broker."[22] For each of these filings, we record the exact time

[22] If a firm filed a preliminary proxy statement before a definitive proxy statement, we use the date of the preliminary proxy statement as the proxy filing date because preliminary proxy filings typically include almost all the information of the definitive proxy statement.

Table 1
Summary statistics

A. Sample size

Item	Total
Company-level data (February 28, 2010 to June 30, 2013):	
Number of unique companies	3,463
Number of unique shareholder meetings	10,701
Fund-level data (February 28, 2010 to September 30, 2011):	
Number of unique actively managed funds	243
Number of unique index funds	44
Number of unique institutions advising funds	51
Number of unique fund-meeting combinations for actively managed funds	12,794
Average number of proposals per meeting	7

B. Descriptive statistics

Variable	Mean	25th	50th	75th	SD
Abnormal return (%)	−0.014	−0.796	−0.044	0.724	1.731
Abnormal volatility	0.110	−0.212	−0.020	0.256	0.574
Abnormal volume	0.037	−0.370	−0.151	0.182	1.041
Assets under management (in millions)	2,769.1	207.7	738.9	2,567.2	5,495.0
Book-to-market ratio	0.660	0.329	0.550	0.868	0.569
Buy	0.023	0	0	0	0.152
Contradict	0.278	0	0	1	0.448
Contradict, fund against management	0.235	0	0	0	0.424
Contradict, fund with management	0.052	0	0	0	0.221
Expense ratio (in fraction)	0.009	0.004	0.011	0.013	0.005
Fraction of company held (in bps)	26.85	1.23	5.56	27.10	59.04
Market capitalization (in millions)	22,416	1,411	4,477	18,971	46,532
Net fraction of company bought (in bps)	−0.002	0	0	0	0.078
Net fraction of portfolio bought (in bps)	−0.095	0	0	0	3.090
Portfolio weight (in bps)	66.742	13.000	42.000	95.000	75.527
Sell	0.029	0	0	0	0.170
Turnover ratio	0.753	0.420	0.650	0.950	0.521

Panel A reports summary statistics for the sample size. Panel B reports descriptive statistics of our main variables (variables are defined in Table B1).

the form was filed. If the filing time is between 4:00 p.m. and 5:30 p.m., we classify the next trading day on which investors were able to start trading on the information as the filing date.[23] Daniel Metzger generously provided the record dates to us.

ISS recommendation date. These dates are obtained directly from ISS and are not included in ISS Voting Analytics.

We construct two data sets from merging the data sources described above. One data set is at the company-meeting level and the other one at the fund-meeting level. Both data sets begin on February 28, 2010 (see above). Panel A of Table 1 provides quantitative information on both data sets. More details on the construction of both data sets can be found in Table A1 in the Internet Appendix. The company-level data set includes 10,701 unique meetings held by 3,463 unique companies during the period between February 28, 2010,

23 Filings filed after 5:30 p.m. are automatically assigned to the following trading day by the SEC, and, thus, we do not need to adjust these filing dates.

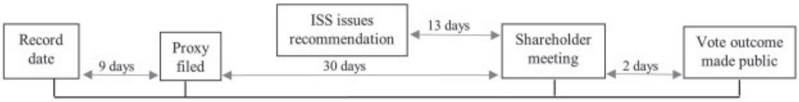

Figure 1
Timeline
The timeline lists the average number of trading days between events. All numbers correspond to the period of February 28, 2010 to June 30, 2013.

and June 30, 2013. On average, shareholders vote on seven proposals at each meeting. The fund-level data set covers 243 unique actively managed U.S. mutual funds during the period between February 28, 2010 and September 30, 2011. We restrict the analysis to actively managed funds because only these funds can make trading decisions, but sometimes we use index funds as a control group. The funds in our sample are advised by 51 unique financial institutions, including almost all large financial institutions. Panel B of Table 1 reports descriptive statistics of the main variables.

2.2 Institutional context and timeline around shareholder meetings

Companies typically hold one shareholder meeting per year, during which they vote for the slate of directors proposed by management, approve the auditors proposed by management, and, since 2011, vote on say-on-pay. Shareholders also vote on additional nonroutine proposals, sponsored by management or shareholders, if such proposals are submitted. Figure 1 reports the typical timeline around shareholder meetings between February 28, 2010 and June 30, 2013. It documents that the average number of trading days from the record date (the date used to determine which shareholders are eligible to vote) to the proxy filing date is nine, and from the proxy filing date to the annual shareholder meeting date is 30. We note that proxy filings include substantial information (e.g., the proposed slate of directors and the executive compensation awarded). Figure 1 also reports an average of 13 trading days between the date ISS issues its voting recommendation and the meeting date. As reported in Figure 1, the average number of trading days between the shareholder meeting date and the date the voting outcome is formally filed ("outcome date") is equal to two.

Between the meeting date and the filing of the voting outcome, companies are permitted to issue a press release announcing the voting results.[24] It is common for companies to issue such a press release (Garner, Geissinger, and Woodley 2017). However, the information included in the press release may vary. For example, in the 2017 proxy season, both General

[24] The SEC notes in its Final Rule on Proxy Disclosure Enhancement that "our amendments to Form 8-K are not intended to preclude a company from announcing preliminary voting results during the meeting of shareholders at which the vote was taken and before filing the Form 8-K, without regard to whether the company webcast the meeting" (see Final Rule at https://www.sec.gov/rules/final/2009/33-9089.pdf, p. 62, footnote 173). We thank Kobi Kastiel for clarifying this for us.

Motors (GM) and Walmart issued press releases on their shareholder meeting dates. Walmart specified the support rate for each voting outcome whereas GM only noted that the proposals passed, but did not reveal the support rates, which were relatively low compared to those of other companies and were only disclosed in the 8-K filing.

Investment advisors, which include mutual funds, typically cast their votes electronically through their proxy advisor. Once the vote is cast, Broadridge (the company that manages electronic voting), the proxy advisor, and the firm can observe the votes cast (Bach and Metzger 2019), but they are all required to keep the observed votes confidential. Nevertheless, it is possible that information pertaining to the votes already cast leaks before the meeting date. Shareholders may also infer the expected voting outcome if management reaches out to them before the meeting in an attempt to persuade them to vote in a certain direction.[25]

3. Trading and Voting at the Fund Level

We begin the analysis with a discussion of the shareholder-alignment hypothesis (Hypothesis 1, see Section 1.1). To test the hypothesis, we relate funds' trading decisions after shareholder meetings to their voting behavior at the meeting itself. We run the following regression at the fund-meeting-trading day level:

$$\textit{Trading outcome}_{ijt}=\beta_0 \textit{After}_{jt}+\beta_1 \textit{Contradict}_{ij}\times \textit{After}_{jt}+\gamma X_{ijt}+\mu_{ij}. \quad (2)$$

We capture the trading behavior of fund i in a firm with meeting index j on day t by using multiple definitions of $\textit{Trading outcome}_{ijt}$. The different definitions of $\textit{Trading outcome}_{ijt}$ are defined further below.

Since each meeting agenda includes multiple elections and proposals, we capture disagreement by investigating whether a particular fund was contradicted by the majority of the other shareholders on at least one proposal. Hence, our main independent variable to test the shareholder-alignment hypothesis is the dummy variable $\textit{Contradict}_{ij}$, which equals one if the voting behavior of fund i is opposed by the majority of other shareholders at meeting j for at least one proposal voted on at that meeting, that is, if the fund voted in support of at least one proposal and that same proposal failed, or if the fund voted against at least one proposal and that same proposal passed; otherwise, $\textit{Contradict}_{ij}$ equals zero. For each meeting, we include all days from the proxy filing date until 30 days after the meeting, and the dummy variable $\textit{After}_{jt}$ equals one for days in the [0, 30] window after the meeting including the meeting date itself.[26] We interact $\textit{After}_{jt}$ with $\textit{Contradict}_{ij}$ to capture how

[25] Recent research suggests that management may successfully influence voting outcomes (e.g., Bach and Metzger 2017; Babenko, Choi, and Sen 2019).

[26] Analyses with more symmetric event windows in which we limit observations to a maximum of 30 trading days before the event yield almost identical results.

funds' trading behavior after meetings is affected by being contradicted at the meeting. In addition, we include fund $\times$ meeting fixed effects μ_{ij}, and a set of controls X_{ijt}, which include the fund's assets under management, the fraction of a company's shares outstanding held by the fund, the company's weight in the fund's overall portfolio, the fund's expense ratio and turnover ratio, and the company's book-to-market ratio.

In addition to testing the shareholder-alignment Hypothesis 1, we are interested in whether funds' trading behavior reflects whether or not they support management, and whether opposition to management confounds opposition by other shareholders. Hence, we further define two dummy variables:

1. *Contradict*, *fund with management*$_{ij}$ is a dummy variable that equals one if, for at least one proposal, the fund consistently voted with management's recommendation and the voting outcome of that same proposal was against management's recommendation; the dummy variable equals zero otherwise.

2. *Contradict*, *fund against management*$_{ij}$ is a dummy variable that equals one if, for at least one proposal, the fund voted against management's recommendation and the voting outcome of that same proposal was consistent with management's recommendation; the dummy variable equals zero otherwise.

Variables 1 and 2 provide a breakdown of the variable *Contradict*$_{ij}$ for all proposals on which management issued a recommendation by conditioning on whether the fund votes with or against management. Note that these variables are not mutually exclusive, because a fund can vote with management's recommendation on one proposal and against management's recommendation on a different proposal at the same meeting, and the fund may vote against the majority of the other shareholders on both proposals. Accordingly, we run the following extension of regression (1):

$$\begin{aligned} \textit{Trading outcome}_{ijt} = & \beta_0 \textit{After}_{jt} + \beta_1 \textit{Contradict fund with management}_{ij} \times \textit{After}_{jt} \\ & + \beta_2 \textit{Contradict, fund against management}_{ij} \times \textit{After}_{jt} + \gamma X_{ijt} + \mu_{ij}. \end{aligned} \quad (3)$$

According to our main hypothesis, we expect that it is the disagreement with other shareholders that matters and not whether the fund opposes or does not oppose management, hence we predict that $\beta_1 = \beta_2$.

We define four variables to capture *Trading outcome*$_{ijt}$ in Equations (2) and (3):

1. *Sell*, a dummy indicator equal to one if the fund sells the stock on the observation day, and zero otherwise.
2. *Buy*, a dummy indicator equal to one if the fund buys the stock on the observation day, and zero otherwise.
3. *Net fraction of portfolio bought* (in basis points, henceforth "bps"), which is equal to the net dollar value of shares bought by the fund on a

given day in a given firm, multiplied by 10,000 and divided by the total dollar value of the fund's overall portfolio at the end of the most recent quarter.

4. *Net fraction of company bought* (in bps), which is defined as the net number of shares bought by the fund in a given firm on a given day, multiplied by 10,000 and divided by the number of the firm's shares outstanding.

Sell and *Buy* are dummy variables for trading directions (for a similar approach, see Wermers 1999; Puckett and Yan 2011), whereas the other two measures capture the magnitude of funds' trading decisions after shareholder meetings (for a discussion of different ownership measures, see Fich, Harford, and Tran 2015).

3.1 Baseline analysis

Table 2 provides the results for estimating Equations (2) and (3) for all four definitions of trading outcomes. For brevity, we report the results for the main variables, but not those for the control variables, which can be found in Table A2 in the Internet Appendix. The coefficients of interests are those on the interactions of the *Contradict* variables with *After*. The shareholder-alignment hypothesis predicts that funds sell more shares and buy fewer shares after meetings in which their votes contradicted those of the majority of other shareholders; that is, we predict the coefficient β_1 (and β_2) in regressions (2) and (3) to be positive with *Sell* as the dependent variable, and negative with *Buy* as the dependent variable. We find strong evidence for these predictions. In column 1, the coefficient for $Contradict_{ij} \times After_{jt}$ indicates that, after a meeting in which funds' votes are contradicted by other shareholders, funds are 0.53% more likely to sell their shares. Similarly, the same interaction and *Buy* as the dependent variable in column 3 shows that funds reduce the probability of buying after being contradicted by 0.48%. Both effects are statistically highly significant. The absolute magnitudes are small, since all variables are measured on a daily basis and funds do not trade most stocks on most days. However, we can evaluate economic significance relative to two benchmarks. First, we observe that the magnitude of the effect on being contradicted (0.0053 for *Sell*, -0.0048 for *Buy*) is about twice that of trades by other funds that are not contradicted at the meeting, which is measured by the coefficient for *After* (-0.0021 for *Sell*, -0.0023 for *Buy*). Second, we compare the effect to the unconditional probability of funds to sell (buy) a stock, calculated as the average frequency of selling (buying) a stock on any given trading day, which is 2.9% (2.3%) and reported at the bottom of Table 2. Hence, funds increase their probability of selling after being contradicted by about 18% (=0.0053/0.029) relative to the baseline probability of selling and reduce their probability of buying by 21% (=0.0048/0.023) relative to the baseline probability of buying.

Table 2
Fund trades after shareholder meetings

	Sell		Buy		Net fraction of portfolio bought		Net fraction of company bought	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
After	−0.0021***	−0.0020***	−0.0023***	−0.0024***	−0.0887***	−0.0870***	−0.0018***	−0.0018***
	(−3.753)	(−3.760)	(−4.632)	(−4.811)	(−8.918)	(−8.796)	(−7.088)	(−7.212)
Contradict × After	0.0053***		−0.0048***		−0.0678***		−0.0021***	
	(5.249)		(−5.154)		(−3.697)		(−4.481)	
Contradict, fund with		0.0033*		−0.0033*		−0.0786**		−0.0017*
management × After		(1.664)		(−1.791)		(−2.171)		(−1.854)
Contradict, fund against		0.0056***		−0.0046***		−0.0696***		−0.0020***
management × After		(5.183)		(−4.715)		(−3.579)		(−4.067)
Fund × Meeting FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.13	.13	.102	.102	.138	.138	.108	.108
N	560,534	560,534	560,534	560,534	560,534	560,534	560,534	560,534
F-test contrasting interaction terms		1.02		0.450		0.05		0.09
Prob>F		0.312		0.503		0.823		0.765
Unconditional mean	0.029		0.023		−0.095		−0.002	

This table reports results for regressions of funds' trades during the February 28, 2010 to September 30, 2011 period. For each meeting, the analyses include the period from the proxy filing date to 30 trading days after the meeting date. The odd-numbered columns report results on the following regression at the fund-meeting-trading day level:

$$Trading\ outcome_{ijt}=\beta_0\ After_{jt}+\beta_1\ Contradict_{ij}\times After_{jt}+\gamma X_{ijt}+\mu_{ij}.$$

The dependent variables for trading outcomes are $Sell_{ijt}$, Buy_{ijt}, $Net\ fraction\ of\ portfolio\ bought_{ijt}$ and $Net\ fraction\ of\ company\ bought_{ijt}$. All variable definitions are provided in Table B1. The even-numbered columns report results on the following regression at the fund-meeting-trading day level:

$$Trading\ outcome_{ijt}=\beta_0\ After_{jt}+\beta_1\ Contradict,\ fund\ with\ management_{ij}\times After_{jt}+\beta_2\ Contradict,\ fund\ against\ management_{ij}\times After_{jt}+\gamma X_{ijt}+\mu_{ij}.$$

We include fund × meeting fixed effects and controls for the fund's assets under management, the fraction of the company held by the fund, the company's weight in the fund's overall portfolio, the fund's expense ratio and turnover ratio, and the firm's book-to-market ratio. The even-numbered regressions report an F-test examining whether the coefficients for *Contradict, fund with management* × $After$, and *Contradict, fund against management* × $After$ are statistically different from each other. t-statistics are reported in parentheses. *$p<.1$; **$p<.05$; ***$p<.01$.

We consider the effects to be economically meaningful when compared to these two benchmarks.

Columns 5 and 7 provide the results for the continuous variables and show that funds sell 0.0678 bps (0.0021 bps) relative to their portfolio (their holdings of the company) if their votes are contradicted by the majority of other shareholders. Funds contradicted at a meeting are more likely to sell their stock, and both effects are significant at the 1% level. We benchmark them in the same way as the binary variables above. The economic magnitudes are the same as the after-meeting trades of funds that are not contradicted: for example, the coefficient for *After* is −0.0887 bps, that on *Contradict* × *After* is −0.0678 bps in column 5. Similarly, a decrease in *Net fraction of portfolio bought* of 0.0678 bps represents an increase of 71% (=0.0678/0.095), and the decrease in *Net fraction of company bought* of 0.0021 bps represents an increase of 105% (=0.0021/0.002) compared to the corresponding unconditional mean. Hence, the impact of disagreement on trading has about the same magnitude as the two benchmarks and is therefore economically meaningful.

In the even-numbered columns of Table 2, we condition on whether the fund supports or opposes management. Funds that are contradicted by the majority of other shareholders are 0.33% (0.56%) more likely to sell, and they are 0.33% (0.46%) less likely to buy if they support (oppose) management. The estimates for the continuous variables in columns 5 and 7 are even closer to each other, and all effects are significant at least at the 10% level. We examine whether the effects for supporting and for opposing management are statically different from each other and report the corresponding F-test at the bottom of Table 2. The p-values for these F-tests are .31 or higher. Thus, being contradicted by the voting outcome affects funds' tendency to sell or buy stocks after the meeting to about the same degree, independently of whether they supported or opposed management.

Taken together, our findings provide strong support for Hypothesis 1 and the argument that trading after meetings aligns the shareholder base. They support the shareholder alignment hypothesis and the conclusion that disagreement matters, and do not suggest that shareholders' beliefs converge after observing meeting outcomes.

3.2 Proposal characteristics

The discussion in the previous section pools all observations in our sample. However, it may be the case that disagreement depends on characteristics of the proposal and that our results in Table 2 are concentrated in certain subsets of proposals. In this section, we differentiate proposals by type, proposal sponsor, and the margin of victory. This analysis is necessarily explorative, since we have to be agnostic about which results we should expect for different types of proposals. Shareholders may vote in favor or against a certain proposal, either because of private information or because they disagree.

We begin by investigating whether disagreement is stronger when shareholders vote on nonroutine proposals, as opposed to when they vote on routine proposals. First, we identify four proposal types, the first three of which are routine: (A) director elections, (B) say-on-pay votes, (C) appointments of auditors, and (D) all other non-routine proposals not included in categories (A) to (C). We now define the dummy variable $Contradict_{ij}(proposal\ type)$ such that it equals one if and only if fund i was contradicted at meeting j on at least one proposal of the specific proposal type. For example, for say-on-pay votes, $Contradict_{ij}(proposal\ type = B)$ equals one if fund i was contradicted by the majority of other shareholders on a say-on-pay proposal in meeting j, and zero otherwise; if there was no say-on-pay proposal voted on at the meeting, $Contradict_{ij}(proposal\ type = B)$ is undefined and the corresponding observations are omitted. Second, we distinguish proposals by sponsor and define $Contradict_{ij}(sponsor)$ accordingly, such that $Contradict_{ij}(management)$ equals one if and only if fund i was contradicted at meeting j on at least one management proposal, and similarly for shareholder proposals. We report the results for the coefficient β_1 on the interactive term $Contradict_{ij} \times After_{jt}$ in regression (2) for all four definitions of *Trading outcome* in panel A of Table 3 in which each line refers to a different proposal type ((A) – (D)) or sponsor ((E), (F)); the first line repeats the baseline results from Table 2 to facilitate comparisons. In each category other than (E), we restrict the sample to meetings that have at least one proposal of the respective category, e.g., at least one director election in type (A), and at least one shareholder proposal in (F). For (E), we restrict the sample to meetings with only management but no shareholder proposals.

Overall, all four analyses by proposal type (categories (A)-(D)) reveal the same qualitative patterns as the baseline analysis in Table 2; that is, the coefficients with *Sell* as the dependent variable are always positive (column 1), whereas those for the other three definitions of trading outcomes are always negative (columns 2 to 4). Some coefficients are now statistically insignificant, which is unsurprising because there is now much less variation in the independent variable $Contradict_{ij}$. No clear pattern distinguishes nonroutine proposals from routine proposals. Thus, overall, these results indicate that our results hold for all types of proposals.

The breakdown by proposal sponsor (categories (E) to (F)) reveals a remarkable pattern: whereas the results for management-sponsored proposals are qualitatively similar to our baseline results, those for shareholder-sponsored proposal show the exact opposite pattern. For all four measures of trading outcomes, the estimates for the coefficient for $Contradict_{ij}(shareholder) \times After_{jt}$ have the opposite signs compared to those observed for management proposals. Since 97.7% of all proposals in our sample are sponsored by management, these proposals dominate the results for the whole sample. Based on our hypothesis development, we interpret this finding as implying that management proposals are frequently associated with

Table 3
Voting and trading by proposal type

		Sell (1)	Buy (2)	Net fraction of portfolio bought (3)	Net fraction of company bought (4)	Obs. (5)
	Proposal type		Controdict$_{ij}$ (proposal type) × After$_{jt}$			
	All proposals (baseline)	0.0053***	−0.0048***	−0.0678***	−0.0021***	560,534
		(5.249)	(−5.154)	(−3.697)	(−4.481)	
A	Director elections	0.0009	−0.0053***	−0.0644**	−0.001	560,534
		(0.616)	(−4.156)	(−2.547)	(−1.511)	
B	Say on pay	0.0014	−0.0057**	−0.0307	−0.0023*	376,847
		(0.573)	(−2.322)	(−0.679)	(−1.940)	
C	Auditor approval	0.0148***	−0.0039	−0.003	−0.0094***	546,500
		(3.222)	(−0.926)	(−0.036)	(−4.414)	
D	Nonroutine	0.0055***	−0.0027***	−0.0590***	−0.0020***	481,286
		(5.580)	(−2.827)	(−3.163)	(−4.142)	
	Sponsor		Controdict$_{ij}$ (proposal type) × After$_{jt}$			
E	Management	0.0098***	−0.0036***	−0.0432**	−0.0025***	398,856
		(9.09)	(−3.640)	(−2.410)	(−4.579)	
F	Shareholder	−0.0013	0.0056***	0.0890**	0.0015**	159,707
		(-0.722)	(3.516)	(2.365)	(2.314)	

This table reports results for regressions of funds' trades during the February 28, 2010 to September 30, 2011 period. For each meeting, the analyses include the period from the proxy filing date to 30 trading days after the meeting date. Panel A report results on the following regression at the fund-meeting-trading day level:

$$Trading\ outcome_{ijt} = \beta_0\ After_{jt} + \beta_1\ Contradict_{ij}(proposal\ type\ or\ sponsor) \times\ After_{jt} + \gamma X_{ijt} + \mu_{ij}.$$

The dependent variables for trading outcomes are $Sell_{ijt}$, Buy_{ijt}, *Net fraction of portfolio bought*$_{ijt}$, and *Net fraction of company bought*$_{ijt}$. All variable definitions are provided in Table B1. The first row repeats the corresponding results from Table 2. For rows A–F, $Contradict_{ij}(proposal\ type)$ and $Contradict_{ij}(sponsor)$ are constructed based on a particular proposal type, respectively, sponsor, specified at the beginning of the row. All variable definitions are provided in Table B1. We include fund × meeting fixed effects and controls for the fund's assets under management, the fraction of the company held by the fund, the company's weight in the fund's overall portfolio, the fund's expense ratio and turnover ratio, and the firm's book-to-market ratio. t-statistics are reported in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

disagreement and the associated trading patterns, whereas there is no indication for such disagreement on shareholder proposals.

4. Extensions and Robustness Checks

In this section, we extend the baseline empirical models used in Section 3 to test for potentially confounding alternative explanations (Section 4.1) and provide a range of robustness tests for our specifications (Section 4.2).

4.1 Heterogeneous preferences

This section explores how trading decisions after shareholder meetings are influenced by shareholders' preferences. The connection between preferences can be conceptualized in two ways. We discussed the first way at the end of Section 1.1.1. That way views disagreement based on preferences as largely isomorphic to disagreement based on beliefs and requires that shareholders disagree based on preferences and learn about each other's preferences from the vote. To the extent that such an isomorphism exists, it was covered by the analysis in the previous section. However, trading after meetings may also originate from preferences that funds have toward specific types of proposals, for example, social preferences or environmental preferences may be important for their evaluation of ESG proposals, or their time horizon may be important for how they evaluate investments, such as mergers.

In this section, we ask whether shareholder characteristics that are arguably more related to preferences than to beliefs affect their trading behavior after shareholders have been contradicted at shareholder meetings, and whether such preference-driven trades confound the effect we document in the previous section. To this end, we extend the baseline regression (2) as follows:

$$\begin{aligned} Trading\ outcome_{ijt} \quad &= \quad \beta_0 \times After_{jt} + \beta_1\ Contradict_{ij} \times After_{jt} \\ &\quad + \beta_2\ Characteristic_{ij} \times \mathit{After}_{jt} + \gamma X_{ijt} + \mu_{ij}. \end{aligned} \tag{4}$$

Hence, we argue that if shareholders' trading behavior after a shareholder vote is influenced by their preferences rather than by their beliefs, then the term $\mathit{Characteristic}_{ij} \times \mathit{After}_{jt}$ should to some extent capture this motivation for the post-meeting trades, and the explanatory power of the term $Contradict_{ij} \times After_{jt}$ should then shrink; that is, the coefficient β_1 should decline in absolute value if we control for funds' characteristics via the variable $\mathit{Characteristic}_{ij} \times \mathit{After}_{jt}$. Based on prior literature we identify eight fund characteristics that can potentially affect funds' trading patterns. We provide an overview of these characteristics and the corresponding literature in the table below.

No.	Measure	Literature
1	Assets under management	Iliev and Lowry (2015) ("fund size")
2	Fraction of company held	Iliev and Lowry (2015) ("percent of firm equity owned by the fund"); Schwartz-Ziv and Wermers (2020)
3	Portfolio weight	Iliev and Lowry (2015) ("percent of fund net assets invested in a firm"); Schwartz-Ziv and Wermers (2020)
4	Vote with management history	Matvos and Ostrovsky (2008); Brav et al. (2021); Bolton et al. (2020)
5	Vote with ISS history	Iliev and Lowry (2015); Ertimur, Ferri, and Oesch (2013); Malenko and Shen (2016)
6	Environmental fund	Morgan et al. (2011) (on social funds); Bolton et al. (2020)
7	Overlapping directors	Calluzzo and Kedia (2019); Morgan et al. (2011)
8	Churn ratio	Morgan et al. (2011); Iliev and Lowry (2015)

Characteristics 1 to 3 all measure different aspects of the funds' size, respectively, for how important the investment in the firm is for the fund. *Assets under management* is the fund's total assets minus total liabilities as of month end in millions. *Fraction of company held* is the number of shares held divided by the number of shares outstanding in bps. *Portfolio weight* is the fraction of the total net assets in the fund's portfolio on a security in bps. Characteristics 4 and

5 measure funds' behavior to either vote with management or vote according to ISS's recommendations. Specifically, *Vote with management history* (*Vote with ISS history*) is the fraction of votes in which the fund consistently voted with management's (ISS's) recommendation between 2007 and 2009. Characteristic 6 identifies environmental funds, which include funds for which either the fund or the fund family signed the Principles for Responsible Investment (PRI); this is one of the few ESG criteria that are available for our sample period.[27] Characteristic 7 identifies whether the fund family and the firm share a director. It is based on the notion that funds have different attitudes to their portfolio companies if they share directors. Characteristic 8 differentiates transient from committed funds based on funds' churn ratio, which captures how frequently a fund rotates its positions on all the stocks of its portfolio. For *Environmental fund* and *Overlapping directors*, $Characteristic_{ij}$ equals one if the fund is classified as an environmental fund or shares overlapping directors with the firm it voted on, and zero otherwise. In all other cases, we divide the sample at the median according to each characteristic. $Characteristic_{ij}$ equals one for all funds that are above the median for the respective characteristic, and zero otherwise.

Table 4 reports the results for the coefficient β_1 on the interaction $Contradict_{ij} \times After_{jt}$ in regression (4). The first line of the table repeats the estimates from the baseline regression (2) in Table 2, which does not include controls for fund characteristics. For each dependent variable, that is, the different definitions of $Trading\ outcome_{ijt}$, the table reports the p-value of a chi-squared test for the equality of the coefficient β_1 on $Contradict_{ij} \times After_{jt}$ in the baseline regression (2) and in regression (4). The coefficient estimates for β_1 cluster in a narrow interval, ranging from 0.0045 (characteristic 3: *Portfolio weight*) to 0.0059 (characteristic 1: *Assets under management*) around the baseline value of 0.0053. The chi-squared test never rejects the hypothesis that β_1 is different in the model that controls for fund characteristics from the model that does not control for fund characteristics, with the lowest p-value being .233. For example, if we control for *Assets under management* in Equation (4), then the coefficient estimate for β_1 with *Sell* as the dependent variable is 0.0059, which is statistically indistinguishable from the estimate of 0.0053 without controls obtained in Table 2 (p-value = .633). Hence, we can safely conclude that the estimates on $Contradict_{ij} \times After_{jt}$ are robust to controlling for fund characteristics.

However, fund characteristics may still matter for trading after shareholder meetings. In our framework, they are captured by the coefficient β_2 from the interaction $Characteristic_{ij} \times After_{jt}$ in regression (4). Note that the regressions include fund $\times$ meeting fixed effects, which absorb fund characteristics, but not the interaction of these characteristics with $After_{jt}$. We report the

[27] The fund is classified as environmental if it signed the PRI before June 1, 2011. A full list of PRI signatories can be accessed at https://www.unpri.org/signatories/signatory-directory.

Table 4
Fund trades after shareholder meetings controlling for fund characteristics

	Sell		Buy		Net fraction of portfolio bought		Net fraction of company bought	
	Contradict × After	Prob > chi2	Contradict × After	Prob > chi2	Contradict × After	Prob > chi2	Contradict × After	Prob > chi2
Baseline	0.0053***	n/a	−0.0048***	n/a	−0.0678***	n/a	−0.0021***	n/a
Assets under management	0.0059***	0.633	−0.0044***	0.799	−0.0588***	0.8444	−0.0023***	0.8312
Fraction of company held	0.0057***	0.4173	−0.0047***	0.9299	−0.0642***	0.7506	−0.0023***	0.5116
Portfolio weight	0.0045***	0.233	−0.0044***	0.5604	−0.0566***	0.4061	−0.0019***	0.5593
Vote with management history	0.0048***	0.734	−0.0060***	0.3064	−0.0657***	0.9483	−0.0021***	0.9835
Vote with ISS history	0.0058***	0.6054	−0.0052***	0.4904	−0.0626***	0.7839	−0.0020***	0.8346
Environmental fund	0.0050***	0.7463	−0.0038***	0.3694	−0.0585***	0.6524	−0.0020***	0.8162
Overlapping directors	0.0053***	0.7198	−0.0048***	0.8446	−0.0685***	0.7578	−0.0021***	0.8193
Churn ratio	0.0048***	0.6683	−0.0052***	0.6648	−0.0660***	0.9314	−0.0021***	0.9646

This table reports results for regressions of funds' trades during the February 28, 2010 to September 30, 2011 period. For each meeting, the analyses include the period from the proxy filing date to 30 trading days after the meeting date. The odd-numbered columns report coefficients β_1 in the following regression at the fund-meeting-trading day level:

$$Trading\ outcome_{ijt} = \alpha + \beta_0 \times After_{jt} + \beta_1 \times Contradict_{ij} \times After_{jt}$$
$$+ \beta_2 \times Characteristic_{ij} \times After_{jt} + \gamma X_{ijt} + \mu_{ij}.$$

The dependent variables for trading outcomes are $Sell_{ijt}$, Buy_{ijt}, $Net\ fraction\ of\ portfolio\ bought_{ijt}$ and $Net\ fraction\ of\ company\ bought_{ijt}$. All variable definitions are provided in Table B1. The even-numbered columns report the p-value from the chi-squared test for the null hypothesis that β_1 in each regression controlling for one characteristic equals β_1 in the baseline case without controlling for $Characteristic_{ij} \times After_{jt}$ (first row of the table). For rows 2–9, the controls for a particular fund characteristic are specified in the beginning of the row. For *Environmental fund* and *Overlapping directors*, $Characteristic_{ij}$ equals one if the fund is classified as an environmental fund or shares overlapping director with the firm it voted on, and zero otherwise. For the other characteristics, $Characteristic_{ij}$ equals one for funds with above-median characteristic, and zero otherwise. We include fund × meeting fixed effects and controls for the fund's assets under management, the fraction of the company held by the fund, the company's weight in the fund's overall portfolio, the fund's expense ratio and turnover ratio, and the firm's book-to-market ratio. *$p < .1$; **$p < .05$; ***$p < .01$.

estimates for β_2 as well as their t-statistics in Table 5. Most coefficient estimates are significant with economic magnitudes that are broadly comparable to those in Table 2, which shows that fund characteristics are relevant for funds' trading decisions. We are particularly interested in those characteristics that induce funds to sell more and buy less, thus reinforcing the patterns observed in Table 2, because these fund characteristics may reduce the effect of $Contradict_{ij} \times After_{jt}$ and potentially provide alternative explanations for our main result. We find such patterns for funds with larger investments in the firm relative to their portfolio, those with a higher churn ratio, and environmental funds. However, while we find numerically slightly lower β_1 coefficients in Table 4 on all four trade outcome variables for funds with a higher *Portfolio weight* and environmental funds, the differences are economically small and

Table 5
Fund trades after shareholder meetings explained by fund characteristics

$\text{Characteristic}_{ij}$ $\times \text{After}_{jt}$	Sell	t-stat	Buy	t-stat	Net fraction of portfolio bought	t-stat	Net fraction of company bought	t-stat
Assets under management	0.0058***	(6.331)	0.0032***	(3.808)	0.0899***	(5.381)	−0.0021***	(−4.758)
Fraction of company held	0.0061***	(6.611)	0.0006	(0.684)	0.0623***	(3.738)	−0.0036***	(−8.351)
Portfolio weight	0.0105***	(11.502)	−0.0043***	(−5.146)	−0.1522***	(−9.158)	−0.0035***	(8.131)
Vote with management history	−0.0060***	(−6.274)	−0.0048***	(−5.466)	−0.0066	(−0.383)	0.000	(0.028)
Vote with ISS history	−0.0044***	(−4.673)	−0.0026***	(−2.966)	−0.0797***	(−4.713)	−0.0029***	(−6.482)
Environmental funds	0.0029**	(2.138)	−0.0094***	(−7.691)	−0.0937***	(−3.865)	−0.0014**	(−2.235)
Overlapping directors	0.0195*	(1.668)	−0.0046	(−0.433)	−0.3723*	(−1.755)	−0.0038	(−0.689)
Churn ratio	0.0156***	(15.925)	−0.0081***	(−9.033)	−0.0542***	(−3.016)	−0.0029***	(−6.226)

This table reports results for regressions of funds' trades during the February 28, 2010 to September 30, 2011 period. For each meeting, the analyses include the period from the proxy filing date to 30 trading days after the meeting date. The odd-numbered columns report coefficients β_2 in the following regression at the fund-meeting-trading day level:

$$Trading\ outcome_{ijt} = \alpha + \beta_0 \times After_{jt} + \beta_1 \times Contradict_{ij} \times After_{jt}$$

$$+ \beta_2 \times Characteristic_{ij} \times After_{jt} + \gamma X_{ijt} + \mu_{ij}.$$

The dependent variables for trading outcomes are $Sell_{ijt}$, Buy_{ijt}, $Net\ fraction\ of\ portfolio\ bought_{ijt}$, and $Net\ fraction\ of\ company\ bought_{ijt}$. All variable definitions are provided in Table B1. The even-numbered columns report the t-statistics in parentheses. Each row controls for a particular fund characteristic specified in the beginning of the row. For *Environmental fund* and *Overlapping directors*, $Characteristic_{ij}$ equals one if the fund is classified as an environmental fund or shares overlapping director with the firm it voted on, and zero otherwise. For the other characteristics, $Characteristic_{ij}$ equals one for funds with above-median characteristic, and zero otherwise. We include fund × meeting fixed effects and controls for the fund's assets under management, the fraction of the company held by the fund, the company's weight in the fund's overall portfolio, the fund's expense ratio and turnover ratio, and the firm's book-to-market ratio. t-statistics are reported in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

statistically insignificant. For example, the interactions for *Sell* in Table 4 are 0.0045 for funds with higher *Portfolio weight*, and 0.0050 for environmental funds, compared to 0.0053 in the baseline regression. Overall, we conclude that the trading behavior analyzed in Table 2, which shows that funds sell more and buy less in firms in which their votes have been contradicted by the meeting outcome, cannot be explained by observable fund characteristics, and is better explained by the disagreement argument.

4.2 Additional tests and robustness checks

4.2.1 Close votes. The analysis in Table 2 disregards the margin of victory, which has attracted much interest in event studies using regression discontinuity design (e.g., Cuñat, Giné, and Guadalupe 2012). In Table 6, we repeat the main results of Table 2 and introduce a new interaction variable *Close*, which takes a

Table 6
Fund trades after shareholder meetings: the case of close votes

	Sell (1)	Buy (2)	Net fraction of portfolio bought (3)	Net fraction of company bought (4)
Contradict × After × Close	0.0092***	−0.001	−0.0906**	−0.0027**
	(3.76)	(−0.458)	(−2.048)	(−2.334)
Contradict × After × (1 − Close)	0.0031***	−0.0039***	−0.0527***	−0.0010*
	(2.828)	(−3.894)	(−2.655)	(−1.941)
Fund × Meeting FE	Yes	Yes	Yes	Yes
R-squared	.13	.102	.138	.108
N	560,532	560,532	560,532	560,532
F-test for contrasting interaction terms	4.91	1.31	0.58	1.69
Prob>F	0.0267	0.252	0.446	0.193

This table reports results for regressions of funds' trades during the February 28, 2010 to September 30, 2011 period. For each meeting, the analyses include the period from the proxy filing date to 30 trading days after the meeting date. The columns report coefficients β_1 and β_2 in the following regression at the fund-meeting-trading day level:

$$Trading\ outcome_{ijt} = \alpha + \beta_0 \times After_{jt} + \beta_1 \times Contradict_{ij} \times After_{jt} \times Close_{ij}$$

$$+ \beta_2 \times Contradict_{ij} \times After_{jt} \times (1 - Close)_{ij} + \gamma X_{ijt} + \mu_{ij}.$$

The dependent variables for trading outcomes are $Sell_{ijt}$, Buy_{ijt}, $Net\ fraction\ of\ portfolio\ bought_{ijt}$, and $Net\ fraction\ of\ company\ bought_{ijt}$. All variable definitions are provided in Table B1. We include fund × meeting fixed effects and controls for the fund's assets under management, the fraction of the company held by the fund, the company's weight in the fund's overall portfolio, the fund's expense ratio and turnover ratio, and the firm's book-to-market ratio. All regressions report an F-test examining whether the coefficients for $Contradict \times After \times Close$ and $Contradict \times After \times (1 - Close)$ are statistically different from each other. t-statistics are reported in parentheses. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

value of one if the voting result on which the fund was contradicted was close, and zero otherwise. We define an election result as close if the proportion voted in favor is between 45% and 55%. If trading after meetings would be best explained by Bayesian learning (information aggregation) models, then we would expect that our results would concentrate in close votes and we should see insignificant results for nonclose votes.[28] Based on differences-of-opinion models, we would not necessarily expect large differences between close votes and nonclose votes, because even nonclose outcomes may carry significant surprises. For example, when a director is normally approved with 90% or more of the vote, and then receives only 70%, shareholders may learn that they have significant disagreement with a sizable fraction of the shareholder base. The results in Table 6 reveal no clear pattern. In only one case is the result for close votes significantly larger than for nonclose votes (column 1, the F-test is reported at the bottom of the table), but even then, the result for nonclose votes remains significant. In the other three cases (columns 2–4), the difference to nonclose votes is not significant, and with *Buy* as the dependent variable, the estimate is numerically higher for nonclose votes. Overall, there is no clear indication that our results are driven by close votes.

28 We owe the insight that predictions from close votes differ between Bayesian learning and disagreement models to an anonymous referee.

Table 7
Fund trades with index funds as the control group

	Sell (1)	Buy (2)	Net fraction of portfolio bought (3)	Net fraction of company bought (4)
After	0.0326***	−0.0282***	−0.0166**	−0.0044***
	(42.490)	(−30.583)	(−2.100)	(−14.633)
Active fund × After	−0.0349***	0.0260***	−0.0724***	0.0025***
	(−33.161)	(20.564)	(−6.671)	(6.024)
Contradict × After	0.0012	0.0048***	0.0031	0.0005
	(.781)	(2.649)	(.195)	(.927)
Active fund × Contradict × After	0.0042**	−0.0097***	−0.0707***	-0.0027***
	(2.051)	(−3.999)	(−3.382)	(−3.486)
Fund × Meeting FE	Yes	Yes	Yes	Yes
R-squared	.121	.234	.135	.084
N	1,039,788	1,039,788	1,039,788	1,039,788

This table reports results for regressions of funds' trades during the February 28, 2010 to September 30, 2011 period. For each meeting, the analyses include the period from the proxy filing date to 30 trading days after the meeting date. The columns report results on the following regression at the fund-meeting-trading day level:

$$Trading\ outcome_{ijt}=\beta_0\ After_{jt}+\beta_1 Active\ fund_{ij}\times After_{jt}$$
$$+\beta_2\ Contradict_{ij}\times After_{jt}+\beta_3 Active\ fund_{ij}\times Contradict_{ij}\times After_{jt}+\gamma X_{ijt}+\mu_{ij}.$$

The dependent variables for trading outcomes are $Sell_{ijt}$, Buy_{ijt}, $Net\ fraction\ of\ portfolio\ bought_{ijt}$, and $Net\ fraction\ of\ company\ bought_{ijt}$. All variable definitions are provided in Table B1. We include fund × meeting fixed effects and controls for the fund's assets under management, the fraction of the company held by the fund, the company's weight in the fund's overall portfolio, the fund's expense ratio and turnover ratio, and the firm's book-to-market ratio. t-statistics are reported in parentheses. $^*p<.1$; $^{**}p<.05$; $^{***}p<.01$.

4.2.2 Index funds. The analysis in Table 2 excludes index funds because they do not have discretion over their trades. However, this feature allows us to use index funds as a control group and control for all time-varying factors that affect index funds and actively managed funds similarly. Hence, we now include index funds in the sample and perform a triple-difference analysis in which we interact all variables from Table 2 with the dummy variable *Active fund*, which equals one for actively managed funds and zero for index funds. Table 7 shows the results using index funds as a control group. We hypothesize that actively managed funds sell more and buy less after being contradicted at shareholder meetings, since only these are the funds that can make strategic trading decisions. Thus, our primary variables of interest are the triple-interaction terms *Active fund* × *Contradict* × *After*, which measure the differences between actively managed funds and index funds. The point estimates in Table 7 are qualitatively, and in almost all cases also quantitatively similar to the corresponding estimates reported in Table 2 on *Contradict* × *After*. We infer that the main conclusions from Table 2 are robust: in contrast to index funds, actively managed funds sell if they find their votes are contradicted by those of other shareholders.

4.2.3 ISS recommendations. We report several other robustness checks of Table 2 in the Internet Appendix. Table A3 in the Internet Appendix breaks up the baseline coefficient *Contradict* based on ISS recommendations instead of management recommendations and repeats the analysis for the baseline regression (2). The results for the binary dependent variables are very similar to those in Table 2, whereas those for the continuous dependent variables show that funds sell more if they vote according to ISS recommendations and other shareholders vote against ISS than in the opposite case, in which sales are insignificantly different from zero. This result differs from that in Iliev and Lowry (2015) (see their table 10) who show based on quarterly holdings data that funds sell if they disagree with ISS. By contrast, our results based on daily data show that funds sell immediately after meetings if they agree with ISS, but the majority of other shareholders does not, which emphasizes that it is the disagreement with other shareholders that is primarily important.

4.2.4 Standard errors. Since we include the period from the proxy filing date to 30 trading days after the meeting, we are concerned that the critique of Bertrand, Duflo, and Mullainathan (2004) may apply. These authors found that long time series of highly autocorrelated variables may lead to spurious significance in differences-in-differences regressions. Hence, we calculate the autocorrelations of our dependent variables. They are equal to 0.07 for both *Sell* and *Buy* and equal to 0.05 for both *Net fraction of portfolio bought* and *Net fraction of company bought*. All of these four autocorrelations are indistinguishable from zero. Hence, there is no indication for autocorrelation in our dependent variables that would induce spurious significance levels. Still, in Table 8, we apply the block bootstrap method recommended by Bertrand, Duflo, and Mullainathan (2004) and treat each fund-meeting combination as one block. This method allows for arbitrary heteroscedasticity and correlations with each block. (For further details, please see Section A.1 in the Appendix.) We find that the results of the nonparametric bootstrap tests conform to those of the parametric tests; thus, our original results in Table 2 are robust.

Similarly, there may be correlations across observation that potentially inflate standard errors from factors that are common to the same calendar date, the same fund, or the same meeting. The baseline specification relies on the assumption that the fund $\times$ meeting fixed effects control for these unobservable factors. In Table 8, we show the key results for several specifications that cluster standard errors by calendar date, calendar month, double cluster by fund and meeting, and by fund $\times$ meeting to permit cross-meeting correlations. Again, while the t-statistics decline, results remain significant.

4.2.5 Control variables and fixed effects. In Table 8, we further show the same results with control variables, but omit the meeting $\times$ fund fixed effects. Specifically, we show specifications without any fixed effects, only fund fixed effects, only meeting fixed effects, with fund and meeting fixed effects, but without interacting them. The results for alternative specifications of fixed effects show a clear pattern: the absolute values of the estimates decline.

Table 8
Bootstrapped p-values, clustered standard errors, and fixed effects

Fixed effects	Clustering	Sell	Block bootstrapped p-value	Buy	Block bootstrapped p-value	Net fraction of portfolio bought	Block bootstrapped p-value	Net fraction of company bought	Block bootstrapped p-value
Fund × Meeting	None		0.5%		0.0%		2.5%		0.5%

Fixed effects	Clustering	Sell	t-statistic	Buy	t-statistic	Net fraction of portfolio bought	t-statistic	Net fraction of company bought	t-statistic
Fund × Meeting	Calendar date	0.0053***	(3.471)	−0.0048***	(−3.550)	−0.0678***	(−2.960)	−0.0021***	(−3.943)
Fund × Meeting	Calendar month	0.0053**	(2.701)	−0.0048**	(−2.442)	−0.0678***	(−3.313)	−0.0021***	(−3.245)
Fund × Meeting	Fund and meeting	0.0053*	(1.770)	−0.0048***	(−2.626)	−0.0678**	(−2.327)	−0.0021**	(−2.212)
Fund × Meeting	Fund × meeting	0.0053***	(2.936)	−0.0048***	(−3.643)	−0.0678**	(−2.438)	−0.0021***	(−2.862)
None	None	0.0016**	(2.201)	−0.0016**	(−2.446)	−0.0089	(−0.678)	−0.0008**	(−2.270)
Fund	None	0.0022***	(3.055)	−0.0020***	(−3.055)	0.0078	(0.576)	−0.0002	(−0.684)
Meeting	None	0.0039***	(4.585)	−0.0033***	(−4.300)	−0.0493***	(−3.112)	−0.0021***	(−5.332)
Fund and meeting	None	0.0044***	(5.103)	−0.0038***	(−4.875)	−0.0476***	(−2.946)	−0.0019***	(−4.614)
Fund, meeting, calendar date	None	0.0043***	(4.943)	−0.0039***	(−4.990)	−0.0473***	(−2.926)	−0.0019***	(−4.596)
Fund, meeting, calendar month	None	0.0044***	(5.092)	−0.0039***	(−4.959)	−0.0487***	(−3.009)	−0.0019***	(−4.657)
Fund × Meeting, calendar date	None	0.0052***	(5.120)	−0.0049***	(−5.357)	−0.0682***	(−3.720)	−0.0021***	(−4.539)
Fund × Meeting, calendar month	None	0.0053***	(5.290)	−0.0048***	(−5.250)	−0.0699***	(−3.810)	−0.0022***	(−4.585)

This table reports results for regressions of funds' trades during the February 28, 2010 to September 30, 2011 period. For each meeting, the analyses include the period from the proxy filing date to 30 trading days after the meeting date. The columns report results on the following regression at the fund-meeting-trading day level:

$$Trading\ outcome_{ijt}=\beta_0\ After_{jt}+\beta_1\ Contradict_{ij}\times After_{jt}+\gamma X_{ijt}+\mu_{ij}.$$

The dependent variables for trading outcomes are $Sell_{ijt}$, Buy_{ijt}, $Net\ fraction\ of\ portfolio\ bought_{ijt}$ and $Net\ fraction\ of\ company\ bought_{ijt}$. All variable definitions are provided in Table B1. For all regressions, we control for the fund's assets under management, the fraction of the company held by the fund, the company's weight in the fund's overall portfolio, the fund's expense ratio and turnover ratio, and the firm's book-to-market ratio. The first row reports the p-values of t-statistics for β_1 via block bootstrap with replacement following Bertrand, Duflo, and Mullainathan (2004). Details are presented in Section A.1 in the Appendix. The rest of the table reports the estimated β_1 under different fixed effect and clustered standard error specifications. t-statistics are reported in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

Statistical significance generally declines, but the binary dependent variables *Buy* and *Sell* retain significance in all cases. The estimates for *Net fraction of portfolio bought* and *Net fraction of company bought* become insignificant in the specifications without meeting fixed effects. Finally, in Table 8, we perform the analysis without including any control variables, whereas fixed effects are still included. The estimates are numerically similar and statistical significance levels are sometimes higher and sometimes lower without showing a clear tendency.

We perform Hausman tests on all specifications without either controls or fixed effects and can reject these specifications against our baseline specifications in Table 2, at least at the 5% level in all cases (not tabulated). We conclude that capturing unobserved heterogeneity across meetings is particularly important when analyzing changes in trading behavior around shareholder meetings, but that there is also some unobserved heterogeneity of trading behavior across funds but within meetings. This heterogeneity is captured only by interactive meeting × fund fixed effects and omitting them leads to biased results (see Bai 2009).

5. Abnormal Volume and Abnormal Price Changes

In this section we test the contrasting predictions of disagreement models and Bayesian learning models with respect to volume and volatility at the meeting level developed in Section 1.2.2. This allows us to provide additional tests of disagreement models, and to distinguish them more carefully from Bayesian learning models, specifically those in which shareholders differ regarding the precisions of their signals, which we discuss in Section 1. We begin with a graphical analysis in Section 5.1 and continue with regression analyses in Sections 5.2 and 5.3.

5.1 Descriptive analysis of volume and volatility

One of the key predictions of disagreement models is the existence of large trading volume without correspondingly large price changes. This implication distinguishes them from Bayesian learning models, which predict either a strict proportionality between trading volume and volatility (models with differently precise priors) or forecast no trading at all (see the table in Section 1.2.2). We begin with a univariate analysis in panel A of Figure 2, which plots average abnormal volume, abnormal realized volatility, and abnormal returns around meeting dates. Following Chae (2005) and Huang, Tan, and Wermers (2020), abnormal volume is estimated as the ratio of daily volume and average daily volume during the pre-voting period −1, where the pre-voting period is defined as the [-252, -21] window before the record date. Abnormal volatility is computed as the ratio of daily realized volatility and the exponential moving average of daily realized volatility over the pre-voting period with a half-life of five days, minus 1, where daily realized volatility is estimated as the square

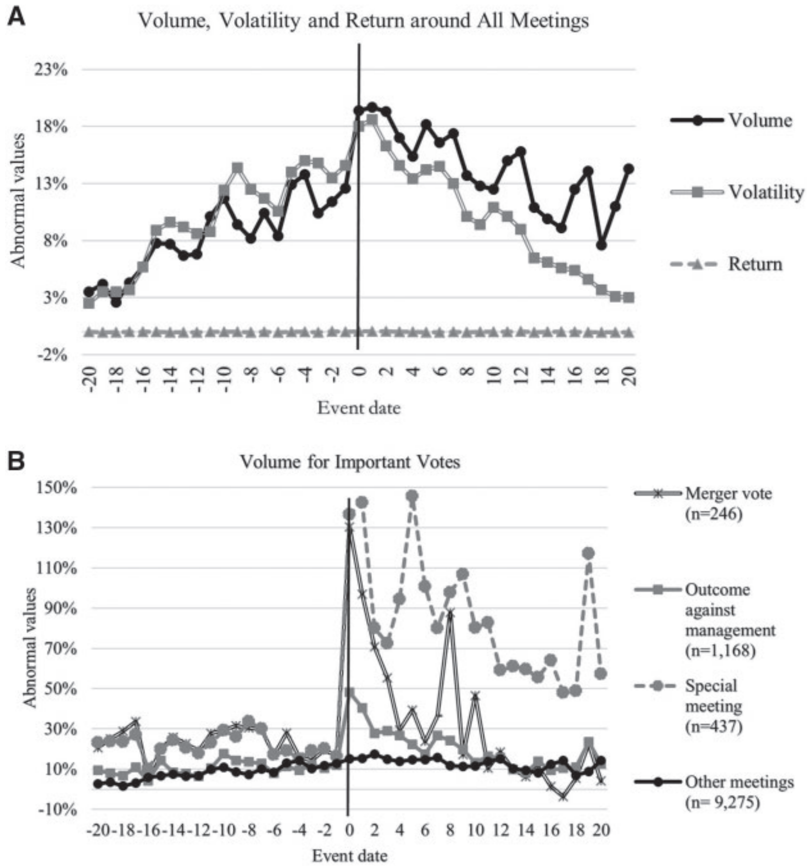

Figure 2
Volume, volatility, and returns around shareholder meetings
Panel A reports the average abnormal volume, abnormal volatility, and abnormal returns on days around shareholder meetings for observations of meetings held during the February 28, 2010 to June 30, 2013 period. Abnormal volume is estimated as the daily volume/average daily volume during the pre-voting period –1, where the pre-voting period is defined as the [-252, -21] window before the record date. Abnormal volatility is computed as the ratio of daily realized volatility and the exponential moving average of daily realized volatility over the pre-voting period with a half-life of five days, minus 1, where the daily realized volatility is estimated by the square root of the sum of squared 5-minute returns within a trading day. Abnormal returns are calculated using the Fama-French-Carhart four-factor model. Panel B reports the average abnormal volume for four types of shareholder meetings: meetings involving a vote on a merger, meetings with at least one voting outcome that contradicts management recommendation, special meetings (defined as meetings with "meetingtype" different from "annual" according to ISS Voting Analytics), and all other meetings.

root of the sum of squared 5-minute returns within a trading day. Abnormal returns are calculated using the Fama-French-Carhart four-factor model.

Volume increases already ahead of the shareholder meeting by about 10% above the level in the pre-voting period and peaks around the meeting date. It jumps by another 10% on the meeting date to about 20% above the pre-meeting level and then declines slowly after the meeting and remains at elevated levels of about 10% to 15% above the pre-meeting level three to four weeks after the meeting. Volatility tracks trading volume closely up to the meeting date, but then reverts to its pre-meeting level more quickly than volume, indicating a dissociation of volume from price changes after the meeting date. During the period from 20 days before to 20 days after the meeting, average stock returns fluctuate around zero, as we would expect with informationally efficient markets. Panel B of Figure 2 shows that trading volume is particularly high after special meetings and merger votes, for which it peaks at about 140% (130%) on the day of the meeting; the effect is smaller (about 50%) for meetings in which the vote on at least one proposal contradicts management's recommendation; for all other meetings, trading volume is still around 15% above the pre-voting period. Taken together, these findings suggest that abnormal volume is higher after important and contentious votes, which arguably have more scope for disagreement among shareholders.

Next, we study the relationship between trading volume and volatility graphically, which allows us to examine this relationship nonparametrically without assuming any specific functional form. Under the null hypothesis that there is no disagreement and only Bayesian learning, we should see very little trading volume if price changes are small (see again the discussion and table in Section 1.2). To assess this relationship, we define normalized returns by scaling abnormal meeting-day returns by the standard deviation of returns. We then sort meetings based on normalized returns into nine quantiles. We choose an odd number of quantiles to ensure that the middle quantile captures the interval with very small price changes around zero. Then we compare post-event volume from 1 to 10 trading days after the meeting date to pre-event volume from 20 to 11 trading days before the meeting date. We skip the 10 trading days before the meeting date because information related to voting outcomes might be leaked right before the meeting date by those able to observe the electronic votes as soon as they are cast (e.g., management and proxy advisors). Figure 3 plots the average trading volume before and after meeting dates for each normalized return quantile. We report the average normalized return for each quantile above the quantile labels in parentheses on the horizontal axis.[29] Like Kandel and Pearson (1995) in their analysis of earnings announcements, we observe a slight U-shaped relationship during the post-meeting window (see their Figure 1), which is largely flat between the second and eighth quantile. To test more formally for abnormal trading volume without price changes, as predicted by disagreement models, we perform a simple t-test to compare trading volume in the post-meeting window [1, 10] with the pre-meeting window $[-20, -11]$ for all quantiles for which the average standardized return is below one in absolute value, that is, in all but the most

[29] The construction of the figure closely corresponds to that of Bollerslev, Li, and Xue (2018) Figure 6. Figure 2 and Table 2 of Kandel and Pearson (1995) are also similar, but they use medians instead of means and do not normalize returns.

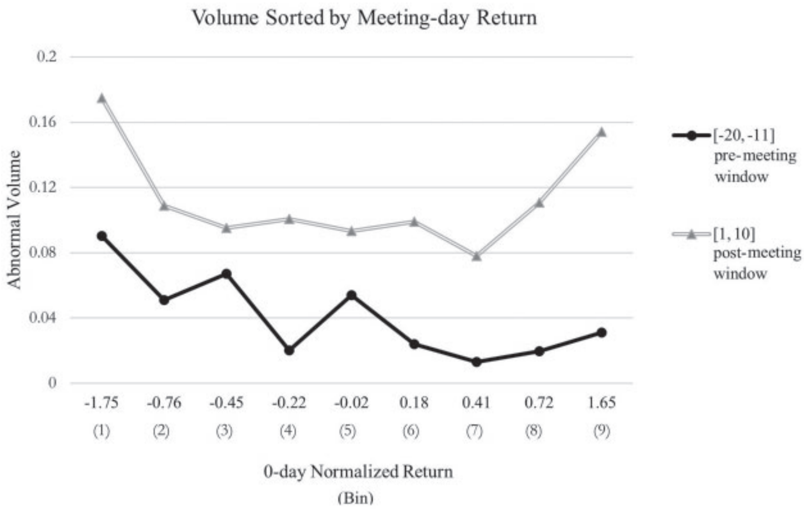

Figure 3
Trading volume and returns
This figure presents the pre- and post-meeting abnormal volume sorted by the normalized returns on the meeting-day. The figure is generated from meetings held during the February 28, 2010 to June 30, 2013 period. The pre-meeting window is defined as 20 to 11 days before the meeting, and the post-meeting window is defined as 1 to 10 days after the meeting. Values for abnormal volume are estimated as the daily volume/average daily volume during pre-voting period -1. The pre-voting period is defined as the $[-252, -21]$ window before the record date. Abnormal returns are calculated using the Fama-French-Carhart four-factor model. Normalized returns are defined by scaling abnormal returns by the standard deviation of returns. The normalized return increases from left to right, where the lower line of the x-axis denotes the nine normalized return quantiles in parentheses, and the upper line denotes the average normalized return within each quantile.

extreme quantiles 1 and 9. For these nonextreme quantiles, post-event trading volume exceeds pre-event trading volume on average by a factor of about 1.7 and the t-value for this comparison is 8.48.

Hence, we conclude that there is significant evidence for abnormal volume without large price changes. However, the plot reveals a U-shaped pattern: for the extreme quantiles with the lowest and highest returns, we observe significantly higher trading volume after the meetings, which suggests some association between price changes and trading volume, consistent with the notion that both disagreement and Bayesian learning remain prevalent in our sample.

5.2 Regression analysis of the relationship between trading volume and volatility

For the regression analysis, we follow Bollerslev, Li, and Xue (2018) and estimate the following equation at the meeting level:

$$\Delta log\left(m_j\right)=a_0+b_0X_j+\left(a_1+b_1X_j\right)\Delta log\left(\sigma_j\right), \tag{5}$$

where m_j is trading volume and σ_j is the volatility of the firm's stock price around meeting j, and X_j is a vector of control variables, notably measures that proxy for shareholder disagreement. The change in log volume $\Delta log\left(m_j\right)$ for each meeting is measured as the difference in log average daily trading volume over the [1,10] after-meeting window and log average trading volume over the [−20, −11] pre-meeting interval as in the previous section. The change in log volatility $\Delta log\left(\sigma_j\right)$ around shareholder meetings is defined similarly.

We test two implications, both of which directly follow from the discussion in Section 1.2.2 and Bollerslev, Li, and Xue (2018). First, if we estimate (5) without any control variables, then the coefficient a_1 measures the elasticity $\epsilon \equiv \frac{\partial ln(m(\sigma))}{\partial ln(\sigma)}$, and we expect that, compared to nonmeeting days, this elasticity will be lower around meeting dates, since shareholders may disagree on how to interpret voting outcomes. We test this implication in panel A of Table 9 by comparing the elasticity on meeting dates and on placebo dates. For each meeting, we choose two placebo dates randomly, one from an interval between 2 and 6 months before the meeting and the second one from an interval between 2 and 6 months after the meeting; these placebo results are reported in column 2.[30] The point estimates are 0.584 for meeting dates and 0.657 for the placebo dates. They are statistically significantly different from each other with a p-value of .0293 (see the chi-squared test for the difference reported at the bottom of the table). Hence, the elasticity drops around meeting dates, which provides support for the first implication and indicates that shareholder meetings are associated with a substantial increase in disagreement. However, the elasticity estimate is still significantly different from zero, which is inconsistent with a pure disagreement model as described in Section 1.2.2 and suggests that Bayesian learning models and the notion that shareholders learn from each other still retain significant explanatory power.

The second implication of disagreement models is that the elasticity estimates around meeting dates should move toward the value estimated on placebo dates if we control for disagreement. Put differently, after controlling for disagreement, the elasticity estimates should be higher compared with estimates without controls for disagreement. Testing the second implication of the model requires that we find proxies for disagreement among shareholders, and shareholder voting provides us with a unique setting in which we can construct measures of disagreement directly from the voting results at the proposal level. Accordingly, we propose six meeting-level measures to proxy for disagreement; the first five are intended to pick up disagreement between different groups of informed experts (shareholders, ISS, management): (1) *ISS against management* is equal to one if ISS recommends to vote against management's recommendation for at least one proposal; (2) *Outcome against management* is equal to one if at least one voting outcome is against management's recommendation; (3) *Outcome against ISS* is equal to one if at least one voting outcome is against ISS's recommendation; (4) *Average*

[30] We draw random numbers from a uniform distribution and ensure that the placebo date falls on the same day of the week as the meeting date itself.

Table 9
Volume-volatility elasticity analysis around shareholder meeting

A. Volume-volatility regressions with controls for disagreement

	Baseline (1)	Placebo (2)	ISS against management (3)	Outcome against management (4)	Outcome against ISS (5)	Ave. fr. of funds against man. (6)	Ave. fr. of fund against ISS (7)	Special meeting (8)	All disagreement measures from columns 3 to 8 (9)
Intercept	0.036***	0.018***	0.036***	0.032***	0.031***	0.026***	0.028***	0.019***	0.016**
	(6.75)	(5.45)	(5.15)	(5.66)	(4.95)	(3.63)	(4.13)	(3.69)	(2.23)
Δ log (σ) (a_1)	0.584***	0.657***	0.614***	0.587***	0.636***	0.641***	0.645***	0.626***	0.684***
	(22.40)	(31.70)	(18.32)	(21.57)	(21.13)	(18.98)	(19.70)	(23.53)	(20.47)
Proxies for disag.	None	None	1	1	1	1	1	1	6
R-squared	.143	.153	.148	.151	.152	.147	.149	.164	.170
N	9,440	17,359	9,368	9,303	9,298	9,373	9,368	9,373	9,298
Chi2 test contrasting to a_1 in Placebo	4.75		1.16	4.14	0.32	0.15	0.09	0.80	0.47
Prob > Chi2	0.0293		0.2816	0.0418	0.5693	0.7015	0.7658	0.3713	0.4922
Chi2 test contrasting to a_1 in baseline		4.75	1.54	0.06	5.23	5.39	6.43	14.21	12.25
Prob > Chi2		0.0293	0.2144	0.8104	0.0222	0.0203	0.0112	0.0002	0.0005

This table reports results for volume-volatility elasticity regressions during the February 28, 2010 to June 30, 2013 period. The columns in panel A report results on the following regression at the meeting level:

$$\Delta log\left(m_j\right)=a_0+b_0X_j+\left(a_1+b_1X_j\right)\Delta log\left(\sigma_j\right),$$

where m_j is trading volume and σ_j is the volatility of the firm's stock price around meeting j, and X_j is a vector of control variables that proxy for shareholder disagreement. The change in log volume $\Delta log\left(m_j\right)$ is the difference in log average daily trading volume over the [1,10] after-meeting window and log average trading volume over the [−20, −11] pre-meeting interval. The change in log volatility $\Delta log\left(\sigma_j\right)$ around shareholder meetings is defined similarly. Column 1 reports elasticity a_1 without control around meeting days (baseline), and column 2 reports a_1 without control on placebo dates; for each meeting, we randomly draw 2 placebo days that are between 2 and 6 months before and after the meeting date with equal distance. Columns 3 to 8 report a_1 after controlling for one of the six disagreement measures. Column 9 controls for all six disagreement measures from columns 3 to 8. "*Chi2 test contrasting to a_1 in Placebo*" examines whether the estimated elasticity a_1 is statistically different from that around placebo days in column 2, and "*Chi2 test contrasting to a_1 in Baseline*" tests whether the elasticity a_1 is statistically different from that around the baseline meeting dates in column 1. Panel B repeats the baseline analysis without control for meetings with different proposal types and sponsor used in. Column 1 reports the results for the whole sample and is identical to column 1 of panel A. Column 2 is restricted to meetings with at least one proposal on director election. Column 3 is restricted to meetings with at least one proposal on say-on-pay. Column 4 is restricted to meetings with at least one proposal on approving auditors. Column 5 is restricted to nonroutine meetings (i.e., meetings with at least one proposal other than director elections, say-on-pay proposals, and approving auditors). Column 6 is restricted to meetings with management-sponsored proposals only. Column 7 is restricted to meetings with at least one shareholder-sponsored proposal. Panel C repeats the analysis from panel A, but interacts the change in log volume $\Delta log\left(m_j\right)$ with an additional dummy variable *Distraction*, which equals one for meetings held on days with above-median number of shareholder meetings, and zero otherwise. *t*-statistics are reported in parentheses. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

Table 9
(Continued)

B. Volume-volatility regressions by proposal and sponsor type

	Baseline (1)	Director elections (2)	Say on pay (3)	Auditor approvals (4)	Nonroutine proposial (5)	Only sponsored by management (6)	Sponsored by shareholder (7)
Intercept	0.036***	0.020***	0.016***	0.018***	0.051***	0.043***	−0.029**
	(6.75)	(3.89)	(2.88)	(3.36)	(7.75)	(7.54)	(−2.55)
Δ log (σ) (a_1)	0.584***	0.623***	0.698***	0.640***	0.557***	0.571***	0.720***
	(22.40)	(23.63)	(19.69)	(23.68)	(16.16)	(19.97)	(17.81)
R-squared	.143	.169	.172	.178	.128	.131	.303
N	9,440	9,084	6,162	8,661	6,211	8,351	1,087
Chi2 test contrasting to a_1 in placebo		12.04	16.49	18.27	2.54	6.69	9.36
Prob > Chi2		0.0005	0.0000	0.0000	0.1108	0.0097	0.0022

C. Volume-volatility regressions with controls for distraction

	Baseline (1)	Random Placebo (2)	ISS against management (3)	Outcome against management (4)	Outcome against ISS (5)	Ave. fr. of funds against man. (6)	Ave. fr. of fund against ISS (7)	Special meeting (8)	All disagreement measures from columns 3 to 8 (9)
Intercept	0.035***	0.018***	0.034***	0.031***	0.030***	0.025***	0.027***	0.019***	0.016**
	(6.62)	(5.45)	(5.00)	(5.50)	(4.76)	(3.54)	(4.00)	(3.72)	(2.19)
Δ log (σ) (a_1)	0.559***	0.647***	0.588***	0.555***	0.605***	0.618***	0.620***	0.623***	0.674***
	(13.21)	(20.49)	(12.73)	(12.84)	(14.13)	(12.87)	(13.41)	(13.90)	(14.69)
Δ log (σ) (a_1)	0.047	0.019	0.051	0.06	0.06	0.043	0.048	0.006	0.018
× Distraction	(0.94)	(0.46)	(1.01)	(1.22)	(1.22)	(0.85)	(0.95)	(0.11)	(0.36)
R-squared	.143	.153	.148	.151	.153	.148	.149	.164	.170
N	9,440	17,359	9,368	9,303	9,298	9,373	9,368	9,373	9,298

fraction of funds against management is the mean of the fractions of funds' votes cast against management, averaged across all proposals at the meeting; (5) *Average fraction of funds against ISS* is the mean of the fractions of funds' votes cast against ISS, averaged across all proposals at the meeting; and (6) *Special meeting* is a dummy variable that equals one for meetings with "meetingtype" different from "annual" according to ISS Voting Analytics; we include Special meeting as a proxy for disagreement since special meetings concern issues that are less routine, and hence more likely to generate disagreement.

Columns 3 to 8 in panel A of Table 9 report the results for estimating Equation (5) when we include one of the six disagreement measures each time as a control. To conserve space, we only report the estimates for the elasticity given by the coefficient a_1 on $\Delta\log(\sigma)$. At the bottom of the table, we report the chi-squared tests for the hypotheses that the elasticity estimates in each of the columns from (3) to (8) are equal to those on the placebo dates (column 2), and on the meeting dates in the baseline regression (column 1), respectively. If our measures are good proxies for disagreement, then elasticity estimates should be close to those on placebo dates. We find that for all six measures, the estimates for the elasticity increase and move closer to the level observed on the placebo dates in column 2, which supports our assumption that these proxies capture the increase in disagreement around shareholder meetings (see table 5 in Bollerslev, Li, and Xue 2018 as a comparison.) In column 9, we report the results for a multivariate regression that includes all six disagreement measures, which increases the elasticity estimate to 0.684. In most cases (columns 5, 6, 7, 8, and 9), we can reject the null hypothesis that the elasticity estimates are equal to those on the meeting date without controls for disagreement (column 1) as indicated by the chi-squared test reported at the bottom of panel A. We can also reject the null hypothesis that the elasticity estimates are significantly different from those measured at the placebo dates. Overall, we conclude from the analysis in panel A of Table 9 that disagreement theory has significant explanatory power for the volume-volatility relationship around meeting dates. While Bayesian learning and disagreement are both prevalent on meeting dates and on nonmeeting dates, the weight shifts significantly around meeting dates, when disagreement becomes more important.

Building on the discussion in Section 3.2, we investigate whether nonroutine (routine) proposals lead to higher (lower) disagreement. Similarly, we infer from the discussion of Table 3 that votes on management proposals lead to more disagreement and votes on shareholder proposals lead to less disagreement. Hence, we expect lower elasticity estimates for shareholder proposals than for management proposals. We test both hypotheses in panel B of Table 9, where we repeat the baseline analysis (without disagreement controls) for the same subsamples defined by proposal types and sponsors we use in Table 3. Column 1 of panel B repeats the baseline analysis from column 1 of panel A for better comparison. Columns 2, 3, and 4, include only those meetings for which, respectively, at least one vote was on director elections, say-on-pay, or auditors.

Column 5 has only meetings that include at least one nonroutine proposal; that is, it excludes those meetings that have only votes on director elections, say-on-pay votes, and auditor appointments. Column 6 includes all meetings with only management proposals, and column 7 has all meetings with at least one shareholder proposal (see Section 3.2 for more details on proposal types). We find support for both hypotheses. First, routine proposals (director elections, say-on-pay votes, and auditor appointments) are all associated with higher elasticity estimates, hence, lower disagreement, than nonroutine proposals (column 5). Second, shareholder proposals (column 7) are associated with higher volume-volatility elasticities and less disagreement than management proposals. Hence, both analyses, at the fund level and that at the meeting level, are broadly consistent with the view that nonroutine proposals are associated with more disagreement, but the meeting-level analysis supports this hypothesis more consistently than the fund-level analysis.

5.3 Alternative explanations

In their survey, Hong and Stein (2007) discuss three different theoretical approaches that may explain disagreement: (1) disagreement based on different interpretations of the same signal; (2) a gradual flow of information, such that some investors receive the same information later than others; and (3) limited attention, such that only some investors process information whereas others do not pay attention because of cognitive overload. Our argument above relies only on the first argument. In this section, we discuss and test the other two approaches. Both gradual information flow and limited attention imply that some investors process information earlier than others. These two theories differ only regarding which friction leads to delayed information processing, and Hong and Stein (2007, p. 118) conclude that “the differences between limited attention and gradual information flow may be somewhat semantic.” Therefore, we focus on the limited-attention argument, which is more suitable in our context, since it is not plausible to assume that the institutional investors in our sample lack the sophistication and resources to receive and interpret shareholder voting results. To explore the potential relevance of limited attention, we make use of the fact that shareholder meetings cluster in certain periods of the year. Accordingly, some shareholder meetings take place on the same day, which requires investors to process the results from a large number of meetings and may lead to delayed information processing. To test for this possibility, panel C of Table 9 repeats the analysis from panel A of the same table, but now interacts the change in log volume, $\Delta log\left(m_j\right)$, with an additional dummy variable *Distraction*, which equals one for those meetings held on days with above-median number of shareholder meetings, and zero otherwise. Hence, the coefficient for $\Delta log\left(m_j\right)$ measures the elasticity for meetings with low distraction, whereas the coefficient for interaction measures by how much the elasticity increases if distraction is high. If disagreement is driven by limited attention, rather than by different interpretations of the same information, then disagreement should be stronger when distraction is high; that is, we expect *lower* elasticity estimates if *Distraction* equals one, and, therefore, a negative coefficient for the interaction term.

The results in panel C of Table 9 do not suggest that limited attention is the source of disagreement. The point estimates for the interaction with *Distraction* are positive and numerically small, suggesting slightly *less* disagreement if investors are distracted by an above-median frequency of shareholder meetings. However, the interaction terms are never statistically significant.

5.4 Shifts in the shareholder base

Based on the results on trading behavior (Section 3) and on volume and volatility (Sections 5.1 and 5.2), we hypothesize that trading after shareholder meetings creates a more homogeneous shareholder base and explore the possibility of such a shift more explicitly in this section. To do so, we go beyond the funds in our sample and include all mutual funds in the CRSP mutual fund database with voting records between February 28, 2010, and June 30, 2013. The discussion above suggests that shareholders who disagree with the choices of the majority sell to those who are more in agreement. Hence, we ask whether firms are held by more shareholders that tend to agree with the majority vote after the meeting.

To test this hypothesis, we define the variable $Against_{ij}$ as the fraction of proposals on which fund i voted against the majority at meeting j. For example, if 5 proposals are voted on at the meeting and the fund votes against the majority for one of them, then *Against* = 0.2. Next, we construct two meeting level measures $Proportion\ against_{jt-1}$ and $Proportion\ against_{jt+1}$, which are the pre- and post-meeting weighted averages of $Against_{ij}$ for all funds i in our sample that voted at meeting j, where $t-1$ $(t+1)$ denotes the quarter immediately before (after) the shareholder meeting. The weights used to construct $Proportion\ against_{jt-1}$ and $Proportion\ against_{jt+1}$ are the shares held by funds by the end of the respective quarter. We think of $Proportion\ against$ as a measure of the heterogeneity of the shareholder base such that a higher value indicates more disagreement among funds. For example, $Proportion\ against_{jt-1}$ would be equal to 0.1 if at the end of quarter t-1 half of the shares are owned by funds that vote against 20% of the proposals (for them *Against* = 0.2), whereas the other half are held by funds who always vote with the majority (for them *Against* = 0.0). We then average $Proportion\ against_{jt-1}$ and $Proportion\ against_{jt+1}$ across all 10,525 meetings for which we can calculate these two measures and find that the mean of $Proportion\ against$ declines from 0.0947 at the end of the quarter immediately before the meeting date (quarter $t-1$) to 0.0930 at the end of the quarter immediately after the meeting date (quarter t+1), and this change is significant at all conventional significance levels (t-statistic = 4.67).[31]

[31] We repeat this exercise by defining $Against_{ij}$ as a dummy variable that equals one if fund i voted against the majority at meeting j on at least one proposal and obtain similar results. With this definition, the average of *Proportion against* drops from 0.2852 to 0.2810 (t-statistic of change is 4.84).

To put this analysis into context, we then analyze changes in mutual fund ownership of all meetings held between February 28, 2010, and June 30, 2013, using the CRSP mutual fund holding data. In particular, we classify funds that own (do not own) shares in the quarter after the meeting but did not own (did own) shares in the quarter before the meeting as entrants (exits), and those that own more (fewer) shares after than before as buyers (sellers); hence, buyers (sellers) include entrants (exits) as a subset. We find that the ownership of buyers in the firm increases by 3.9% and the ownership of sellers declines by 3.2%, whereas entrants and exits both account for a 1.3% change in ownership.[32] Hence, most of the changes in ownership come from funds that partially adjust their positions and not from funds that entirely enter or exit from the shareholder base.

6. Disagreement and Corporate Governance

In this section we discuss the implications our results have for corporate governance. Our results above suggest that trading after shareholder voting reduces the heterogeneity among shareholders. Several recent theoretical arguments suggest that homogeneity and the cohesiveness of groups are important for decision-making in groups to be effective. Garlappi, Giammarino, and Lazrak (2017, 2020) and Donaldson, Malenko, and Piacentino (2020) show in different contexts that groups of decision-makers that disagree with each other reach inefficient decisions or may not reach any decision at all. Two aspects are important here. The first one is dynamic: if decision-makers anticipate that their preferred choices may not prevail in the future because others do not share their beliefs, then they will block policies preferred by others, which can lead to deadlock (Donaldson, Malenko, and Piacentino 2020) and underinvestment (Allen and Gale 1999; Garlappi, Giammarino, and Lazrak 2017). The second aspect is that the source of diversity is important. A large literature shows that diversity may be beneficial if decision-makers complement each other, for example, if they have complementary information or skills.[33] However, unlike with differences of information or skills, diversity based on either different opinions or different preferences implies that group members cannot convince each other and learn from each other to reach a consensus. The last aspect seems critical for the negative conclusions about diversity based on disagreement.

The theoretical arguments that creating a more cohesive shareholder base is important to enhance the effectiveness of governance are supported by the

[32] Note that these changes in ownership are consistent with the increase in homogeneity shown before. To see this, consider a stylized numerical example in which buyers purchase 3.4% of the firm's shares and sellers sell 3.4%. Assume buyers have a value of *Against* that is on average 0.05 lower than that of the sellers. Then *Proportion against* for the firm would decline by 0.05*0.034 = 0.0017, which is equal to the change we observe in the data (= 0.0947 – 0.0930).

[33] On skills, see Hamilton, Nickerson, and Owan (2012). See Williams and O'Reilly (1998) for a review of the earlier research on group decision-making in organizational behavior.

empirical literature, which we review in the Introduction and do not repeat here. There, we show that prior studies provide ample evidence for the notion that the cohesiveness of the shareholder base matters for firm values and profitability.[34] Hence, we infer from our findings and this literature that forming a more homogeneous shareholder base through trading after shareholder meetings may be important to enhance firm value.

We conclude that correctly identifying the frictions in corporate governance is important in order to correctly address these frictions. Much of the literature on corporate governance studies the frictions between those who make decisions and those for whom decisions are made, and focuses on two major mechanisms to mitigate these frictions: agency-theoretic arguments emphasize the alignment of incentives whereas information-based arguments emphasize disclosure and incentives for information revelation. However, if frictions emanate from differences in beliefs or preferences, then neither of these mechanisms would be effective. In particular, heterogeneous preferences imply that the firm does not have a uniquely defined objective (e.g., DeMarzo 1993), and if shareholders interpret the same information differently, then more disclosure and more available information may increase the divergence of opinions rather than reduce it (see the discussion in Section 1.1.1). Instead, the literature on disagreement has emphasized trading as a strategy to reduce frictions from differences of opinions. Allen and Gale (1999), Boot, Gopalan, and Thakor (2008), and, more recently, Garlappi, Giammarino, and Lazrak (2017, 2020), all suggest that trading may be critical for restoring efficiency: if those who are biased toward a certain alternative can buy out those who are biased against it, then agreement is more likely, decisions become time consistent, and projects are more likely matched with investors who support them. Moreover, shareholders whose preferences or views do not prevail may benefit more from selling their shares than from having their own preferred choices implemented.[35] Based on these arguments and the findings of our paper, we conclude that frictions from disagreement deserve attention in the corporate governance debate, just as much as frictions from agency problems and asymmetric information. In this respect, our analysis provides indications about which types of proposals are generally associated with more disagreement. Moreover, we propose several measures of disagreement, which can be used as empirical indicators and can be validated using volume-volatility elasticities.

Two further implications result from this discussion. First, more disclosure of voting results is likely to be beneficial. If shareholders could better understand

[34] See Cronqvist and Fahlenbrach (2009), Kandel, Massa, and Simonov (2011), Brav et al. (2021), Hadlock and Schwartz-Ziv (2019), and Schwartz-Ziv and Volkova (2020). See the Introduction for a more detailed discussion of this literature.

[35] This directly follows from Levit, Malenko, and Maug (2020) and more indirectly from Boot, Gopalan, and Thakor (2008).

how other shareholders voted on particular items, shareholders could make more reliable inferences about whether or not the opposing shareholders are likely to stay with the firm or not. This knowledge would enable shareholders to buy shares in firms with like-minded shareholders. Thus, this interpretation of our results supports regulatory measures for more disclosure of shareholders' voting decisions.[36] Second, and based on the same argument, more liquid markets for shares are probably beneficial, because they would facilitate the process in which shareholders gravitate to firms with a better-matching shareholder base.

7. Conclusion

In this paper we analyze trading volume, price responses, and the relationship between trading decisions after shareholder votes and voting decisions for a sample of funds. The funds in our sample are more likely to sell, and less likely to buy a stock if their vote was inconsistent with the voting outcome. We interpret this behavior in the context of models in which shareholders interpret the same information differently. We analyze the dynamics of trading volume and return volatility after shareholder meetings by using an approach that allows us to nest Bayesian learning and disagreement within the same framework. We conclude from our findings that trading is best interpreted as a combination of disagreement with Bayesian learning, such that meetings mark a significant shift toward trades that are motivated by disagreement. We acknowledge repeatedly throughout the paper that disagreement may derive from different preferences as well as from differences in beliefs. However, the theoretical literature provides little guidance on how heterogeneous preferences may affect trading volume and the relationship between prices and volume. For this reason, we build on differences-of-opinion models in our discussion in the main body of the paper. This gap in the literature should be filled by future research.

Our results have important implications for corporate governance. If corporate governance institutions address frictions from agency issues or asymmetric information, then they are appropriately addressed through measures that align incentives and ensure the disclosure of information. However, if frictions in governance arise from disagreement among shareholders, then incentive alignment and information disclosure may be ineffective, and in some cases even harmful. Instead, trading such that shareholders with different views buy out each other may be optimal. Measures that enhance liquidity and better disclosure of voting results, which facilitate a process in which shareholders can identify firms with a shareholder base that

36 Indeed, recent regulatory efforts attempt to extend the requirement to disclose the votes cast from mutual funds to all financial institutions, see, for example, https://www.federalregister.gov/documents/2019/12/26/2019-26563/regulatory-agenda-semiannual-regulatory-agenda, paragraph 522. Additionally, platforms, such as ProxyDemocracy and MoxyVote, have collected votes from institutions that have voluntarily disclosed their votes (e.g., from pension funds) to promote the disclosure of votes from various types of shareholders.

matches their own preferences and beliefs, are likely to be beneficial. Hence, identifying the source of frictions in governance is important and should be a focus of empirical research on governance.

Appendix A

A.1. The Model of Kandel and Pearson (1995)

In this section, we provide more details on the model of Kandel and Pearson (1995) and its empirical implementation by Bollerslev, Li, and Xue (2018). In the model, investors observe a public signal $\tilde{u}_i+\tilde{\varepsilon}_i$ of the asset payoff $\tilde{u}_i$, but they disagree about its interpretation. Let α_i be the fraction of more optimistic investors in stock i, who have some prior belief $\mu_{i0}=E_0[\tilde{u}_i+\tilde{\varepsilon}_i]$ about the information contained in a publicly available signal, whereas the other $1-\alpha_i$ investors in stock i interpret the same signal more pessimistically and attribute a mean $E_p[\tilde{u}_i+\tilde{\varepsilon}_i]=\mu_{ip}<\mu_{i0}$ to the same signal. Moreover, the two types of investors differ with respect to the precision of their priors $s_{i0}\neq s_{ip}$. Let r denote the inverse of the coefficient of absolute risk aversion and let h be the precision of the signal. For simplicity, assume that both types of investors have the same precision h.[37]

Suppress the index i and let all symbols refer to some representative stock. Then the parameters in Equation (1) can be obtained as (Bollerslev, Li, and Xue 2018, equation (2.2)):

$$\beta_0=r\alpha(1-\alpha)h(\mu_0-\mu_p),$$
$$\beta_1=r\alpha(1-\alpha)(s_0-s_p). \tag{A1}$$

With these definitions, agreement about the interpretation of the signal implies that optimistic and pessimistic investors agree on μ so that $\mu_0=\mu_p$. Hence, agreement implies that $\beta_0=0$ from (A1). From Equation (1), $|\beta_0|$ measures the component of trading volume that is independent of price changes, and Equation (A1) shows that this magnitude is proportional to the different interpretations optimists and pessimists give to the signal, the precision h of the signal, and the heterogeneity of the shareholder base, measured by $\alpha(1-\alpha)$.

The slope of the relationship between trading volume and price changes comes from the difference in the precision of prior information, which determines the weights investors give to the signal relative to their priors: investors with more precise priors give less weight to new signals. Hence, investors trade more for a given change in the valuation of the stock if their updating rules for the signal differ more because of these differences in weights. If all investors have the same prior information, then $s_0=s_p$ and, from (A1), $\beta_1=0$, and investors do not trade since they agree on how new information should be incorporated into prices.

Bollerslev, Li, and Xue (2018) derive the following relationship for ϵ (see their equations (2.4) and (2.5)):

$$\varepsilon\equiv\frac{\partial m(\sigma)/m(\sigma)}{\partial\sigma/\sigma}=\frac{1}{1+\psi(\gamma/\sigma)}, \tag{A2}$$

where ψ is a function that depends on the density of the standard normal distribution and the argument γ/σ of ψ can be interpreted as a normalized measure of disagreement between the two groups of investors that have different opinions. The parameter γ is given by (Bollerslev, Li, and Xue 2018, equation (2.5)):

$$\gamma=\frac{|\beta_0|}{|\beta_1|}=\frac{h\left|\mu_0-\mu_p\right|}{\left|s_0-s_p\right|}. \tag{A3}$$

[37] See Kandel and Pearson (1995, equation (5)) and Bollerslev, Li, and Xue (2018, equations (2.1) and (2.2)). The notation follows that of Bollerslev, Li, and Xue (2018) and their simplifications of the Kandel-Pearson model, which assumes that the signal precisions of both groups of investors are identical.

Bollerslev, Li, and Xue (2018) interpret γ as a measure of disagreement, which is normalized by the volatility σ in Equation (A2). In particular, if $\gamma=0$, then $\psi(\gamma/\sigma)=0$ in Equation (A2) and the elasticity $\varepsilon=1$.

A.2. Bootstrapped p-values

We apply block bootstrap with replacement to compute p-values of t-statistics in Table 2. Block bootstrap maintains the autocorrelation structure within each block (see Bertrand, Duflo, and Mullainathan 2004, section IV.B).

The data in Table 2 have 13,210 unique fund-meeting combinations. Observations corresponding to each fund-meeting combination are treated as one block and kept together. We perform 200 iterations of the bootstrap and for each iteration, we draw 13,210 blocks from the original data with replacement. For each such bootstrapped sample, we rerun the same regressions as in Table 2 and retain the coefficients and standard errors. In addition, we obtain for each regressor and each iteration a bootstrapped t-statistic as follows:

$$\mathrm{t_r}=\frac{(\beta_\mathrm{r}-\beta_0)}{\mathrm{se}(\beta_\mathrm{r})},\ \mathrm{r}=1,\ldots,200,$$

where β_r and $\mathrm{se}(\beta_\mathrm{r})$ are the estimated coefficient and standard error from the bootstrapped sample in the rth iteration and β_0 is the coefficient estimate from the original sample in Table 2. Let $\mathrm{t_0}=\frac{\beta_0}{\mathrm{se}(\beta_0)}$ denote the t-statistic in Table 2. From Bertrand, Duflo, and Mullainathan (2004), the sampling distribution of $\mathrm{t_r}$ is random and changing as N (the number of blocks) grows; the difference between the sampling distribution of $\mathrm{t_r}$ and the distribution of $\mathrm{t_0}$ becomes small as N converges to infinity, even in the presence of arbitrary autocorrelation within blocks and heteroscedasticity.

Table 8 presents the percentage of the values of $|\mathrm{t_r}|$ (the absolute value of $\mathrm{t_r}$)that exceed $|\mathrm{t_0}|$. Bertrand, Duflo, and Mullainathan (2004) report in their table V one minus the two-sided p-value, which corresponds to the probability that the alternative hypothesis ($\beta\neq 0$) is true.

Appendix B

Table B1
Glossary of variables

Variable	Definition	Data source
Abnormal number of trades	Daily number of trades/average daily number of trades during pre-voting period – 1. The pre-voting period is defined as the [-252, -21] window before the record date	TAQ
Abnormal return	Daily abnormal returns as estimated using the Fama-French-Carhart four-factor model. Exactly following Savor (2012), betas for market excess return, SMB, HML, and UMD are estimated by OLS regressions for a 255 trading day-period starting 31 trading days before the event day with at least 30 data points. Using the [-252, -21] pre-voting period window to estimate betas generates quantitatively similar results	CRSP, data library of Kenneth French
Abnormal volatility	The ratio of daily realized volatility and the exponential moving average of daily realized volatility over the pre-voting period with a half-life of five days, minus 1. The pre-voting period is defined as the [-252, -21] window before the record date. Daily realized volatility is estimated by the square root of sum of squared 5-minute returns within a trading day	TAQ
Abnormal volume	Daily volume/average daily volume during the pre-voting period −1. The pre-voting period is defined as the [-252, -21] window before the record date	CRSP
Active fund	An indicator variable that equals one if the fund is identified as an active fund, and zero if it is identified as an index fund. We follow Appel, Gormley, and Keim (2016) to classify funds as index versus actively managed funds. Specifically, we define a fund as an index fund if the CRSP Mutual Fund Database classifies it as a "Pure Index fund" (category "D") or if its fund name includes a string that identifies it as an index fund. The strings we use to identify index funds are bloomberg, composite, dj, dow, dow, etf, exchange-traded fund, ftse, holdrs, idx, ind, index, indx, ishares, jones, kbw, market, mkt, morningstar, msci, nasdaq, nyse, powershares, russ, russell, s&p, sandp, sp, spdr, streettracks, stoxx, wilshire, 100, 1000, 1500, 2000, 3000, 400, 4000, 500, 5000, 600, and 900. All other funds are classified as active funds. We exclude from our analysis a small number of funds that we are unable to match to a fund name	CRSP US Mutual Fund Database
After	Dummy variable equals one for all days from the meeting date until 30 days after the meeting, and zero otherwise	ISS Voting Analytics
Assets under management	Total assets minus total liabilities as of month end in millions	CRSP US Mutual Fund Database
Average fraction of funds against ISS	Mean of the fraction of funds' votes cast against ISS, averaged across all proposals at the meeting	ISS Voting Analytics
Average fraction of funds against management	Mean of the fraction of funds' votes cast against management, averaged across all proposals at the meeting	ISS Voting Analytics

Table B1
(Continued)

Variable	Definition	Data source
Book-to-market ratio	Book-to-market in June of year t = (book value of stockholders' equity + balance sheet deferred taxes and investment tax credit, if available–book value of preferred stock for fiscal year t-1)/market value of equity in December of year t-1	CRSP, Compustat
Buy	Dummy variable equals one if the fund buys the stock on a given day, and zero otherwise	ANcerno
Churn ratio	Following Gaspar, Massa, and Matos (2005), we define churn ratio as $CR_{i,t} = \frac{\sum_{j \in Q} \lvert N_{j,i,t} P_{j,t} - N_{j,i,t-1} P_{j,t-1} - N_{j,i,t-1} \Delta P_{j,t} \rvert}{\sum_{j \in Q} \frac{N_{j,i,t} P_{j,t} - N_{j,i,t-1} P_{j,t-1}}{2}}$, where $P_{j,t}$ and $N_{j,t}$ represent the price and the number of shares of company j held by institutional investor i in quarter t	CRSP US Mutual Fund Database
Close	Dummy variable equals one if the proportion voted in favor is between 45% and 55%, and zero otherwise	ISS Voting Analytics
Contradict	Dummy variable equals one if, for a given meeting, the fund voted in support of at least one proposal and that same proposal failed, or if the fund voted against at least one proposal and that same proposal passed; the dummy variable is zero otherwise	ISS Voting Analytics
Contradict, fund against management	Dummy variable equals one if, for at least one proposal of a given meeting, the fund voted against management recommendation and the voting outcome of that same proposal was consistent with management recommendation; the dummy variable is zero otherwise	ISS Voting Analytics
Contradict, fund with management	Dummy variable equals one if, for at least one proposal of a given meeting, the fund consistently voted with management recommendation and the voting outcome of that same proposal was against management recommendation; the dummy variable is zero otherwise	ISS Voting Analytics
Environmental fund	Dummy variable equals one if the fund or the fund family signed the Principles for Responsible Investment (PRI)	Principles for Responsible Investment
Expense ratio	Fraction of fund's assets used for administrative and other operating expenses	CRSP US Mutual Fund Database
Fraction of company held	Number of shares held /number of shares outstanding in bps	CRSP US Mutual Fund Database
Fund against ISS, outcome with ISS	Dummy variable equals one if, for at least one proposal of a given meeting, the fund voted against ISS recommendation and the voting outcome of that same proposal was consistent with ISS recommendation; the dummy variable is zero otherwise	ISS Voting Analytics
Fund with ISS, outcome against ISS	Dummy variable equals one if, for at least one proposal of a given meeting, the fund consistently voted with ISS recommendation and the voting outcome of that same proposal was against ISS recommendation; the dummy variable is zero otherwise	ISS Voting Analytics

Table B1
(Continued)

Variable	Definition	Data source
Distraction	Dummy variable equals one for meetings held on days with above-median number of shareholder meetings, and zero otherwise	ISS Voting Analytics
ISS against management	Dummy variable equals one if ISS recommends voting against management for at least one proposal, and zero otherwise	ISS Voting Analytics
Market capitalization	Price × number of shares outstanding in millions	CRSP
Merger vote	Dummy variable equals one if the meeting features a vote on a merger (issagendaitemid = M0405), and zero otherwise	ISS Voting Analytics
Net fraction of company bought	Net number of the firm's shares bought by the fund on a given day/number of firm's shares outstanding, in bps	ANcerno, CRSP
Net fraction of portfolio bought	Net dollar value of shares bought by the fund on a given day in a given firm divided by the total dollar value of the fund's overall portfolio at the end of the most recent quarter, in bps	ANcerno, CRSP
Nonroutine meeting	A meeting that has at least one nonroutine proposal	ISS Voting Analytics
Nonroutine proposal	Proposals other than director elections, say-on-pay proposals, and approving auditors	ISS Voting Analytics
Outcome against ISS	Dummy variable equals one if at least one outcome is against ISS recommendation, and zero otherwise	ISS Voting Analytics
Outcome against management	Dummy variable equals one if at least one outcome is against management recommendation, and zero otherwise	ISS Voting Analytics
Overlapping directors	Dummy variable equals one if the fund family and the firm share a director, and zero otherwise. See Li and Schwartz-Ziv (2020) for computational details	N-CSR filings, GMI rating
Portfolio weight	Fraction of the total net assets in the portfolio on a security, in bps	CRSP US Mutual Fund Database
Sell	Dummy variable equals one if the fund sells the stock on a given day, and zero otherwise	ANcerno
Special meeting	Variable is equal to one if "meetingtype" is different from "annual"	ISS Voting Analytics
Turnover ratio	Turnover ratio of the fund	CRSP US Mutual Fund Database
Vote with ISS history	The fraction of votes in which the fund consistently voted with ISS's recommendation between 2007 and 2009	ISS Voting Analytics
Vote with management history	The fraction of votes in which the fund consistently voted with management's recommendation between 2007 and 2009	ISS Voting Analytics

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