

# When Shareholders Disagree: Trading After Shareholder Meetings

Finance Working Paper N° 594/2019

January 2019

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ECGI Working Paper Series in Finance

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## Abstract

This paper analyzes how trading after shareholder meetings changes the composition of the shareholder base. Mutual funds in our sample sell, or buy less, if their votes are opposed to the voting outcome, independently of whether funds oppose or support management. Trading volume peaks at the meeting date and remains at elevated levels up to four weeks after shareholder meetings; it is higher even when stock prices do not change. These findings are difficult to reconcile with models in which shareholders trade because of differences in information. We explore recently-published models of trading based on disagreement and differences of opinions, which offer sharp predictions on the relationships between volume, volatility, and the autocorrelations of volume. We find strong support for these models in the data, and little to support models in which voting aggregates information. We conclude that shareholders disagree when they vote at meetings, and their beliefs may diverge even more strongly after the meeting. Hence, trading after meetings creates a shareholder base with more homogeneous beliefs. We argue that these findings have important implications for corporate governance.

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Keywords: Shareholder Meetings, Voting, Disagreement, Trading, Volume

JEL Classifications: G11, G12, G14, G30, G40

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## Abstract

This paper analyzes how trading after shareholder meetings changes the composition of the shareholder base. Mutual funds in our sample sell, or buy less, if their votes are opposed to the voting outcome, independently of whether funds oppose or support management. Trading volume peaks at the meeting date and remains at elevated levels up to four weeks after shareholder meetings; it is higher even when stock prices do not change. These findings are difficult to reconcile with models in which shareholders trade because of differences in information. We explore recently-published models of trading based on disagreement and differences of opinions, which offer sharp predictions on the relationships between volume, volatility, and the autocorrelations of volume. We find strong support for these models in the data, and little to support models in which voting aggregates information. We conclude that shareholders disagree when they vote at meetings, and their beliefs may diverge even more strongly after the meeting. Hence, trading after meetings creates a shareholder base with more homogeneous beliefs. We argue that these findings have important implications for corporate governance.

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# 1 Introduction

There is a large empirical literature on shareholder voting in corporate finance, which analyzes how shareholder voting corrects decision-making in the firm.<sup>1</sup> 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. In this framework, shareholders and management may not have the same preferences because they have different interests, e.g., when management has the opportunity to appropriate private benefits or when voting constrains managerial discretion.<sup>2</sup> 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, or if they have different preferences, e.g., if some shareholders are more aligned with management or have access to private benefits of control as blockholders.<sup>3</sup>

In this paper, we start from a different perspective and emphasize differences of opinions rather than differences in preferences.<sup>4</sup> Differences of opinions may arise if shareholders interpret the same information differently. Conflicts may arise from differences in beliefs that cannot be attributed to differential access to information but derive from different models shareholders use to interpret the same information. We argue that the patterns of volume and return volatility as well as individual shareholders' trading decisions around shareholder meetings are better understood from this perspective.

We ask two main research questions. First, we ask how shareholders' voting decisions and their trades after shareholder meetings are related. If we look at trading decisions after meetings from the perspective of

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<sup>1</sup> 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 (2018) for contributions to the say-on-pay debate; Malenko and Shen (2016) on the role of proxy advisory firms; and Iliev and Lowry (2015) and Calluzzo and Kedia (2018) on mutual fund voting. All these papers are recent and contain extensive discussions of the prior literature.

<sup>2</sup> The discussion of private benefits in the voting context goes back at least to Grossman and Hart (1988). The literature uses voting premiums to measure private benefits following Zingales (1994).

<sup>3</sup> Information aggregation through voting was modeled in the political science literature by Austen-Smith and Banks (1996). It was applied in the corporate finance literature, e.g., by Maug and Rydqvist (2009). We discuss this literature in more detail below.

<sup>4</sup> 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 appears to be Kakhbod et al. (2019).

standard information-aggregation models on voting, then there should be no systematic relationship between voting and post-meeting trades, because voting aggregates information, and shareholders learn each other's information once the voting outcome is disclosed and becomes publicly available information. Second, we want to understand what explains the large trading volume we observe after shareholder meetings. Again, if looked at in the light of information-aggregation models, these large abnormal trading volumes are puzzling, because the disclosures of meeting results and other news released at shareholder meetings should lead shareholders' beliefs to converge, eliminating the need for trading.<sup>5</sup>

We perform analyses at two levels. To begin, we analyze trading and voting at the fund level and ask if there is a systematic relationship between voting and trading after the meeting. The theoretical foundation for our hypothesis development at the fund level is the model of Boot, Gopalan and Thakor (2008), who analyze the public-private trade-off in a disagreement 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 entrepreneur. The argument does not depend on whether the decision-maker in the firm is management, as in the case of Boot et al. (2008), or shareholders, as in our context. The critical question for all shareholders is whether they endorse the decisions taken by the majority at the meeting, and whether they believe the stock price is justified given their beliefs.

Using data on daily trades of mutual funds in the ANcerno database for which we can identify the funds' corresponding votes in ISS Voting Analytics, we find that the funds in our sample are significantly more likely to sell, and less likely to buy, if their voting decision was opposed by the majority of other shareholders for at least one proposal that was voted on at the shareholder meeting. They reduce their holdings, independently of whether the fund supports management, but the majority of other shareholders opposes management, or the reverse. We conclude that the fund's decision to trade is not based on whether it supports or opposes

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<sup>5</sup> In their discussion of the prior literature, Hong and Stein (2007) associate large trading volumes generally with disagreement.

management, but whether its view of the correct decision the firm should take is shared by the majority of other shareholders.

This finding is difficult to reconcile with voting models based on information aggregation, in which shareholders vote differently only if they observe different signals. In information-aggregation models, shareholders update their beliefs as soon as they observe the voting result, which eliminates pre-voting differences in their assessments of the value of the firm, and of its 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 disagreement models, shareholders do not update their beliefs. Rather, they rebalance their portfolios if their views are opposed by the majority of other shareholders. They conclude that the decision taken at the shareholder meeting is incorrect and does not maximize firm value, inducing them to sell.

We complement the fund-level analysis with a meeting-level analysis of trading volume around shareholder meetings. Rational expectation models cannot generate predictions for the large abnormal trading volume we observe around shareholder votes (Milgrom and Stokey (1982)). Noisy rational expectation models are consistent with larger trading volumes, but they leave no room for trading volume absent changes in stock prices (Kim and Verrecchia (1991b)). Yet, we can reject the hypothesis that trading volume is zero for meetings with small price changes, which is inconsistent with noisy rational expectations models, but fully in line with disagreement models of price formation (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 in the stock. Hence, we turn to disagreement models to interpret our evidence and test two models.

First, we adapt the methodology of Bollerslev, Li and Xue (2018), who develop an empirical test of the model of Kandel and Pearson (1995). The Kandel-Pearson model accommodates trading volume without price changes, which implies that the elasticity of trading volume with respect to return volatility is below unity when shareholders disagree and is smaller the larger is the disagreement among shareholders. By contrast, a noisy rational-expectations, which can be nested in the Kandel-Pearson model as a special case, predicts this elasticity to be equal to one. We find that the volume-volatility elasticity is significantly lower than unity; it is below the

value we observe around placebo dates without news releases, and it is significantly lower on meeting dates for which several measures of disagreement are higher.

Second, we test the predictions of the model of Banerjee and Kremer (2010), who develop a dynamic model of trading and price changes based on differences of opinion. Their model develops the realistic scenario that, in regular times, markets learn mainly easy-to-absorb information, which leads to convergence of beliefs. Occasionally, however, the market learns information that is more complex and ambiguous, which gives rise to disagreement. These spikes in disagreement are followed by a period of convergence of beliefs, associated with higher trading volume and with a higher autocorrelation of trading volume. We test these and other predictions of the Banerjee-Kremer model and find that they are all supported by the data. Hence, the models of Bollerslev et al. (2018) and Banerjee and Kremer (2010) provide complementary perspectives on the relationships between trading volume, return volatility, and the autocorrelation of volume, and the implications of both models are consistent with our data.

Hence, we follow the lead of three models, all of which are based on the notion that shareholders interpret the same information differently: Boot et al. (2008) inform our fund-level analysis, whereas Bollerslev et al. (2018) and Banerjee and Kremer (2010) provide tests for the meeting-level analysis. Our results support these models, whereas the evidence is difficult to reconcile with Bayesian-learning models.<sup>6</sup> We conclude that models that emphasize differences of beliefs between shareholders provide a better interpretation of the empirical evidence: Shareholder meetings increase disagreement, and shareholders who disagree with the majority sell after shareholder meetings. Hence, we conclude that trading after shareholder meeting aligns the shareholder base so that shareholders buy if their views are close to those of other shareholders, whereas those whose beliefs are less aligned with the majority sell. We infer that trading after meeting results in a more homogeneous shareholder base.

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<sup>6</sup> We use the term Bayesian learning to classify all models in which shareholders agree on the interpretation of new information and update their beliefs in accordance with Bayes' rule. For further clarification see Section 3.3.



This shift of emphasis from the more conventional agency perspective of corporate governance to one based on divergent beliefs between shareholders has important consequences for corporate governance, which we explore in greater detail in the Conclusion section. If shareholders disagree on decisions because they use different models to interpret the same public information, then differences between them cannot be reconciled through more public disclosure, given that more information may even increase disagreement. The trading after shareholder meetings, and the creation of a more homogeneous shareholder base may be important for the cohesiveness of decision-making inside the firm. The lack of cohesiveness of the shareholder base has recently been associated with lower valuations (Volkova (2018)).<sup>7</sup>

Our paper contributes to the voting literature by providing novel empirical evidence and by taking a new conceptual perspective. To begin, we are first to match daily trading data with voting data and to show how funds' voting stance relates to their trading decisions. Our results indicate that, when funds observe that their vote contradicts the vote outcome, they are more likely to sell and less likely to buy stock after the meeting.<sup>8</sup> Further, we are also first to document the patterns of trading volume and volatility around shareholder meeting dates, showing very large abnormal volume and volatility around shareholder meetings, even for extended periods after the meeting. By contrast, prior literature has focused on stock returns, with inconclusive results.<sup>9</sup> Finally, we explore a new angle for why shareholders may vote differently at shareholder meetings. The explanation closest to ours is Bolton et al. (2018), who distinguish shareholders that are consistently more supportive of management from those that are consistently more likely to oppose management, a tendency they label "investor ideology." We refer to differences in "ideology" as differences in models shareholders use to

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<sup>7</sup> The trade-off between the advantages of the cohesiveness and the advantages of diversity of decision-making bodies is the topic of a recent literature and beyond the scope of this paper. See, e.g., Hamilton, Nickerson and Owan (2012); Giannetti and Zhao (2016); Garlappi, Giammarino and Lazrak (2017); Delis et al. (2017).

<sup>8</sup> In contemporaneous research, Heath et al. (2018) provide evidence based on quarterly holdings that is consistent with ours, but less conclusive, probably because quarterly holdings are too noisy to achieve statistical significance.

<sup>9</sup> Some studies find no or negligible price effects around shareholder meetings (see Karpoff, Malatesta and Walkling (1996) and Gillan and Starks (2000), and Karpoff (2001) for a survey). Other studies document significant abnormal returns around shareholder meeting dates, but typically examine only a small subset of the votes. Specifically, Cuñat, Gine, and Guadalupe (2012) find positive abnormal returns around governance-related shareholder proposals passed by a small margin. However, most meetings do not include such proposals.

interpret the same data. The prior literature has focused on two explanations. Theories of asymmetric information and information aggregation attribute differences in voting decisions to private signals shareholders observe before voting at shareholder meetings (Maug and Rydqvist (2009); Levit and Malenko (2011); Van Wesep (2014)). However, these models imply that shareholders' beliefs converge after observing the meeting outcome, giving rise to lower volatility and volume after the meeting, which is not in line with our evidence. A second set of explanations attributes differences in voting decisions to differences in preferences, which may arise if fund managers have private benefits from their ties to the firm.<sup>10</sup> We are not aware of models that generate testable predictions on trading, volatility, and volume associated with these explanations. In the Conclusion, we argue that these explanations are unlikely to account for our evidence.

Our analysis also contributes to the literature on the composition of the shareholder base. It resonates the findings of Hadlock and Schwartz-Ziv (2018), who find a negative interdependence in blockholders' investment decisions, and Volkova (2018), who finds that blockholder diversity has a negative influence on firm value. Similarly, our discussion relates to the literature on exit, which argues that large shareholders may sell shares in a company when they believe it to be overvalued based on their private assessment, which may have a disciplinary impact on managers' (Edmans (2009); Admati and Pfleiderer (2009)). However, our argument emphasizes differences in beliefs between shareholders, not differences in information. Moreover, the activism literature sees exit as a mechanism to align the interests of shareholders and management, whereas our argument emphasizes the alignment of beliefs between different shareholders of the same firm through trading.

We place our paper in the context of the larger literature on disagreement models in finance. This literature originated to explain the large trading volume observed in financial markets, which is difficult to reconcile with rational expectations models.<sup>11</sup> The part of this literature closest to ours discusses earnings

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<sup>10</sup> E.g., if they manage firms' pension funds (Cvijanovic, Dasgupta and Zachariadis (2016); Davis and Kim (2007)); or if shares are voted by unions that represent labor interests rather than shareholder interests (Agrawal (2012); Kim and Ouimet (2014)). Matvos and Ostrovsky (2010) document heterogeneity in mutual funds' voting behavior and also emphasize this explanation. See also Morgan et al. (2011).

<sup>11</sup> Early examples include Varian (1985); Varian (1989); Varian (1992); 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.

announcements (see Bamber, Barron and Stevens (2011) for a survey) and relates differences of opinions to measures based on analyst forecasts, news releases, and, more recently, social media.<sup>12</sup> Compared to this literature, our setup is unique in that we can observe trading decisions and voting decisions for an important subset of shareholders. We hope that our contribution leads to further explorations of the applicability of disagreement models in corporate governance research.

## 2 Hypothesis development

We develop hypotheses based on two different theoretical foundations: (1) 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 (2) Bayesian learning models, in which investors share the same understanding on how to interpret publicly available information. We derive hypotheses from both frameworks. Section 2.1 introduces disagreement models, which are less well known. Since we perform empirical analyses at the fund level and at the meeting level, we derive predictions at both levels, first about the relationship between trading and voting at the individual fund level (Section 2.2), and then about the dynamics of trading volume at the meeting level (Section 2.4).

### 2.1 Disagreement models

The literature on disagreement, or differences of opinion has conventionally adopted one of two different modeling approaches. The first approach assumes that individuals have different priors but revise these priors consistent with Bayesian updating as new information becomes available.<sup>13</sup> The heterogeneous-priors approach implies that individuals agree once they observe sufficiently many common signals so that the weight of heterogeneous priors declines as more information becomes available. A second group of disagreement models

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<sup>12</sup> On analyst forecasts and recommendations, see Diether, Malloy and Scherbina (2002) and Bamber et al. (2011), among others. On internet news see Fedyk (2018). On social media, see Cookson and Niessner (2018) and Giannini, Irvine and Shu (2018).

<sup>13</sup> This approach 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). In Allen and Gale (1999) and Boot et al. (2008), investors randomly become either optimists or pessimists.

assumes that individuals interpret the same signals differently, because they interpret information based on different models of the world.<sup>14</sup> We refer to this approach as the “heterogeneous-models” approach, which provides a more radical departure from conventional Bayesian-learning models compared to the heterogeneous-priors approach since it implies that beliefs may diverge more as more information becomes available. The discussion in this paper borrows more from the heterogeneous-models approach, since we wish to interpret events in which disagreement appears to increase after more information has been disclosed to the market.

Differences-of-opinion models assume that individuals have heterogeneous beliefs even though they have access to the same information. This assumption stands in contrast to more conventional Bayesian-learning models, which attribute differences in beliefs to differential access to information. In disagreement models, individuals 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.

Disagreement may arise because commonly observed signals are ambiguous and require models to interpret them. For example, investors may gather valuation-relevant information about different dimensions of the firm, such as its product-market strategy, corporate governance, technology, or brand value, and these pieces of information may have contradicting implications. In addition, investors observe a myriad of variables that describe the firm’s economic environment. Then investors have to decide how these pieces of information should be weighed against each other, which requires a complex model in the context of which information can be interpreted, e.g., a valuation model of the cash-flow generating process of the firm or an equilibrium model of the macroeconomy. Investors may differ with respect to the models they use to aggregate information into a coherent interpretation of the facts. E.g., they may observe a shock to the same variable, such as a change in oil prices, but disagree on whether the price change will be permanent or transitory.

It is important to note that disagreement from using different models is not irrational and cannot be resolved by processing more information. Kurz (1994b) defines rational beliefs as those that are not contradicted

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<sup>14</sup> Examples of this approach include Harris and Raviv (1993), Kandel and Pearson (1995), and Boot, Gopalan and Thakor (2006).

by the data, and Kurz (1994a) shows that rational beliefs do not necessarily converge to rational expectations. Similarly, Acemoglu, Chernozhukov and Yildiz (2016) show that convergence of beliefs may not even occur if agents have access to infinitely many common observations, even though they update their beliefs consistent with Bayesian learning.

## 2.2 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. The key concept for developing our main shareholder-level hypothesis is the notion of a shareholder base, which may change endogenously to increase agreement among shareholders.

### 2.2.1 Disagreement and the shareholder base

Boot et al. (2008) develop a model of the shareholder base and we extend their reasoning to the voting context. Consider a firm with many shareholders in a public market. Shareholders have to make a decision on anything from electing new directors to approving a merger or a change in the governance structure. Shareholders have the same interest in maximizing shareholder value but differ in their beliefs about whether a particular choice is value-maximizing or not. In the first stage, shareholders vote based on their beliefs. In the second stage, after voting results from the shareholder meeting have been disclosed to all shareholders, shareholders trade. For our purposes, the key insight of Boot et al. (2008) is that in a liquid public market in which search costs for finding a buyer are practically zero, the firm will always be held by those shareholders whose beliefs are most closely aligned with those who make decisions in the firm, which is management in the model of Boot et al. (2008), and the majority of other shareholders in the context of shareholder voting. The firm is owned by those investors who value the firm the most, conditional on the decisions taken by the firm, and conditional on investors' beliefs. As soon as current shareholders realize that the firm will adopt policies which they do not endorse, whereas other investors do, the former will sell to the latter. Now assume that shareholders do not know other shareholders' beliefs about the desirability of a particular proposal before the meeting. Then they 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. Then those shareholders who disagree with the majority will value

the firm less than the majority of other shareholders who agree with the voting outcome, causing those shareholders who disagree with the majority to sell.

**Hypothesis 1 (Alignment of the shareholder base):** Shareholders whose vote is contradicted by the majority of shareholders at the meeting will sell after the meeting, whereas those who voted with the majority of other shareholders will hold their shares, or buy additional shares.

Our setting differs from that in Boot et al. (2008) in that management makes decisions in the context of their model, whereas we study meetings in which shareholders choose. This difference is immaterial, since the critical aspect is whether a particular shareholder's beliefs are aligned with the beliefs of those who determine the final decision, independently of whether it is managers or shareholders who make this decision. Similarly, no part of this argument refers to whether the proposal is sponsored by shareholders or by management. It may be the case that shareholders who voted against management find themselves in the majority, causing those who supported management to sell, and vice versa. Finally, the argument above makes no presumption that the proposal, if passed, will be implemented, or, conversely, that it will not be implemented if it is defeated. As long as the probability of implementation is affected by the voting outcome, the result will hold. It may even be sufficient for shareholders to learn that they are in the company of other shareholders who have different beliefs about critical decisions in the firm to induce them to sell.

The hypothesis requires us to assume that shareholders were not perfectly aligned before the meeting, e.g., 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. Hence, any alignment of the shareholder base is probably temporary and easily disrupted. In addition, we need to assume that disagreement among shareholders, or at least the extent of their disagreement, came to some extent as a surprise, otherwise shareholders 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.

## 2.3 Bayesian learning models

If investors have common priors, Bayesian updating based on common information implies that they also have the same beliefs after learning new information, such as the meeting outcome, vote tallies, or other information that may have been disseminated at the time of the shareholder meeting. Similarly, 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. Hence, if shareholders' beliefs would be different before the shareholder meeting because of heterogeneous information, these differences in beliefs would be reduced, if not eliminated, with the disclosure of the voting results. Finally, even if investors have heterogeneous priors, but 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 cases, (1) common priors with common information, (2) heterogeneous 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. We refer to all three cases as Bayesian learning models, since they all involve that shareholders agree on the interpretation of new signals and on how shareholders update their priors in accordance with Bayes' rule.

In information-based models, 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 the majority of 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 information. In particular, the beliefs that made a shareholder vote for or against a particular proposal at the meeting will not be informative about trading behavior after the meeting.

**Hypothesis 2 (Trading and voting with common models):** Shareholders' direction of trade after the meeting is independent of their voting stance at the meeting.

Hence, information-based models predict that shareholders hold on to their portfolio and revise their beliefs after shareholder meetings and trade less. By contrast, disagreement models predict that shareholders hold on to their beliefs and revise their portfolio holdings.

## 2.4 Dynamics of trading volume

### 2.4.1 Trading volume with Bayesian learning

In this section we derive hypotheses about the trading volume after shareholder meetings and how trading volume is related to price changes and return volatility. Accommodating a significant role for trading volume is difficult in conventional asset pricing theories, 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)). Models with exogenous liquidity traders (Kyle (1985)) can accommodate trading volume by assuming that prices are not fully revealing. In liquidity-trading models such as Kyle (1985), informed trading is proportional to price changes.

Kim and Verrecchia (1991a), (1991b) develop a noisy rational expectations model with Bayesian learning in which market participants who differ in risk aversion have asymmetric prior information and learn a new signal, which they interpret identically.<sup>15</sup> Kim and Verrecchia show that trading volume is strictly proportional to absolute price changes in such a model. The reason is that shareholders give different weights to new information, even if they interpret it identically, so their posterior beliefs differ and give rise to trading. Based on these models we have:

**Hypothesis 3 (Trading with Bayesian learning):** Trading is proportional to price changes. There is no (abnormal) trading without price changes.

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<sup>15</sup> Kim and Verrecchia (1991b) characterize their model as a rational expectations model. However, instead of assuming noise trading they assume a stochastic asset supply, which serves the same purpose of preventing prices from being fully revealing. Hence, we classify their model as a noisy rational expectations model.



## 2.4.2 Disagreement models and trading volume

This section develops the implications of disagreement models on trading volume to motivate univariate tests. We will derive more specific implications on volume-volatility elasticities in Section 4.2 and on volume autocorrelations in Section 4.4 below in order to keep the derivations of more technical, model-based predictions together with the discussion of the associated results.

Well-known no-trade theorems imply that shareholders with rational expectations do not trade with each other even after observing private information (Milgrom and Stokey (1982); Tirole (1982)). It takes considerable modeling effort to generate trading volume in rational models with common priors, e.g., by introducing frictions in the trading process and different preferences (see Karpoff (1986) and Kyle and Wang (1997)). The literature on disagreement models emerged to address the dynamics of trading volume that remained inexplicable in the context of earlier models. (e.g., Karpoff (1986); Varian (1992); Harris and Raviv (1993)). In particular, while noisy rational expectations models can accommodate trading volume, they cannot accommodate larger trading volumes that are not associated with correspondingly large price changes. By contrast, disagreement models imply that those who have lower valuations of a stock sell to those with higher valuations, which generates trades but may or may not be associated with price changes. E.g., in simple disagreement models of price formation such as Kandel and Pearson (1995), stock prices are a weighted average of investors' valuations, and these averages may not change even if the individual valuations of all investors change. Hence, we obtain a robust implication of disagreement models:

**Hypothesis 4 (Volume and price changes):** There is abnormal volume even when there are no abnormal prices changes.

## 3 Data and institutional context

This section describes how we collect the data and construct the sample (Section 3.1) and the institutional context (Section 3.2).

### 3.1 Data and sample selection

In this section, we describe the data sets used in the paper. The *Glossary of Variables* provides variable definitions.

*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 ISS's recommendations and data on the votes cast by mutual funds reported on SEC form N-PX.

*Mutual fund holding data.* Data on mutual fund holdings are obtained from the CRSP mutual fund holding files. Appendix A of Schwartz-Ziv and Wermers (2017) describes how we match these data to ISS Voting Analytics.

*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 dropped the fund identification variable after September 2011, so we cannot match later trades to funds' votes and, therefore, do not use them. ANcerno (also known as Abel Noser) is a consulting firm working with institutional investors to monitor execution costs. Hu et al. (2018) describe the ANcerno data, and the studies that have used this dataset. Puckett and Yan (2011) estimate that, while the institutions included in ANcerno are larger than the average 13F institution, they are similar to 13F institutions with respect to stock holdings, stock trades, and return characteristics. The ANcerno database captures clients' complete transaction histories, including date of execution, execution price, number of shares traded, and whether the transaction is a buy or sell. Since the database does not disclose the actual identities of the funds, we follow the matching procedures adopted by Busse et al. (2018) 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. We further match these S12 funds to the CRSP mutual fund data through the MFLINK data provided by WRDS (see Wermers (2000)). We are able to match our voting data to 1,169 Wharton Financial Institution Center Numbers (WFICNs), which are unique and permanent fund portfolio identifiers. Our final sample includes only funds for which we can observe at least one trade from 15 months before to nine months after a meeting date.

*Daily trading measures.* The TAQ (Trade and Quote) 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 (see Appendix A.1 for further details).<sup>16</sup> For each of these filings, we record the exact time the form was filed. If the filing time is between 4:00 PM and 5:30 PM, we classify the next trading day on which investors were able to start trading on the information as the filing date.<sup>17</sup> Record dates were generously provided to us by Daniel Metzger.

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

### 3.2 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 non-routine 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 date the proxy filing date is 9, and from the proxy filing date to the annual shareholder meeting date it is 30. We note that proxy filings include substantial

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<sup>16</sup> 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.

<sup>17</sup> Filings filed after 5:30 PM are automatically assigned to the following trading day by the SEC, and thus we do not need to adjust these filing dates.

information (e.g., the proposed slate of directors and the executive compensation awarded). Figure 1 also reports that there are on average 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 2.

We estimate that between January 1, 2006 and February 27, 2010, this figure is equal to 51. The timespans differ substantially between the two periods because, for meetings held before February 28, 2010, companies report the voting outcome in a 10-K or a 10-Q filing (the annual or quarterly financial report, respectively) for the quarter in which the shareholder meeting is held. This practice typically resulted in a long lag in reporting the voting outcome. For meetings held on or after February 28, 2010, companies were required to report the outcome on form 8-K within four days of the meeting. Accordingly, all analyses in this paper are for the period after February 27, 2010, for which we can be almost certain that the market observed the voting outcome on, or shortly after, the meeting date. Between the meeting date and the filing of the voting outcome, companies are permitted to issue a press release announcing the voting results.<sup>18</sup> Our sample includes 10,701 unique meetings held by 3,463 unique companies, 298 actively managed funds, and 20,005 unique fund-meeting combinations. The funds in our sample are advised by 56 unique financial institutions, including almost all large financial institutions (see Table 1, Panel A). Panel B of Table 1 reports descriptive statistics of the main variables. 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 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.

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<sup>18</sup> 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 (<https://www.sec.gov/rules/final/2009/33-9089.pdf>), p.62, footnote 173). We thank Kobi Kastiel for clarifying this to us.

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, 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.

## 4 Analysis

### 4.1 Trading and voting at the fund level

We begin the analysis with a discussion of the shareholder-alignment hypothesis (see Section 2.2.1). To test the hypothesis, we relate funds' trading decisions after shareholder meetings to their voting behavior at the meeting itself. We begin with a discussion of trading directions (see Wermers (1999) and Puckett and Yan (2011) for a similar approach) and define two dummy variables:

- (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.

Then we run regressions with these two dependent variables at the fund-meeting-day level. For each meeting, we include all days from the proxy filing date until 30 days after the meeting. To test the shareholder-alignment hypothesis, we define three independent variables to capture funds' voting behavior at the shareholder meeting. Each variable captures how the fund voted in relation to other shareholders. Since each meeting agenda includes multiple elections and proposals, we capture disagreement by investigating whether a particular fund was contradicted by other shareholders on at least one proposal. We define the following variables at the fund-meeting level:

- (1) *Voting outcome contradicts fund vote for at least one proposal.* This dummy variable equals one 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; the dummy variable equals zero otherwise.
- (2) *Fund with management, outcome against management.* This dummy variable equals one if, for at least one proposal, the fund voted consistently with management's recommendation and the voting outcome of that same proposal was against management's recommendation; the dummy variable equals zero otherwise.
- (3) *Fund against management, outcome with management.* This dummy variable equals one if, for at least one proposal, the fund voted against management recommendation and the voting outcome of that same proposal was consistent with management recommendation; the dummy variable equals zero otherwise.

Note that the dummy variables (2) and (3) 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. In addition, variables (2) and (3) provide a breakdown of variable (1) for all proposals on which management issued a recommendation by conditioning on whether the fund votes with or against management. We are interested in how the fund votes after the meeting and, therefore, include the dummy variable *After meeting*, which equals one for all days after the meeting date, including the meeting date itself. We interact the three independent variables that describe the fund's voting behavior with *After meeting*. In addition, we include fund\*meeting fixed effects, controls for the fund's assets under management, the fraction of company's shares outstanding held by the fund (in bps), the company's weight in the fund's overall portfolio (in bps), the fund's expense and turnover ratios, the firm's market capitalization, and the firm's book-to-market ratio.

The results are reported in Table 2. The coefficients of interests are those on the interactions of *Sell* and *Buy* with *After meeting*. 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. We find strong evidence for these predictions. In column (1) the coefficient on *Voting outcome contradicts fund votes for*

*at least one proposal \* After meeting* indicates that, after a meeting in which funds votes are contradicted by other shareholders, funds are 0.8% more likely to sell their stocks. The effect is statistically highly significant and economically meaningful. The unconditional probability of funds to sell a stock, reported at the bottom of the table, is 2.81%. Hence the increase of 0.8% represents an increase of 28% ( $0.008/0.0281$ ) relative to the baseline probability of selling. The effect with Buy as the dependent variable in column (3) is weaker, but still statistically significant at the 5%-level and equal to a decrease of about 9% ( $0.002/0.022$ ) relative to the baseline probability of buying.

In columns (2) and (4) we condition on whether the fund supports or opposes management. The coefficient for *Fund with management, outcome against management for at least one proposal \* After meeting* is 0.8% and that for *Fund against management, outcome with management for at least one proposal \* After meeting* is 0.6%. We examine whether the effects are statically different from each other and report the corresponding F-test at the bottom of Table 2. The value is equal to 1.01 for *Sell* and 1.45 for *Buy*, well below conventional significance levels. Thus, funds' tendency to sell or buy stocks after the meeting when their own vote was contradicted by the voting outcome is affected to about the same degree, independently of whether they supported or opposed management.

Next, we investigate the magnitude of funds' trading decisions after shareholder meetings and define two measures to capture the magnitude and direction of funds' daily trades (see Fich, Harford and Tran (2015) for a discussion of different ownership measures):

- (1) *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.
- (2) *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.

Columns (5) to(8) of Table 2 report the results for these variables. Column (5) ((7)) shows that funds sell 16.6 (buy 1.3) basis points, relative to their portfolio (their holdings of the company) if their votes are contradicted

by the majority of other shareholders. This effect is significant at the 1% level (5% level) and has about the same magnitude as the unconditional means of *Net fraction of portfolio bought* (*Net fraction of company bought*) in the sample (-0.173, respectively -0.017); these magnitudes are economically meaningful. As before, we condition on whether funds support or oppose management and report the coefficients of interest in columns (6) and (8) and the F-tests for their equality at the bottom of the table. The effects are indistinguishable if we measure trades relative to funds' portfolios in column (6), but significantly different if we measure trades relative to the holding of the company in column (8). In the latter case, the effect becomes insignificant if funds oppose management, potentially because funds do not sell large dollar volumes in their holdings of larger firms.

Taken together, our findings provide strong support for Hypothesis 1 and the argument that trading after meetings aligns the shareholder base. The findings reject Hypothesis 2, which is based on Bayesian learning. Funds who are outvoted at shareholder meetings conclude that the policies of the firm will not be value-maximizing given their beliefs. Accordingly, they value the firm less than other shareholders and decide to reduce their holdings.

Since we include long time periods before and after the meeting date, 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, we conclude that there is no relevant autocorrelation in our dependent variables to induce spurious significance levels.

Finally, we observe that many funds rarely trade during the sample period. Therefore, in Table 3 we repeat the analysis of Table 2 but include only funds with above median trading frequency<sup>19</sup>. We observe larger

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<sup>19</sup> For each fund-stock-day observation, we define a dummy variable *Traded* equal to 1 if a given fund has traded a given stock on a given day, and zero otherwise. Then we compute the trading frequency as the average value of *Traded* across all stocks and days included in the sample, separately for each fund. We include in Table 3 only the funds that have an above median trading frequency.



effects for this subsample, which are generally about twice as large as those for the whole sample. The size of the coefficients of interests relative to the baseline effects reported as the bottom of the table is also larger. E.g., the effect of *Voting outcome contradicts fund vote for at least one proposal* on *Net fraction of portfolio bought* is now 136% of the baseline effect ( $-0.354/-0.261=1.36$ ). The pattern of the F-tests for equality of the effects when funds oppose or support management is the same as in Table 2.

## 4.2 Abnormal volume and abnormal price changes

We begin the meeting-level analysis with a univariate analysis of volume and volatility (Section 0) and then relate volume to price changes (Section 4.2.2).

### 4.2.1 Univariate analysis of volume and volatility

Panel A of Figure 2 plots average abnormal volume, abnormal realized volatility, and abnormal returns around meeting dates. Abnormal volume is estimated as the fraction of daily volume and average daily volume during the pre-voting period, where the pre-voting period is defined as the  $[-252, -21]$  window before the record date. Abnormal volatility is computed as the fraction 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, where 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. The number of observations reported in Panels B and C pertains to unique meetings that fall into each category.

Volume increases already ahead of the shareholder meeting by about 10% above the level in the pre-voting period. It jumps by another 10% and peaks on the meeting date at about 20% above the pre-meeting level and then declines slowly after the meeting and remains at elevated levels of about 10%~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 back to its pre-meeting level more quickly. During the period from 20 days before to 20 days after the meeting, average stock returns (in percent) fluctuate around zero, as we would expect with informationally efficient markets.

It is possible that meetings have an impact on volume and volatility only for a small subset of meetings that include unusual or important votes. To address this possibility, we define a *routine meeting* as a meeting that satisfies two requirements: First, it includes only the basic proposals companies are required to include on their agenda, i.e., appointing directors, approving the company’s auditors, and/or voting on executive compensation (*say-on-pay*); second, we require that for all proposals voted on at a routine meeting, the voting outcome be consistent with management’s recommendation. All other meetings are defined as *non-routine meetings*. In Panel B of Figure 2, we report the abnormal volume and volatility for routine meetings versus non-routine meetings around meeting dates. Interestingly, while the development of the trading volumes of routine meetings and non-routine meetings is indistinguishable before and after meeting, volatility for non-routine meetings before the meeting date is significantly higher than that for routine meetings.

To follow up on this observation, we distinguish three types of meetings: 1) meetings pertaining to a shareholder vote on a merger (*Merger vote*), 2) meetings in which the vote outcome is against management’s recommendation on at least one proposal (*Outcome against management*), and 3) meetings for which “meeting type” is different from “annual” according to ISS Voting Analytics (*Special meeting*). The figure also includes the complement of all meetings that do not fall into any of the three prior categories (*Other meetings*). Panel C of Figure 2 shows that trading volume is particularly high after merger votes (special meetings), for which it peaks at about 130% (140%) on the day of (day after) the meeting, whereas the effect is correspondingly somewhat smaller, but still sizeable at about 50% (40%), for meetings in which the voting outcome contradicts management’s recommendation for at least one proposal. For all other meetings, we still observe increased trading volume at around 15% above the pre-record period. Taken together, these findings suggest that volume after the meeting peaks particularly for important and contentious votes.

Shareholders may react not only to voting outcomes at meetings, but also to other information that may be disclosed at or around shareholder meetings. To investigate this possibility, we collect news items for firms in our sample from RavenPack. The RavenPack database provides a comprehensive sample of firm-specific news from the Dow Jones News Wire. To capture news specifically about a given firm, we use the “relevance score” provided by RavenPack, which ranges from 0 to 100, with a score of 0 (100) indicating that

the entity is passively (predominantly) mentioned. We require news items in our sample to have a “relevance score” of at least 90. To include only fundamental news, we select acquisitions, mergers, analyst-ratings, assets, bankruptcy, credit, credit-ratings, dividends, earnings, equity-actions, labor-issues, product-services, and revenues from a total of 29 news groups.<sup>20</sup>

We define the *Abnormal number of news items* as the daily number of news items divided by the average daily number of news items during the pre-record period, defined as the [-252, -21] window before the record date, and plot this variable in Figure 3. We observe a significant concentration of news releases at the meeting date, but no major run-up in the weeks preceding the meeting, when the abnormal number of news items is about 2% above the daily average before the meeting date. Moreover, there is a significant drop in the disclosure of news items about three to four days after the meeting, and the abnormal number of news items stays about 4% to 6% below the pre-record average for the remaining part of the post-meeting window.

Hence, news disclosures on the meeting date may contribute to increased levels of volume and volatility on and the few days immediately after the meeting. However, the contrast between the below-average number of news items between four and 20 days after the meeting and increased levels of volume and volatility during the same period noted above makes news releases unlikely candidates for explaining increased post-meeting trading volumes and volatility. News releases may nonetheless contribute to disagreement, since disagreement is likely associated with the disclosure of complex information from various sources, which forces investors to use models to integrate different pieces of information into a coherent picture. We do not undertake any further analysis on the relationship between news and disagreement, nor do we attempt to disentangle the contribution of voting results, news releases at the meeting, and information disclosed by other sources.

#### 4.2.2 The relationship between volume and returns

Next, we study the relationship between trading volume and volatility and test Hypothesis 4, which predicts trading volume without price changes based on disagreement models. We analyze the relationship graphically,

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<sup>20</sup> Note that applying these filters introduces no look-ahead bias because RavenPack assesses all news articles within milliseconds of receipt and immediately sends the resulting data to users. All information is thus available at the time of news release.

which allows us to examine this relationship non-parametrically without assuming any specific functional form. Under the null hypothesis that there is no disagreement, i.e. only Bayesian learning, we should see no, or very little trading volume if price changes are small (Hypothesis 3). 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 one to ten trading days after the meeting date to pre-event volume from 20 to 11 trading days before the meeting date. We skip the ten trading days before the meeting date because information related to vote 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).

Panel A of Figure 4 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 brackets on the horizontal axis.<sup>21</sup> We observe a slight U-shaped relationship during the post-meeting window: For the four extreme quantiles (two lowest, two highest) we observe higher trading volumes after the meeting. Importantly, the higher volume for extreme return quantiles is not uniquely associated with the information disclosed at shareholder meeting, since we already observe higher trading volume in the extreme return quantiles with the largest absolute price changes during the [-20, -11] pre-meeting window. The distinguishing feature of disagreement models is that they predict significant trading volume even without or only small price changes. To test this implication, 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 average value; these are all but the most extreme quantiles 1 and 9. For these 7 quantiles, on average, post-event trading volume exceeds pre-event trading volume 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 Hypothesis 4, which predicts

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<sup>21</sup> The construction of the figure corresponds closely to Bollerslev et al. (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.

abnormal volume based on disagreement models, whereas we can reject Hypothesis 3, which is based on Bayesian learning.

Panels B and C of Figure 4 repeat the same exercise, but now we sort meetings based on normalized returns over the 5-day interval from the meeting date to four days after the meeting (Panel B) and up to 10 days after the meeting (Panel C). While we find that post-meeting trading volume exceeds pre-meeting volume for quantiles with a mean standardized return below-one, based on  $[0,4]$  normalized returns (t-value: 6.11) and on  $[0,10]$  normalized returns (t-value: 5.92), the shape of both graphs becomes distinctly more U-shaped, indicating a closer correlation between price changes and trading volume over the longer intervals. This observation is consistent with the model of Banerjee and Kremer (2010), which implies that disagreement is maximal on the meeting date and declines as investors' interpretations converge after the meeting. We discuss the predictions of the model of Banerjee and Kremer (2010) in more detail in Section 4.4.

### 4.3 The relationship between trading volume and volatility

Both disagreement models and Bayesian learning models are consistent with increased levels of volatility at the meeting date. However, disagreement among shareholders gives rise to specific relationships between volume and volatility, which we explore in this section.

#### 4.3.1 Model and predictions

The 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 based on rational expectations, noisy rational expectations, Bayesian learning, and disagreement. We provide a brief outline of the model here, with as many details as necessary to develop empirical implications and relegate the more technical details to Appendix A.2.1.

Let  $V_{it}$  denote trading volume in some period  $t$  for some stock  $i$  and let  $\Delta P_{it}$  denote absolute price changes at time  $t$  for the same stock. All investors observe a public signal of the asset payoff, but they disagree on its interpretation. In particular, some investors are endowed with optimistic priors and some with pessimistic

priors. 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

$$V_t = |\beta_0 + \beta_1 \Delta P_t|. \quad (1)$$

The parameters  $\beta_0$  and  $\beta_1$  depend on specific model assumptions about information and disagreement among investors (see Equation A.1 in the Appendix) and the KP model nests three other models as follows:

1. **Rational expectations.** Both types of investors agree, *and* they are symmetrically informed, i.e. they have common priors. Then  $\beta_0 = 0, \beta_1 = 0$ , and trading volume is zero. Rational expectations models form the theoretical benchmark, even though they have no explanatory power in our context.
2. **Noisy rational expectations with Bayesian learning.** Both types of investors agree on the interpretation of the signal; then  $\beta_0 = 0$ . However, investors can have different qualities of prior information, so that some investors have more precise priors than others (Kim and Verrecchia (1991b)). *Then  $\beta_1 \neq 0$  and  $V_t = |\beta_1 \Delta P_t|$* , so volume is proportional to price changes.
3. **Disagreement with common priors.** If both types of investors are symmetrically informed, but disagree on the interpretation of public signals, then  $\beta_0 \neq 0$  *and*  $\beta_1 = 0$ : Trading volume is positive, but unrelated to price changes ( $V = |\beta_0|$ ). Hence, with pure disagreement without learning, trading volume is unrelated to volatility.

The KP model itself allows for differential prior information ( $\beta_1 \neq 0$ ) and disagreement ( $\beta_0 \neq 0$ ) and nests all the other three models above as special cases. Bollerslev, Li, and Xue (2018) (henceforth BLX) derive testable implications from the KP model. Instead of testing the exact functional relationship (1), which is cast in terms of absolute price changes and unlikely to hold empirically, they derive moment conditions that are predicted to hold on average in the data. Let  $m$  denote expected volume and let  $\sigma$  denote volatility. Then define the elasticity of volume with respect to volatility and denote it by  $\mathcal{E}$ . BLX derive the following relationship for  $\mathcal{E}$  (see their equations 2.4 and 2.5):

$$\mathcal{E} \equiv \frac{\partial m(\sigma)/m(\sigma)}{\partial \sigma/\sigma} = \frac{1}{1+\psi(\gamma/\sigma)}, \quad (2)$$

where  $\psi$  is a function that depends on the density of the standard normal distribution and the argument  $\gamma/\sigma$  of  $\psi$  can be interpreted as a normalized measure of disagreement between the two groups of investors that have different opinions. (See Equation (A.1) in the Appendix.) Based on the discussion above, we can distinguish four models and their predictions about this elasticity:

<b>Model</b>	<b><math>V</math></b>	<b><math>\beta_0</math></b>	<b><math>\beta_1</math></b>	<b><math>\mathcal{E}</math></b>
Rational expectations	0	0	0	not defined
Pure disagreement	$> 0$	$\neq 0$	0	0
Bayesian learning	$> 0$	0	$\neq 0$	1
Disagreement with learning	$> 0$	$\neq 0$	$\neq 0$	$0 < \mathcal{E} < 1$

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 and an associated relationship between trading volume and price changes ( $\mathcal{E} = 0$ ). By contrast, a model with Bayesian learning is at the other end of the spectrum, since it implies strict proportionality between trading volume and price changes ( $\mathcal{E} = 1$ ). Rational expectations models are included as a theoretical benchmark, but for them the volume-volatility elasticity  $\mathcal{E}$  is undefined since trading volume is zero. The general, and in all likelihood the most realistic case, is that investors disagree on the interpretation of new information to some extent, but they also learn from each other. This is the case of the KP model in which  $0 < \mathcal{E} < 1$  is possible. In our empirical analysis, we estimate the volume-volatility elasticity around shareholder meetings to test which of these models explains the empirical patterns we have documented above.

#### 4.3.2 How volume changes with volatility

We now examine which of the three models specified in Section 4.3.1 explains the abnormal volume we observe around shareholding meetings. We first discuss the implication of the disagreement model of Kandel and Pearson (1995) that the elasticity of volume with respect to price changes  $\mathcal{E}$  defined in equation (2) is below unity, and lower for meetings with more disagreement among shareholders. We then follow Bollerslev et al. (2018) and estimate the following equation at meeting level:

$$\Delta \log(m_j) = a_0 + b_0 X_j + (a_1 + b_1 X_j) \Delta \log(\sigma_j), \quad (3)$$

where  $m_j$  is trading volume and  $\sigma_j$  is the volatility of meeting  $j$ , and  $X_j$  is a vector of control variables, notably measures that proxy for shareholder disagreement. The change in log volume  $\Delta \log(m_j)$  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  $\Delta \log(\sigma_j)$  around shareholder meeting is defined similarly.

We test two implications, both of which follow directly from the discussion in Section 4.3.1 and Bollerslev et al. (2018). First, if we estimate (3) without any control variables, then the coefficient  $a_I$  measures the elasticity  $\mathcal{E}$ ; we expect this elasticity to be lower around meeting dates compared to non-meeting days, and below unity. Second, if we include disagreement measures as controls, then for a variable  $X$  that increases in disagreement, we expect the coefficient  $b_I$  to be negative and the estimates  $a_I$  to increase relative to the estimates without including controls.

To test the first implication, we estimate equation (3) without controls for all meeting dates in column (1) of Table 4. The point estimate is 0.584, which is significantly below unity at 1% level. We perform placebo tests by estimating the same equation for arbitrarily chosen dates, which are located three months before and after the meeting (column (2)). We estimate changes in log volatility and log volume by subtracting log averages for the interval [-20, -11] from log averages computed for [1,10] relative to the placebo dates as well. The elasticity estimate for the placebo dates is 0.657, and significantly above the elasticity estimated for meeting dates at 1% level. Hence, we find substantial support for the first implication of the disagreement model and conclude that shareholder meetings are associated with substantial increases in disagreement.

The second implication of the model requires that we find proxies for disagreement among shareholders. There is no guidance on this question from prior literature, since we are interested in the extent to which shareholders disagree about voting outcomes. We propose six measures to proxy for disagreement: (1) *Realized uncertainty*: we obtain the average fraction of votes in favor of each proposal voted on at meeting  $j$ ,  $\alpha_j$ , and define *Realized uncertainty* as  $\alpha_j(1-\alpha_j)$  as a measure for disagreement. In the Appendix we show that the coefficients  $\beta_0$  and  $\beta_1$  are directly proportional to *Realized uncertainty* (see equation (A.1) in Appendix A.2.1). (2)



*Analyst forecast dispersion* (abbreviated *Anal. for. Dispersion* in the table), which is the standard deviation of analysts' most recent earnings forecasts (see Diether et al. (2002); Banerjee (2011)). (3) *Outcome against management* (abbreviated *Outc. against man.* in the table) is equal to one if at least one outcome is against management recommendation. (4) *Predicted uncertainty*: We predict the fraction of votes cast in favor and define *Predicted uncertainty* (abbreviated *Pred. uncertainty* in the table) as a dummy variable, which assumes a value of one if the predicted fraction of votes in favor is between 40% and 60% for at least one proposal voted on at meeting  $j$ , and zero otherwise; we hypothesize that disagreement is larger if the uncertainty about the voting outcome is greater.<sup>22</sup> (5) *Special meeting*: a dummy variable that equals one for meetings with “meetingtype” different from “annual” according to ISS Voting Analytics . (6) *Merger vote*, a dummy variable that equals one for meetings on which shareholders vote on a merger proposal.

Columns (3) to (8) of Table 4 report the results for estimating equation (3) 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,  $a_1$  (coefficient on  $\Delta \log(\sigma)$ ), the coefficients for the disagreement measures  $b_0$ , and  $b_1$  (coefficient for the interaction of disagreement measure with  $\Delta \log(\sigma)$ ). The predictions of the disagreement model are that  $b_1 < 0$  and that the elasticity estimates  $a_1$  move towards those observed around non-meeting dates if we include controls for disagreement.

The effects have the predicted direction for both coefficients,  $a_1$  and  $b_1$ , for four of the six disagreement measures; they are highly significant for *Outcome against management*, *Special meeting*, and *Merger vote*. For *Realized uncertainty* the estimates for  $b_1$  have the predicted signs but are insignificant. In all four cases, the estimates for the elasticity  $a_1$  move much closer to the level observed at the placebo dates in column (2), which confirms that, these proxies for disagreement among shareholders capture the abnormal disagreement around shareholder

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<sup>22</sup> The predictors for support rates include market capitalization, a dummy for whether ISS recommended to vote in support of the proposal, a dummy for whether management recommended to vote in support of the proposal, total fraction of shares held by institutional investors, a dummy controlling for the type of proposals (issagendaitemidid), and year and industry dummies.

meetings.<sup>23</sup> With *Analyst forecast dispersion* and *Predicted uncertainty* and as controls, both coefficients of interest have the opposite of the predicted signs, and for *Analyst forecast dispersion* they are highly significant. This is somewhat puzzling and seems to stand in contrast to Diether et al. (2002) and Banerjee (2011), who have used the dispersion of analyst forecasts to measure disagreement among shareholders around earnings announcements. However, note that voting outcomes at shareholder meetings and earnings announcements are economically different pieces of information, and analysts' disagreement about earnings does not appear to be closely related to disagreement about voting outcomes.

In addition to the bivariate regressions, Table 4 includes multivariate regressions in columns (9) and (10). In column (7) we include all disagreement measures, whereas in column (10) we exclude *Analyst forecast dispersion*, which appears to be associated with less rather than more disagreement, and *Special meeting*.<sup>24</sup> When we control for disagreement with the remaining four measures, the elasticity estimate increases to 0.624, and, therefore, much closer to the level at the placebo dates observed in column (2). Hence, once we control for measures which potentially capture disagreement, the elasticity moves closer to unity, indicating that our measures related to voting account for disagreement. Overall, we interpret our results as significant support for the disagreement model of Kandel and Pearson (1995) and the new development of Bollerslev et al. (2018).

#### 4.4 Autocorrelations

Disagreement based on differential interpretations of the same signal implies that trading volume increases, and that trading subsequent to news disclosures is positively autocorrelated (e.g., Harris and Raviv (1993); Banerjee and Kremer (2010)). In this section, we explore the specific implications of Banerjee and Kremer (2010), since their model generates sharp empirical predictions about the relationship between trading volume and volatility after events on which information is released, information which different shareholders may interpret differently.

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<sup>23</sup> See Table 5 of Bollerslev et al. (2018) for a parallel argument in a high-frequency context with macroeconomic news announcements.

<sup>24</sup> Note that merger votes and special meetings have significant overlaps.

#### 4.4.1 Model and predictions

Banerjee and Kremer (2010) (henceforth: BK) develop a dynamic model in which shareholders may disagree either because of heterogeneous priors or because they have heterogeneous models to interpret new information. The critical insight of their model is that trading volume should be broken down into two components:

1. **Belief convergence:** If shareholders disagree before new information becomes available (heterogeneous priors), but agree on the interpretation of newly available information, beliefs converge and disagreement declines. BK refer to the associated trades as “belief-convergence trades” or “learning trades,” since these trades are associated with Bayesian learning based on a common interpretation of newly available signals.
2. **Belief divergence.** If shareholders agree on past information but disagree on the interpretation of a newly available signal (heterogeneous models), beliefs diverge and disagreement increases. BK call the associated trades “idiosyncratic” and they give rise to volume spikes, but these spikes are not correlated with volume in prior periods.

BK favor an interpretation of their model in which the stock market switches between extended regular periods of belief convergence, which are disrupted by exceptional periods marked by disclosures that lead to belief divergence. During regular periods, investors learn new information that is easy to interpret and on which market participants agree, so that Bayesian learning and belief-convergence trades dominate. These regular periods are disrupted by infrequent disclosures of more significant and complex news, which is difficult to interpret and gives rise to belief divergence. Belief divergence is associated with larger stock price reactions and spikes in trading volume, whereas belief-convergence trades give rise to positive autocorrelation of volume. We interpret shareholder meetings as periods in which the market learns important new pieces of information, which tend to be complex and ambiguous and require models to be properly interpreted and evaluated. We have documented elevated levels of volume and volatility above (see Section 4.2 and the discussion of Figure 2), which do not help us to distinguish disagreement models from Bayesian learning models, since Bayesian learning models generate the same prediction. However, conditional on the disagreement framework in BK, we

can infer the level of disagreement by assuming that shareholder meetings associated with large increases in volatility are also those meetings associated with release of information that increases disagreement. With this assumption we can make more specific predictions:<sup>25</sup>

**Hypothesis 5 (Autocorrelations):** (i) Shareholder meeting days are associated with higher volume and volatility and are followed by higher autocorrelations of volume. (ii) Shareholder meetings associated with high (low) volatility have volume autocorrelations that are increasing (decreasing) in trading volume.

Part (i) of the hypothesis follows from the notion that shareholder meetings create additional disagreement and are followed by learning associated with increased belief-convergence trades. The argument for part (ii) and the need to condition on trading volume is more subtle. Consider a news release that leads to a large increase in disagreement. Then the increase in volume is large, giving rise to larger convergence trades and higher positive autocorrelation on the days after the meeting. However, there is a countervailing effect. Anticipating the possibility of larger shocks, shareholders will reduce their ex ante exposure to the firm, which reduces belief convergence trades and autocorrelations after the news event. BK show that the second, countervailing effect dominates if the shock to disagreement is small, whereas the first effect dominates if the shock to disagreement is sufficiently large. Since the theoretical disagreement parameter cannot be measured, predictions are cast in terms of volatility, which serves as a proxy for the significance of news releases in this context.

#### 4.4.2 Testing predictions on volume, volatility, and autocorrelations

We begin by building on the discussion in Section 4.2 and testing for increased levels of volume and volatility more formally by running the following panel regression for all meetings for all trading days from 45 days before the meeting to 45 days after the meeting:

$$m_{t,i} = \alpha_0 + \mu_i + \mu_d + \alpha_e D_t^{[1,10]} + \varepsilon_t. \quad (4)$$

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<sup>25</sup> Hypothesis 5 (i) is based on Prediction 3 (part 2) and Hypothesis 5 (ii) is based on Prediction 2 of Banerjee and Kremer (2010).

Here,  $m_{t,i}$  is the abnormal trading volume of meeting  $i$  on event date  $t$ ;  $\mu_i$  are meeting fixed effects;  $\mu_d$  are calendar-month fixed effects, and  $D_t^{[1,10]}$  is a dummy variable that assumes a value of one for event days from 1 to 10. We run the same regression with abnormal volatility  $\sigma_{t,i}$  as the dependent variable. Table 5 shows the results. The coefficient on  $D_t^{[1,10]}$  with abnormal volume as the dependent variable is 0.04 and with volatility it is 0.01. Both coefficients are significant at 5% and 1% levels, respectively. Hence, we can safely conclude that volume and volatility are both significantly larger after shareholder meetings.

Next, we test part (i) of Hypothesis 5, which predicts that the first-order autocorrelations of trading volume increase after meeting dates, and run the following panel regression:

$$m_{t,i} = \alpha_0 + \mu_i + \mu_d + \rho m_{t-1,i} + \rho_e D_{t-1}^{[1,10]} m_{t-1,i} + \varepsilon_t. \quad (5)$$

In equation (2),  $\rho$  measures the autocorrelation outside of the post-event window [1,10] and  $\rho + \rho_e$  measures the autocorrelation in the event window. The notation  $D_{t-1}^{[1,10]}$  indicates that we have to lag the dummy variable as well to include trading volume from days zero to nine. Hypothesis 5 (i) predicts that  $\rho_e > 0$  and we test this prediction in column (3) of Table 5. We find that the autocorrelation increases by  $\rho_e = 0.16$  in the post-event window, compared to  $\rho = 0.22$  outside of this window, but the effect is statistically not significant.

Finally, we test part (ii) of Hypothesis 5. We adapt the research design of Banerjee and Kremer (2010) and group firms into quintiles based on average abnormal volatility and average abnormal volume and create a set of 5×5 volatility × volume portfolios and index portfolios by p (volatility index) and k (volume index). E.g., portfolio (2,3) refers to the stocks that are in the second-highest volatility quintile and in the third-highest volume quintile. We run the following panel regression:

$$m_{t,i} = \alpha_0 + \mu_i + \mu_d + \rho m_{t-1,i} + \sum_{p,k} \rho_{p,k} D_{p,k,t-1}^{[1,10]} m_{t-1,i} + \varepsilon_t. \quad (6)$$

Equation (6) differs from equation (5) only by estimating the changes in the autocorrelation of returns in the post-event window separately for each volatility-volume portfolio. Hypothesis 5 (ii) implies that the autocorrelation is decreasing in volume for the low-volatility portfolios ( $p=1$ ), i.e.,  $\rho_{[1,1]} > \rho_{[1,5]}$ . We test this implication formally with an F-test for  $\rho_{[1,1]} = \rho_{[1,5]}$ . Furthermore, Hypothesis 5 (ii) implies that the

autocorrelation is increasing in volume for the high-volatility portfolios ( $p=5$ ), i.e.,  $\rho_{[5,1]} < \rho_{[5,5]}$ , and we test if  $\rho_{[5,1]} = \rho_{[5,5]}$ . Figure 5 shows the results graphically. Panel A displays the average estimated autocorrelation  $\rho + \rho_{p,k}$  for the low-volatility portfolios and Panel B shows the same for the high-volatility portfolios. The patterns of both graphs support the predictions of Hypothesis 5. For the lowest volatility quintile, autocorrelations decline from 0.25 for the lowest volatility-lowest-volume portfolio (1,1) to 0.17 for the highest-volatility-lowest-volume portfolio (1,5). Similarly, autocorrelations increase from 0.23 in the highest-volatility-lowest-volume portfolio (5,1) to 0.66 in the highest-volatility-highest volume portfolio (5,5). The tests for equality of the comparisons (1,1) vs. (1,5) and (5,1) vs. (5,5) both reject at the 1% level. Hence, we find strong support for Hypothesis 5 (ii).

All our results are consistent with the predictions of the disagreement model of Banerjee and Kremer (2010). Shareholder meetings are associated with significantly higher levels of trading volume and volatility, and followed by higher autocorrelations of volume, although the latter effect is statistically not significant. Autocorrelation increases significantly with volume for meetings in the highest-volatility quintile and decrease with volume for meetings in the lowest-volatility quintile. Hence, the model of Banerjee and Kremer (2010), which associates rare but significant news events with increases in disagreement, provides a good template for understanding the volume-volatility relationships after shareholder meetings.

#### 4.5 Asymmetric information models and price responses

The discussion in the previous section has explored the explanatory power of disagreement models. In this section we discuss the specific implication of models based on learning and information aggregation. It is unlikely that shareholders disagree completely about all information, and all the time. In fact, the model of Banerjee and Kremer (2010) discussed above provides a more nuanced perspective, in which periods of disagreement are followed by periods of learning with convergence of beliefs. In addition, enhanced levels of volatility, as observed above, indicate that the market processes new information. Hence, disagreement analysis complements theories based on learning and information aggregation.

In this section we explore a particular class of voting models in which the voting process itself aggregates the private information of shareholders. In order to see the potential empirical relevance of these

models, consider a situation in which all information is shared by all shareholders, and there is no disagreement between shareholders based on either differences of beliefs or differences in preferences. In such a scenario, all shareholders would always agree on whether a proposal serves their interests or not, and voting decisions would be perfectly correlated across shareholders, i.e. all shareholders would vote in exactly the same way. A model based on these premises cannot explain voting outcomes in which shareholders vote differently on the same proposal. One conventional explanation in the literature is that shareholders have different interests, e.g., institutional shareholders may have business ties to the companies they hold shares in (Cvijanovic et al. (2016)) or shares may be owned by unions that have different interests from those of other shareholders (Agrawal (2012); Kim and Ouimet (2014)).

In this section, we pursue a different argument, which builds on the notion that shareholders observe private signals and then make their voting decisions based on three pieces of information: their prior, their private signal, and what they believe other shareholders' signals to be in the event that their own vote decides the outcome, i.e. in the event that their vote is pivotal. Theories of voting based on this framework have been developed in the political science literature (e.g., Feddersen and Pesendorfer (1996)), and have been applied to shareholder voting by Maug and Rydqvist (2009), Levit and Malenko (2011) and Van Wesep (2014). These models can accommodate the fact that shareholders' voting decisions are imperfectly correlated across shareholders and that marginal voting outcomes are possible without recurring to conflicts of interests.

These models have one testable empirical implication, which has not been tested in the empirical literature so far. Specifically, they imply that the stock price of the firm *drops* if the proposal is accepted by a small margin. We derive this implication more formally in Appendix A.2.2 and provide a more intuitive reasoning here. The key insight is that, under the assumptions made in these models, each proposal becomes a real option. The argument involves the following steps. Shareholders screen proposals, and voting provides a mechanism for aggregating the information possessed by all shareholders. Shareholders vote strategically, and may vote differently from the direction indicated by their private signal and the common prior because they also take into account the information they infer from being pivotal. Hence, shareholders ignore some information. However, since there are no conflicts of interests among shareholders, their choices to sometimes

ignore their signals will not bias the outcome towards accepting or rejecting the proposal. Hence, shareholders will accept all proposals that are value-increasing based on their collective information and reject all proposals that are value-decreasing. The aggregation of information may, therefore, be inefficient, but it is not biased and even a proposal that is *ex ante* value-reducing will generate value at the proposal-filing stage, because it is simply an out-of-the-money real option, which commands a positive premium. Hence, on average, the stock price of the firm will increase after acceptance and decline after rejection of the proposal, because the firm loses the real option premium if the proposal is rejected. However, the value of the firm will also drop if the proposal is accepted by a sufficiently small margin. A small margin indicates that shareholders were almost indifferent between accepting and rejecting the proposal, hence the increase in value to the firm is negligible, whereas the firm still loses the real option premium. In some sense, discovering that acceptance is marginal is disappointing because it indicates that the potential upside of the proposal did not materialize. Hence, we have:

**Hypothesis 6 (Returns to marginal voting outcomes):** If the proposal is accepted by a small margin, stock prices decline.

We test Hypothesis 6 in Table 6 by regressing abnormal returns on a dummy variable that assumes a value of one if at least one proposal voted on at the meeting is accepted by a marginal majority. We say acceptance is marginal if the number of votes cast in favor is at least 50%, but not more than 52% (columns (1), (2)), not more than 55% (columns (3), (4)), or not more than 60% (columns (5), (6)).<sup>26</sup> We perform the analysis for returns in two event windows: only the meeting date itself, and from the meeting date up to four trading days after the meeting. All specifications include the market capitalization of the firm and the number of proposals at the meeting as controls.

Table 6 provides no evidence to support Hypothesis 6. In fact, in columns (1) and (3), the coefficient on the marginal-acceptance dummies is always positive, and, therefore, has the opposite sign of what we should expect based on the information-aggregation model; it is marginally significant in column (4). Hence, while we

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<sup>26</sup> See Cunat, Gine and Guadalupe (2012) for an analysis of close shareholder votes with a similar range of definitions.



find no evidence to support the information-aggregation model. In fact, the weak evidence we have points in the opposite direction.

Note that we have to run the regressions at the meeting level, even though the theoretical argument is at the proposal level. Hence, our results may be weak only because stock returns reflect the combined impact of all proposals voted at the meeting. However, the fact that the regressions have to be run at the meeting level should not bias the results, but it will create additional noise in the regression and make the estimates less precise. In Table A1 in the Online Appendix, we mitigate this concern by running the regressions in Table 6 again with additional controls that capture the heterogeneity of shareholder meetings. However, the results are unchanged. Overall, the increase in return volatility around shareholder meetings is a clear indication of learning and information processing by the stock market. However, the specific implications of information-aggregation models are not borne out by the data.

## 5 Conclusion

In this paper we analyze trading volume, price responses, and the relationship between trading decisions and voting decisions for a selected subset of funds after shareholder votes. We observe that the funds in our sample, are more likely to sell, and less likely to buy a stock if the funds' vote was inconsistent with the voting outcome. This behavior cannot be reconciled with conventional voting models based on Bayesian learning and information aggregation, which predict that shareholders' beliefs converge after observing voting outcomes, thus eliminating the scope for trading. We argue that trading after shareholder meetings is best understood by models based on disagreement and differences of opinion in which shareholders interpret the information from meeting outcomes differently. As a result, the composition of the shareholder base changes after shareholder meetings and shareholders whose beliefs are less aligned with those of the majority sell to investors with better-aligned beliefs.

To buttress this argument, we analyze the dynamics of trading volume and return volatility after shareholder meetings based on two recent studies that offer sharp predictions about the relationship between volume and volatility (Bollerslev et al. (2018)) and about the autocorrelations of trading volume (Banerjee and Kremer (2010)) after events in which significant and complex news items are revealed, to which we count

shareholder meetings. We find strong evidence to support both models and conclude from our findings that trading after shareholder meetings is best interpreted through the lens of disagreement models, whereas it is difficult to reconcile our findings with conventional models of trading and voting based on Bayesian learning.

Our findings open a new perspective on corporate governance by emphasizing conflicts between shareholders related to their beliefs, which has implications for theoretical as well as empirical work in this area. Conventional agency theory traces conflicts between different stakeholders to conflicts of interest. When analyzing differences between shareholders, these differences are attributed to differential claims to cash flow rights or to private benefits from control. By contrast, disagreement theory attributes conflicts to differences of opinions, which cannot be bridged through disclosure and learning each other's information. In fact, additional information may lead to a further divergence of beliefs if the same information is interpreted differently by different shareholders, and investor relations may be better understood as *interpreting* information for investors rather than disclosing new information. One implication of this insight is that the cohesiveness of decision-making may be better established by aligning the composition of the shareholder base with the decision-makers in the firm. This may be important, since some of the studies cited in the Introduction imply that a lack of cohesiveness may be detrimental to decision-making, and, ultimately, firm value. By contrast, views based on agency theory see the main challenge to better decision-making in aligning the incentives of decision-makers with those of shareholders. The perspective based on differences of opinion has been explored in the theoretical literature on which we draw in this paper but has found no entry so far into the empirical literature on corporate governance. While the focus of our study is limited to shareholder voting, we believe that other areas of corporate governance would also benefit from exploring disagreement models and the notion of aligning beliefs, e.g., when discussing dual-class shares, the role of blockholders, and the public-private trade-off.

The discussion in the paper omits a detailed analysis of models in which shareholders trade because of differences in preferences. E.g., blockholders may extract private benefits of control, and losing a vote may prevent them from extracting these private benefits, inducing them to sell. We are not aware of models that formalize such an intuition, which makes it difficult to test them. However, we believe such an approach would most likely not help explaining our evidence. First, the trades of the funds in our sample spread across almost

300 funds and it is unlikely that many of them have close relationships with their portfolio firms to create private benefits and the observed trading patterns. Second, while a preference-based approach may help with explaining the fund-level evidence, it will probably not generate implications for the dynamics of trading volume and volatility we document. Thus, we do not pursue this approach in the current paper.

## A Appendix

### A.1 Data

To identify the dates on which voting outcomes are made public, we use Seek Edgar, which allows us 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.” For the January 1, 2006 to February 27, 2010 period we exclude from our sample a small number of observations that match these criteria but are filed more than 5 months after the meeting date, because companies are required to file 10-Ks and 10-Qs within 45 days after the end of a quarter. Hence, even if a meeting is held at the beginning of a quarter, the voting outcome should be filed within 5 months.

For the February 28, 2010 to June 30, 2013 period, and also thereafter, companies were required to report their voting results within four trading days in an 8-K filing, although some companies may file the voting outcome after four trading days; accordingly, we exclude voting outcome filings filed more than 14 trading days after the meeting date from our sample, since we assume these filings have been mismatched.

### A.2 Models

#### A.2.1 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 et al. (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  $\alpha_i$  be the fraction of more optimistic investors in stock  $i$ , who have some prior belief  $\mu_{iO} = E_O[\tilde{u}_i + \tilde{\varepsilon}_i]$  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  $E_P[\tilde{u}_i + \tilde{\varepsilon}_i] = \mu_{iP} < \mu_{iO}$  to the same signal. Moreover, the two types of investors differ with respect to the

precision of their priors  $s_{iO} \neq s_{iP}$ . Let  $r$  denotes 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  $h$ .<sup>27</sup>

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

$$\begin{aligned}\beta_0 &= r\alpha(1 - \alpha)h(\mu_O - \mu_P) \\ \beta_1 &= r\alpha(1 - \alpha)(s_O - s_P)\end{aligned}\quad (A.1)$$

With these definitions, agreement about the interpretation of the signal implies that optimistic and pessimistic investors agree on  $\mu$  so that  $\mu_O = \mu_P$ . Hence, agreement implies that  $\beta_0 = 0$  from (A.1). From equation (1),  $|\beta_0|$  measures the component of trading volume that is independent of price changes and equation (A.1) 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  $s_O = s_P$  and, from (A.1),  $\beta_1 = 0$ , and investors do not trade since they agree on how new information should be incorporated into prices.

The parameter  $\gamma$  is given by (Bollerslev et al. (2018), Equation (2.5)):

$$\gamma = \frac{|\beta_0|}{|\beta_1|} = \frac{h|\mu_O - \mu_P|}{|s_O - s_P|}\quad (A.2)$$

Bollerslev et al. (2018) interpret  $\gamma$  as a measure of disagreement, which is normalized by the volatility  $\sigma$  in equation (1). In particular, if  $\gamma = 0$ , then  $\psi(\gamma/\sigma) = 0$  in equation (1) and the elasticity  $\mathcal{E} = 1$ .

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<sup>27</sup> See Kandel and Pearson (1995), equation (5); and Bollerslev et al. (2018), equations (2.1) and (2.2). The notation follows Bollerslev et al. and their simplifications of the Kandel-Pearson model, which assumes that the signal precisions of both groups of investors are identical.

## A.2.2 Strategic voting

This section provides a formal discussion of information-aggregation models and derives Hypothesis 6. The analysis is based on Maug and Rydqvist (2009) and adapts their notation. Levit and Malenko (2011) and Van Wesep (2014) use similar models, which are based on earlier models in the political voting literature.

Consider a proposal that has been put on the agenda of the shareholder meeting. Shareholders make a decision on the proposal, which can be either acceptance or rejection. There are two states of the world  $G, B$  (good, bad), which occur with probabilities  $p$  and  $1 - p$ , respectively. The increase in firm value is  $H > 0$  if the proposal is accepted in state  $G$ ; it is  $L < 0$  if it is accepted in state  $B$ . If the proposal is rejected, firm value does not change. For simplicity, the value of the firm without the proposal is normalized to zero.

Shareholders screen proposals. Assume there are  $N$  shareholders indexed by  $i = 1, \dots, N$ , and each shareholder observes a signal  $S_i \in \{g, b\}$ . Maug and Rydqvist (2009) show that there exists a responsive pure-strategy equilibrium such that  $k \leq N$  shareholders vote responsively (“sincerely”) based on their signal, whereas  $N - k$  shareholders ignore their information.<sup>28</sup> Assume the proposal is accepted if the number of yes-votes  $y$  that support the proposal exceeds a critical value  $\underline{y}$ .<sup>29</sup> Let  $\beta(y, k) = Pr(G|y, k)$  denote the beliefs from observing  $y$  yes votes if  $k$  shareholders vote sincerely. Maug and Rydqvist (2009) provide an expression for  $\beta$  (see their equation (22)). To simplify notation, let  $V(y, k)$  denote the rational Bayesian inference about the proposal value from knowing that there are  $y$  positive signals from a total of  $k$  signals:

$$V(y, k) = \beta(y, k)H + (1 - \beta(y, k))L. \quad (\text{A.3})$$

Then the stock price after the vote,  $P_V(y)$  equals:

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<sup>28</sup> More precisely, this is the unique responsive pure-strategy equilibrium. Levit and Malenko (2011) analyze symmetric mixed-strategy equilibria. The implications of both types of equilibria are identical for our purposes, so it suffices to constrain the discussion to pure-strategy equilibria.

<sup>29</sup> The cut-off  $\underline{y}$  depends on the majority requirement, but potentially also on the votes of shareholders who are committed to vote in favor of the proposal, e.g., because they have preferences with respect to the outcome.

$$P_B = \begin{cases} V(y, k) & \text{if proposal is accepted } (y \geq \underline{y}). \\ 0 & \text{if proposal is rejected } (y < \underline{y}) \end{cases} \quad (\text{A.4})$$

The value of the firm before the vote,  $P_B$ , is

$$P_B = E[V(y, k) | y \geq \underline{y}], \quad (\text{A.5})$$

where expectations are taken with respect to the distribution of vote counts  $y$ .

Each shareholder infers from being pivotal that  $\underline{y} - 1$  other shareholders must support the proposal and forms beliefs about the probability of the good state  $G$  based on three pieces of information: (1) her inference of being pivotal, i.e. the number of yes-votes without her own equals  $\underline{y} - 1$ ; (2) her own signal; and (3) from the (common) knowledge of the number  $k$  of shareholders who vote responsively. Hence, if a shareholder observes a positive signal, the beliefs guiding her voting decision are  $\beta(\underline{y}, k)$ ; if she observes a negative signal, her beliefs are  $\beta(\underline{y} - 1, k)$ . Voting responsively requires that

$$V(\underline{y} - 1, k) < 0 \leq V(\underline{y}, k). \quad (\text{A.6})$$

If the first inequality in (A.6) is violated, the shareholder always votes in favor. If the second equality in (A.6) is violated, the shareholder always votes against.

From (A.5) and (A.6), it follows that the proposal is accepted if and only if  $V(\underline{y}, k) \geq 0$ . This is the first property of an information-aggregation equilibrium claimed in the text, i.e. information aggregation is unbiased. In addition, the analysis in Maug and Rydqvist (2009) implies that, generally,  $k > N$ , i.e. fewer than  $N$  shareholders vote responsively with their signals, so that information aggregation is inefficient. Based on this argument, the pre-vote value of the firm  $P_B$  can be written from (A.6) as

$$P_B = E[\text{Max}\{V(\underline{y}, k), 0\}], \quad (\text{A.7})$$

which shows that it is correct to think of proposals as real options with a strike price of zero and an option premium  $P_B$ . We can also assume that the pre-vote value of the proposal is strictly positive except for degenerate cases, hence  $P_B > 0$ .

We are now in a position to derive meeting-day returns  $R$ , which are simply the changes in stock prices at the meeting,

$$R(y) = P_V - P_B = \begin{cases} V(y, k) - P_B & \text{if proposal is accepted } (y \geq \underline{y}). \\ -P_B & \text{if proposal is rejected } (y < \underline{y}) \end{cases} \quad (\text{A.8})$$

Note from (A.4) and (A.8) that the martingale-property of stock prices is preserved, since  $E[P_V(y)] = P_B$  from comparing (A.4) and (A.7) so  $E[R(y)] = 0$ . Finally, note from (A.6) that  $V(\underline{y}, k) \simeq 0$ , so that  $R(\underline{y}) \simeq -P_B$ , which provides a formal restatement of Hypothesis 6: After a marginal acceptance, the stock price drops by the real option premium  $P_B$ .



## B Glossary of Variables

Variable	Definition	Data source
Abnormal number of news items	The daily number of news items divided by the average daily number of news items during the pre-record period, defined as the [-252, -21] window before the record date	RavenPack
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 (in trading days) before the record date.	TAQ
Abnormal return (in percent)	Abnormal returns as estimated using the Fama-French-Carhart four-factor model 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.	CRSP, data library of Kenneth French
Abnormal volatility	Daily realized volatility / exponential moving average of daily realized volatility during pre-voting period with half-life of 5 days – 1. The pre-voting period is defined as the [-252, -21] window (in trading days) 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 pre-voting period – 1. The pre-voting period is defined as the [-252, -21] window (in trading days) before the record date.	CRSP
After meeting	Dummy variable equals one if the observation corresponds to the days on or after the meeting, and zero if it corresponds to the days before the meeting.	ISS Voting Analytics
Anal. for. dispersion	Standard deviation of analyst earnings forecasts	IBES
At least one proposal received 50%-52% (50%-55%, or 50%-60%) support rate	Dummy variable equals one if at least one of the proposals received 50%-52% (50%-55%, or 50%-60%) support rate, and zero otherwise.	ISS Voting Analytics
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 and Compustat
Buy	Dummy variable equals one if the fund buys the stock on the observation day, and zero otherwise.	ANcerno
Fraction of company held by the fund (in bps)	Number of shares held * 10000/number of shares outstanding.	CRSP US Mutual Fund Database
Fund against mgmt., outcome with mgmt. for at least one proposal	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
Fund expense ratio (in fraction)	Ratio of total investment that shareholders pay for the fund's operating expenses, which include 12b-1 fees.	CRSP US Mutual Fund Database
Fund opposes mgmt. on at least one proposal	Dummy variable equals one if, at a given meeting, the fund votes inconsistently with management recommendation on at least one proposal, and zero if it votes consistently with management recommendation on all proposals. The former would apply if management recommended to vote "Against" a proposal, but the fund voted "For", or if management recommended to vote "For", but the fund voted "Against" or "Withhold", or if the fund did not vote consistently with management recommendation of the SOP frequency vote.	ISS Voting Analytics

Fund turnover ratio	Turnover ratio of the fund.	CRSP US Mutual Fund Database
Fund with mgmt. outcome against mgmt. for at least one proposal	Dummy variable equals one if, for at least one proposal of a given meeting, the fund voted consistently with management recommendation and the voting outcome of that same proposal was against management recommendation; the dummy variable is zero otherwise.	ISS Voting Analytics
Fund's asset under management (in millions)	Total assets minus total liabilities as of month-end.	CRSP US Mutual Fund Database
Market capitalization	Stock price at end of year * number of shares outstanding	CRSP
Market capitalization (in millions)	Price * number of shares outstanding (in thousands)/1,000.	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 (in bps)	Net number of the firm's shares bought by the fund on a given day * 10,000/number of firm's shares outstanding.	ANcerno and CRSP
Net fraction of portfolio bought (in bps)	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.	ANcerno and CRSP
Non-routine meeting	A meeting that is not defined as a routine meeting.	ISS Voting Analytics
Outcome against management	Dummy variable equals one if at least one outcome is against management recommendation.	ISS Voting Analytics
Portfolio weight (in bps)	Security's percentage of the total net assets in the portfolio * 100.	CRSP US Mutual Fund Database
Predicted uncertainty	At least one proposal predicted to receive between 40%-60% support rate. To predict support rates we use a model that controls for market capitalization, includes a dummy for whether ISS recommended to vote in support of the proposal, a dummy for whether management recommended to vote in support of the proposal, total fraction of shares held by institutional investors, a dummy controlling for the issagendaitemid (i.e., the type of proposals), and year and industry dummies.	ISS Voting Analytics
Realized uncertainty	Average, on meeting level, of: fraction voted for the proposal*(1- fraction voted for the proposal)	ISS Voting Analytics
Routine meetings	Routine meetings are defined as meetings (i) that involve only the standard proposals companies are required to put forward annually, i.e., proposals on appointing directors, approving the company's auditors, and/or voting on say-on-pay, and (ii) for which the voting outcome is consistent with management recommendation for all proposals.	ISS Voting Analytics
Sell	A binary variable which equals one if the fund sells the stock on the observation day, and zero otherwise.	ANcerno
Small company	A dummy variable which equals one if the company's market capitalization is below the sample median, and zero otherwise.	CRSP
Special meeting	Variable is equal to one if "meetingtype" is different from "annual."	ISS Voting Analytics

Voting outcome  
contradicts fund vote  
for at least one  
proposal

This 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.

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Analytics

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## C References

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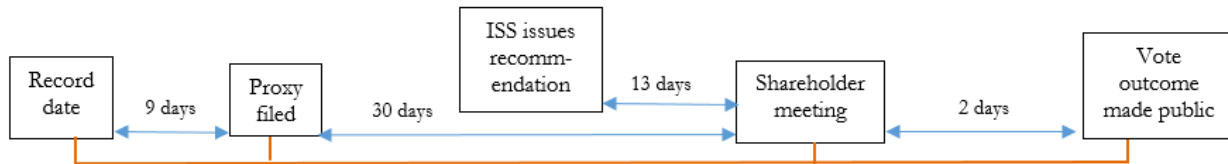
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## D Figures

### Figure 1: Timeline

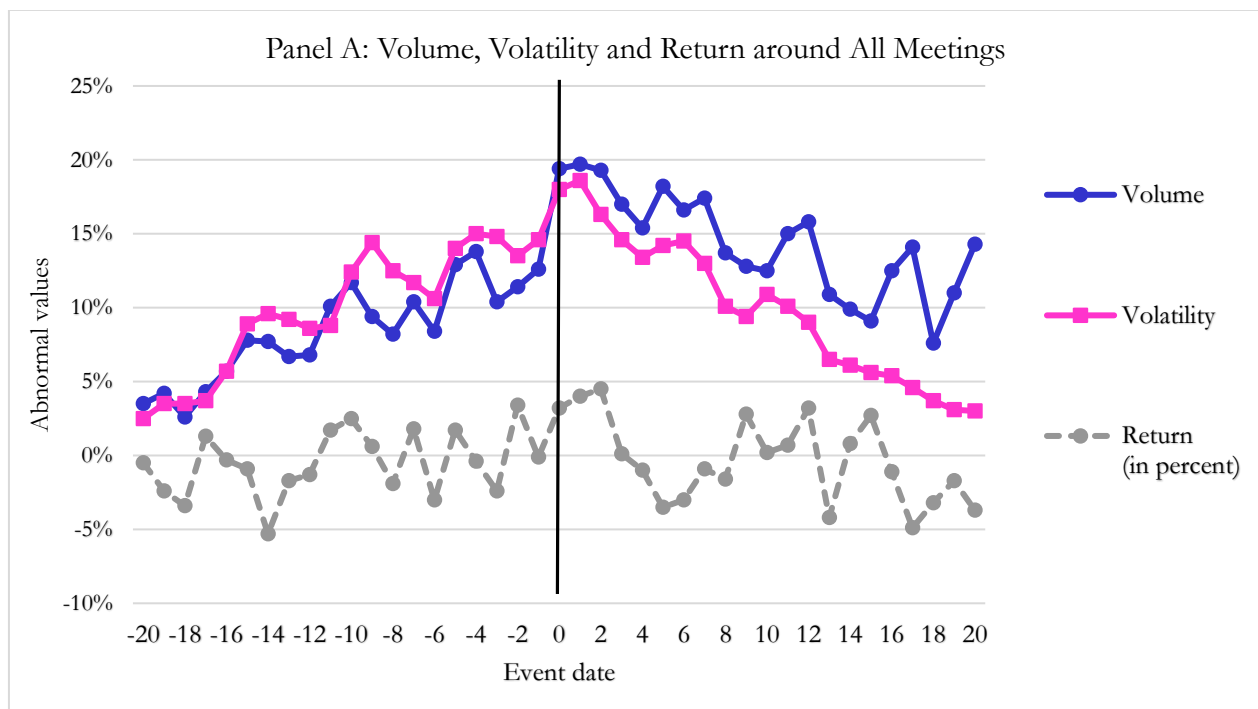
The numbers on the timeline represent the average number of trading days between events. All numbers correspond to the February 28, 2010-June 30, 2013 period.

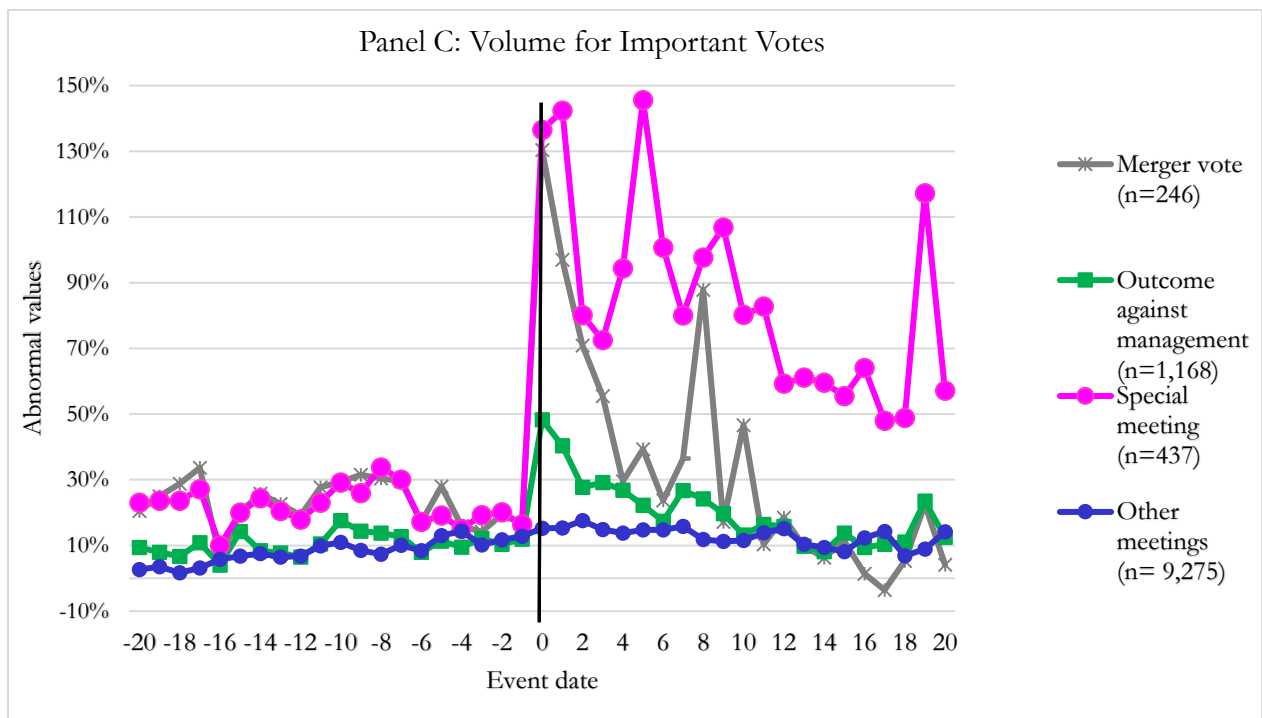
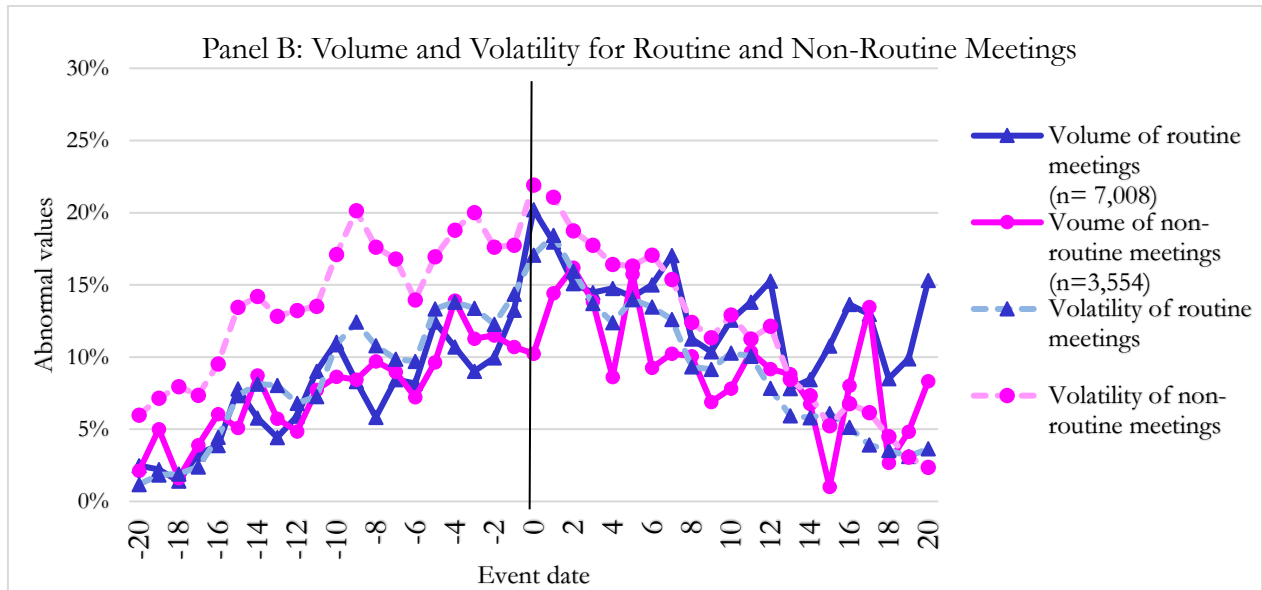




## Figure 2: Market Response around Shareholder Meetings

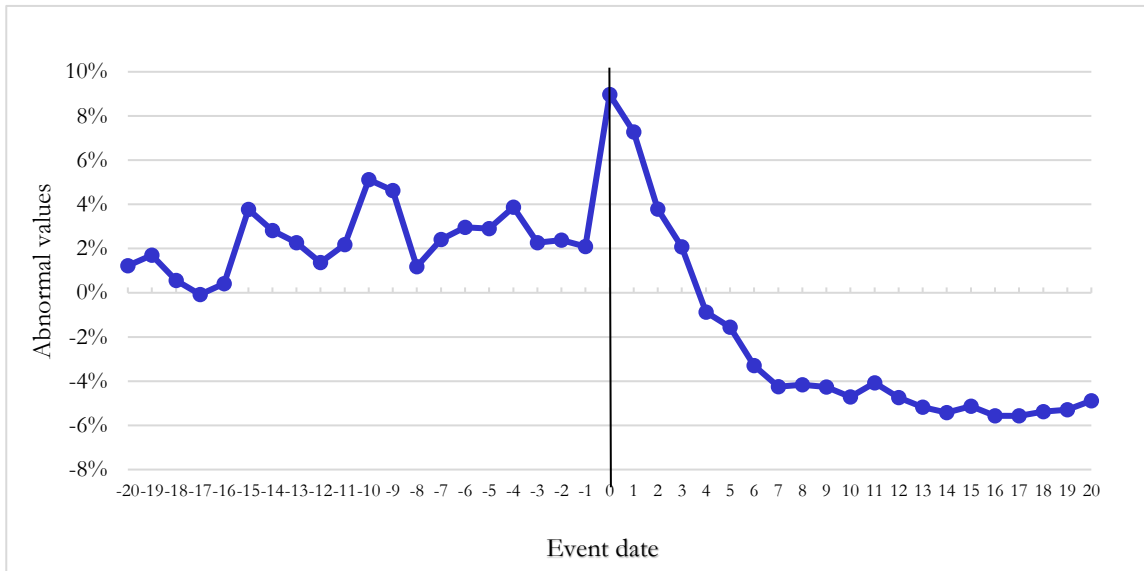
*Panel A* reports the average abnormal volume, abnormal volatility, and abnormal returns on days around shareholder meetings. *Panel B* reports the average abnormal volume and volatility around routine versus non-routine meetings. Routine meetings are defined as meetings (i) that involve only the standard proposals companies are required to put forward annually, i.e., proposals on appointing directors, approving the company’s auditors, and/or voting on say-on-pay, and (ii) for which the voting outcome is consistent with management recommendation for all proposals. All other meetings are defined as non-routine meetings. *Panel C* reports the average abnormal volume for four types of shareholder meetings: meetings involving a vote on a merger (“Merger vote”), meetings with at least one voting outcome that contradicts management recommendation (“Outcome against management”), meetings with “meetingtype” different from “annual” according to ISS Voting Analytics (“Special meeting”), and the rest of the meetings (“Other meetings”). All Panels report observations for meetings held during the February 28, 2010-June 30, 2013 period. Abnormal volume is estimated as the daily volume / average daily volume during 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 daily realized volatility / the exponential moving average of daily realized volatility over pre-voting period with a half-life of five days, where 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. The number of observations reported in Panels B and C pertains to unique meetings that fall into each category.





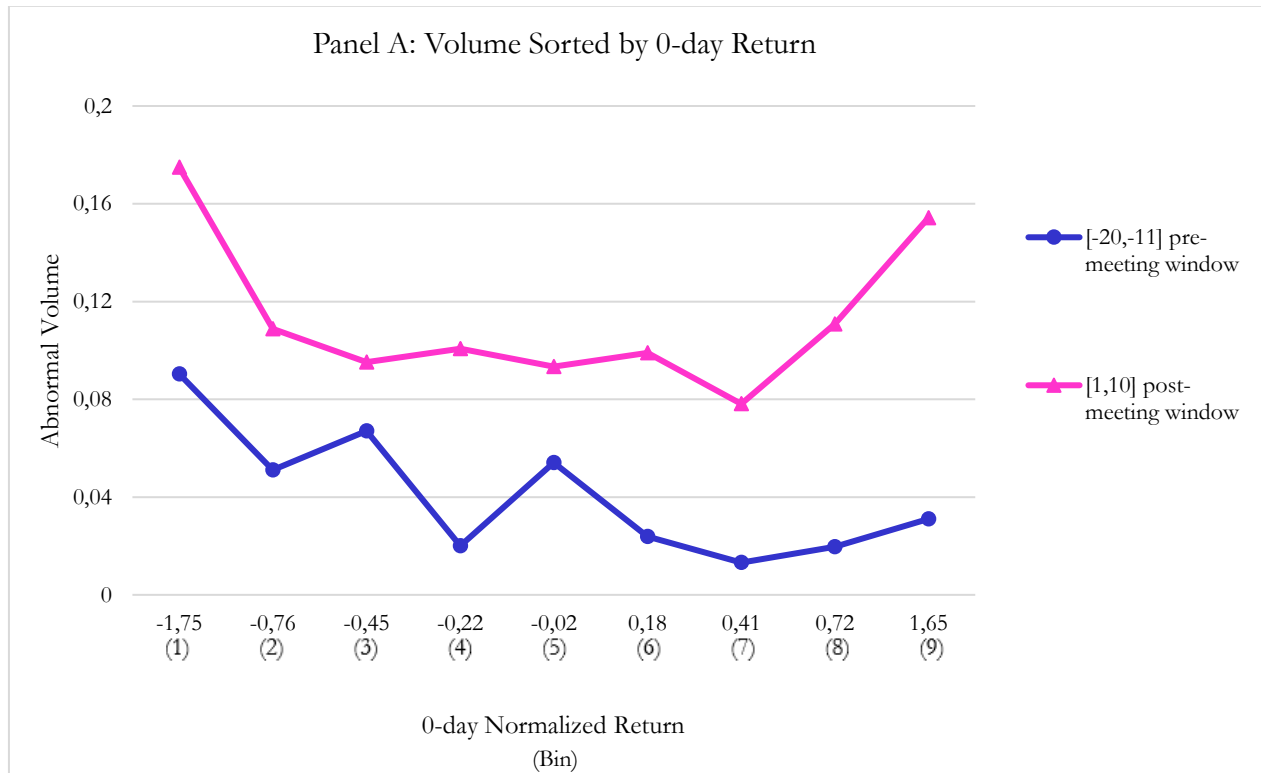
### Figure 3: Abnormal Number of News Items

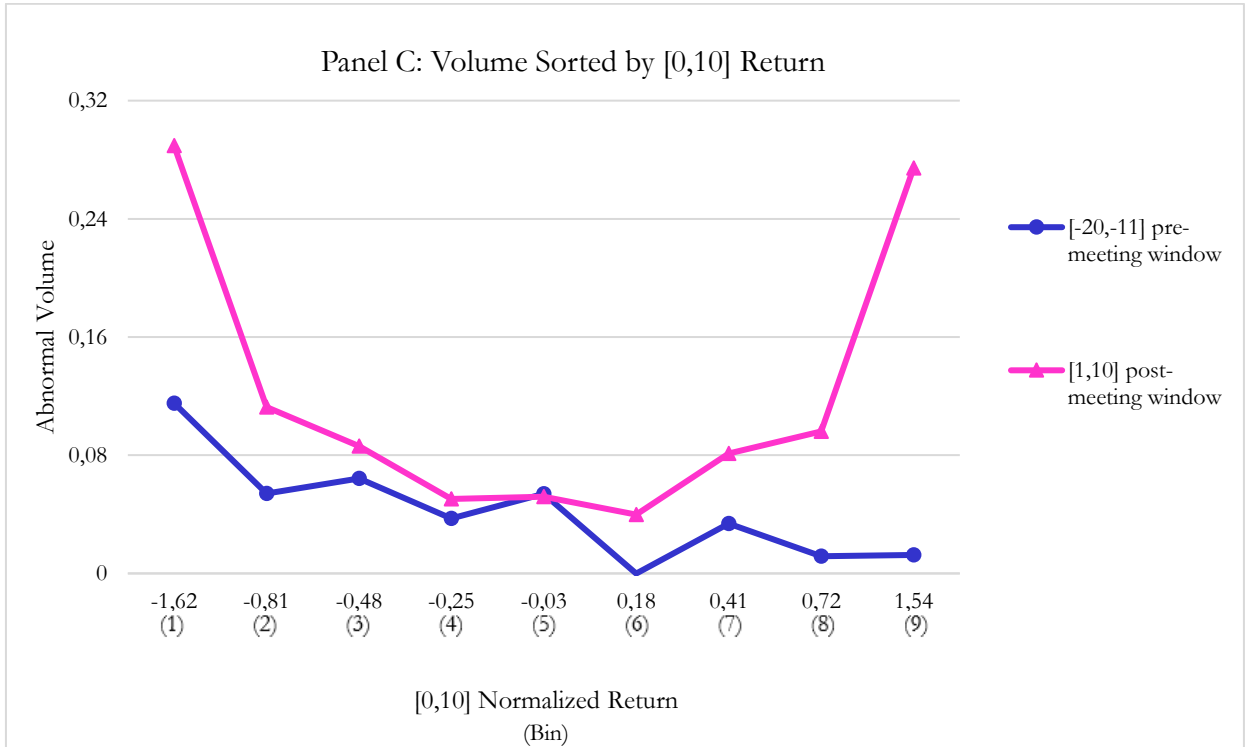
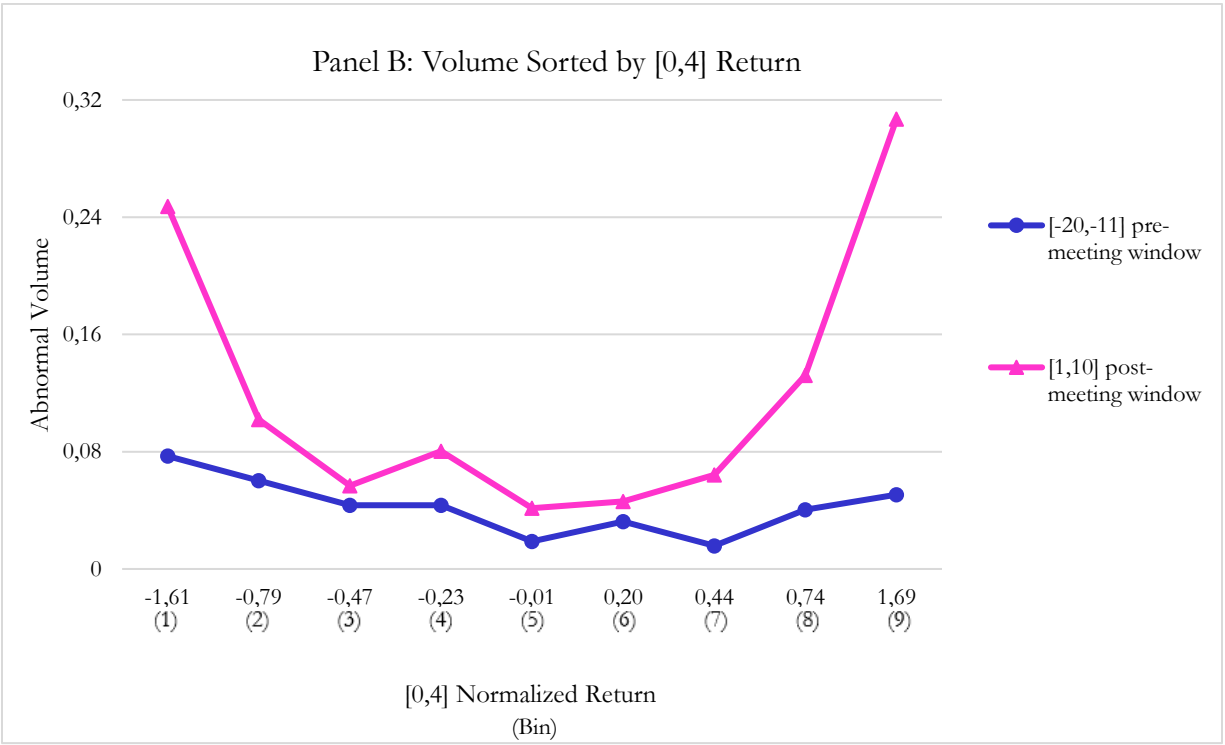
The figure reports the average daily abnormal number of news items surrounding the meeting date. The number of news items reflect the average daily number of fundamental news items from RavenPack with “relevance score” of at least 90. Abnormal number of news items are calculated as the daily number of news items divided by the average daily number of news items during the pre-record period, defined as the [-252, -21] window before the record date. The analysis includes meetings held between February 28, 2010 and January 1, 2013. T-statistics are reported in parentheses. \*, \*\*, and \*\*\* indicate  $p < .10$ ,  $p < .05$ , and  $p < .01$ , respectively.



#### Figure 4: Trading Volume and Returns

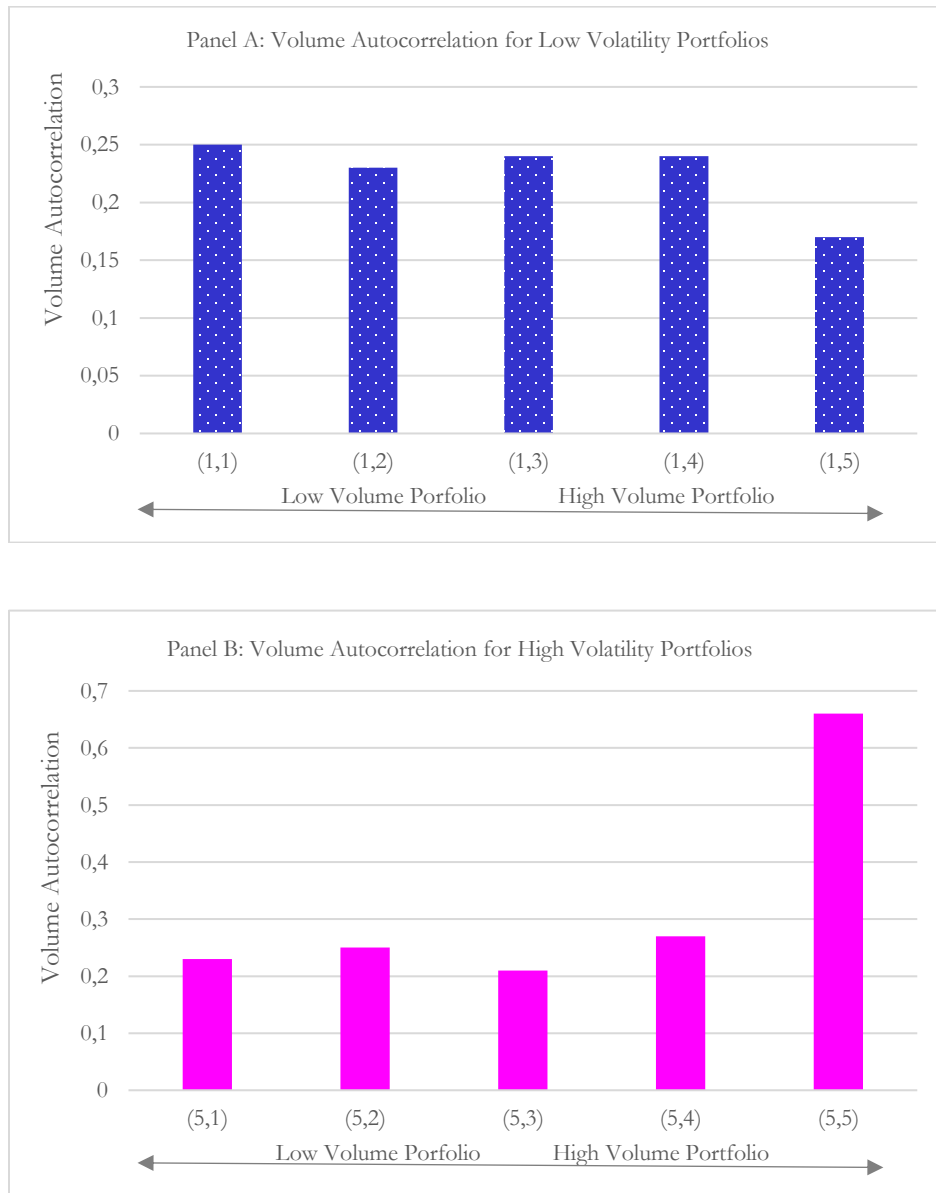
This figure presents the pre- and post-meeting abnormal volume sorted by the normalized returns on the meeting-day (Panel A), returns from meeting day to four days after the meeting (Panel B), and from meeting day to ten days after the meeting (Panel C). All panels are generated from meetings held during the February 28, 2010-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 measured in percentage and 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, and the upper line denotes the average normalized return within each quantile.





### Figure 5: Autocorrelations

This figure tests part (ii) of Hypothesis 5 by presenting the distribution of volume autocorrelation for low and high volatility portfolios. We first group firms into quintiles based on average abnormal volatility and average abnormal volume and create a set of "5×5" volatility × volume portfolios and index portfolios by p (volatility index) and k (volume index). Volume autocorrelations  $\rho + \rho_{p,k}$  are estimated from panel regression in equation (6) using all trading days from 45 days before the meeting to 45 days after the meeting for meetings held during the February 28, 2010-June 30, 2013 period. Panel A displays the average estimated autocorrelation of volume for the five low volatility portfolios (1,1), (1,2), ..., (1,5), and Panel B shows the same for the five high-volatility portfolios (5,1), (5,2), ..., and (5,5).



## E Tables

**Table 1: Summary statistics**

Panel A reports summary statistics on the sample size. Panel B reports descriptive statistics of our main variables (variables are defined in the Glossary of Variables).

### Panel A: Sample Size

<u>Item</u>	<u>Total</u>
<i>Company-level data (February 28, 2010-June 30, 2013):</i>	
Number of unique companies	3,463
Number of unique shareholder meetings	10,562
<i>Fund-level data (February 28, 2010-September 30, 2011):</i>	
Number of unique actively managed funds	298
Number of unique institutions advising funds	56
Number of unique fund-meeting combinations for actively managed funds	20,005

### Panel B: Descriptive Statistics

Variable	Mean	25th percentile	50th percentile	75th percentile	S.D.
Abnormal number of trades	0.070	-0.320	-0.098	0.240	0.748
Abnormal return (in percent)	-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
Book-to-market ratio	0.660	0.329	0.550	0.868	0.569
Buy	0.023	0.000	0.000	0.000	0.023
Fraction of company held by the fund (in bps)	26.85	1.23	5.56	27.10	59.04
Fund assets under management (in millions)	2769.1	207.7	738.9	2567.2	5495.0
Fund expense ratio (fraction)	0.009	0.004	0.011	0.013	0.005
Fund turnover ratio	0.753	0.420	0.650	0.950	0.521
Market capitalization (in millions)	22416	1411	4477	18971	46532
Net fraction of company bought (in bps)	-0.016	0.000	0.000	0.000	1.326
Net fraction of portfolio bought (in bps)	-0.132	0.000	0.000	0.000	11.117
Portfolio weight (in bps)	66.742	13.000	42.000	95.000	75.527
Sell	0.028	0.000	0.000	0.000	0.165

**Table 2: Fund's Trades when They Oppose Management**

This table reports OLS regressions of funds' trades during the February 28, 2010-September 30, 2011 period at the fund-meeting-day level. The analyses examine if, and to what extent, a fund is likely to buy or sell its stocks after a meeting at which the voting outcome contradicts the vote cast by that fund for at least one proposal. The analyses include the period from the proxy filing date to 30 trading days after the meeting date, and includes only actively managed funds. The dependent variables are: *Sell* which equals one if the fund sells the stock on the observation day, and zero otherwise; *Buy* which equals one if the fund buys the stock on the observation day, and zero otherwise; *Net fraction of portfolio bought* (in bps) which is equal to the net dollar value of the firm's shares bought by the fund on a given day \* 10,000/total dollar value of the fund's overall portfolio at the end of the most recent quarter; and *Net fraction of company bought* (in bps) which is equal to the net number of the firm's shares bought by the fund on a given day \* 10,000/number of firm shares outstanding. We capture whether a voting outcome is inconsistent with a fund's vote using three variables: *Voting outcome contradicts fund vote for at least one proposal* which is a dummy variable that equals one if for at least one proposal of 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; *Fund with management, outcome against management* which is a dummy variable that equals one if, for at least one proposal of a given meeting, the fund voted consistently with management recommendation and the voting outcome of that same proposal was against management recommendation; the dummy variable is zero otherwise; *Fund against management, outcome with management* which is a dummy variable that 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. *After meeting* is an indicator variable that equals one if the observation corresponds to the day of or the days after the meeting, and zero if it corresponds to a day before the meeting. We include fund\*meeting fixed effects, controls for the fund's assets under management, the fraction of company held by the fund (in bps), the company's weight in the fund's overall portfolio (in bps), the fund's expense and turnover ratios, the firm's market capitalization, and the firm's book-to-market ratio. The even numbered regressions report an F-test examining whether the coefficients of the two interaction terms included in the corresponding specification are statistically different from each other. The specifications include a Fund\*Meeting fixed effects. T-statistics are reported in parentheses. \*, \*\*, and \*\*\* indicate p<.10, p<.05, and p<.01, respectively.

	Sell (binary)		Buy (binary)		Net fraction of portfolio bought (in bps)		Net fraction of company bought (in bps)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
After meeting	-0.005*** (-8.454)	-0.005*** (-8.558)	-0.002*** (-3.887)	-0.002*** (-3.625)	-0.122*** (-3.250)	-0.112*** (-3.029)	-0.020*** (-4.275)	-0.020*** (-4.358)
Voting outcome contradicts fund votes for at least one proposal * After meeting	0.008*** (10.336)		-0.002** (-2.275)		-0.166*** (-3.243)		-0.013** (-2.020)	
Fund with mgmt., outcome against mgmt. for at least one proposal * After meeting		0.008*** (9.243)		-0.001* (-1.804)		-0.160*** (-3.119)		-0.018*** (-2.780)
Fund against mgmt., outcome with mgmt. for at least one proposal * After meeting		0.006*** (5.704)		-0.003*** (-2.827)		-0.157** (-2.290)		0.008 (.866)
R-squared	0.119	0.119	0.089	0.089	0.176	0.176	0.065	0.065
N	698,170	698,170	698,170	698,170	698,170	698,170	698,170	698,170
F test contrasting coefficient of the interaction terms		1.01		1.45		0.00		5.82
Prob>F		0.316		0.228		0.968		0.0159
Unconditional mean of dependent variable		0.028		0.022		-0.173		-0.017



**Table 3: Frequently Trading Funds' Trades when They Oppose Management**

This table reports OLS regressions of funds' trades during the February 28, 2010-September 30, 2011 period at the fund-meeting-day level for funds with above median trading frequency. The analyses examine if, and to what extent, a fund is likely to buy or sell its stocks after a meeting at which the voting outcome contradicts the vote cast by that fund for at least one proposal. The analyses include the period from the proxy filing date to 30 trading days after the meeting date, and includes only actively managed funds. The dependent variables are: *Sell* which equals one if the fund sells the stock on the observation day, and zero otherwise; *Buy* which equals one if the fund buys the stock on the observation day, and zero otherwise; *Net fraction of portfolio bought* (in bps) which is equal to the net dollar value of the firm's shares bought by the fund on a given day \* 10,000/total dollar value of the fund's overall portfolio at the end of the most recent quarter; and *Net fraction of company bought* (in bps) which is equal to the net number of the firm's shares bought by the fund on a given day \* 10,000/number of firm shares outstanding. We capture whether a voting outcome is inconsistent with a fund's vote using three variables: *Voting outcome contradicts fund vote for at least one proposal* which is a dummy variable that equals one if for at least one proposal of 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; *Fund with management, outcome against management* which is a dummy variable that equals one if, for at least one proposal of a given meeting, the fund voted consistently with management recommendation and the voting outcome of that same proposal was against management recommendation; the dummy variable is zero otherwise; *Fund against management, outcome with management* which is a dummy variable that 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. *After meeting* is an indicator variable that equals one if the observation corresponds to the day of or the days after the meeting, and zero if it corresponds to a day before the meeting. We include fund\*meeting fixed effects, controls for the fund's assets under management, the fraction of company held by the fund (in bps), the company's weight in the fund's overall portfolio (in bps), the fund's expense and turnover ratios, the firm's market capitalization, and the firm's book-to-market ratio. The even numbered regressions report an F-test examining whether the coefficients of the two interaction terms included in the corresponding specification are statistically different from each other. The specifications include a Fund\*Meeting fixed effects. T-statistics are reported in parentheses. \*, \*\*, and \*\*\* indicate p<.10, p<.05, and p<.01, respectively.

	Sell (binary)		Buy (binary)		Net fraction of portfolio bought (in bps)		Net fraction of company bought (in bps)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
After meeting	-0.014*** (-13.224)	-0.013*** (-13.292)	-0.001 (-1.248)	-0.001 (-1.008)	-0.135* (-1.911)	-0.113 (-1.637)	-0.035*** (-4.317)	-0.036*** (-4.565)
Voting outcome contradicts fund votes for at least one proposal * After meeting	0.017*** (12.131)		-0.005*** (-4.191)		-0.354*** (-3.671)		-0.021* (-1.889)	
Fund with mgmt., outcome against mgmt. for at least one proposal * After meeting		0.015*** (10.524)		-0.005*** (-4.174)		-0.373*** (-3.856)		-0.029*** (-2.675)
Fund against mgmt., outcome with mgmt. for at least one proposal * After meeting		0.013*** (6.601)		-0.004** (-2.216)		-0.233* (-1.779)		0.024 (1.621)
R-squared	0.121	0.121	0.089	0.089	0.186	0.186	0.067	0.067
N	346,487	346,487	346,487	346,487	346,487	346,487	346,487	346,487
F test contrasting coefficient of interaction terms		0.9		0.49		0.74		8.39
Prob>F		0.3424		0.484		0.3884		0.0038
Unconditional mean of dependent variable	0.042		0.032		-0.261		-0.024	

**Table 4: Volume-Volatility Elasticity Analysis around Shareholder Meeting**

This table estimates volume-volatility elasticity at shareholder meeting level. Column (1) reports the results for the specification  $\Delta \log(m_i) = a_0 + a_1 \Delta \log(\sigma_i)$  around the meeting date, and column (2) reports, as a placebo test, the same for the day that is 3 months before or 3 months after the meeting date. Columns (3) to (8) report the results for estimating equation (3)  $\Delta \log(m_i) = a_0 + b_0 X_i + (a_1 + b_1 X_i) \Delta \log(\sigma_i)$  when we include one of the six disagreement measures  $X_i$  as a control.  $\Delta \log(m_i)$  ( $\Delta \log(\sigma_i)$ ) is the change in log volume (log volatility). *Realized uncertainty* in column (3) is defined by  $\alpha_j(1-\alpha_j)$ , where  $\alpha_j$  is the average fraction of votes in favor for each proposal voted on at meeting  $j$ . *Anal. for. dispersion* in column (4) is the standard deviation of analysts' most recent earnings forecasts. *Outcome against mananagement* in column (5) is equal to one if at least one outcome is against management recommendation. *Predicted uncertainty* in column (6) is a dummy variable equal to one if the predicted fraction of votes in favor is between 40% and 60% for at least one proposal voted on at a meeting, and zero otherwise. *Special meeting* in column (7) is a dummy variable equal to one if the meeting is with "meetingtype" different from "annual" according to ISS Voting Analytics. *Merger vote* in column (8) is a dummy variable equal to one for meetings on which shareholders vote on a merger proposal. Column (9) controls for all six disagreement measures, and column (10) controls for *Realized uncertainty*, *Outcome against management*, *Predicted uncertainty* and *Merger vote*. All columns are generated for meetings held during the February 28, 2010-June 30, 2013 period. T-statistics are reported in parentheses. \*, \*\*, and \*\*\* indicate  $p < .10$ ,  $p < .05$ , and  $p < .01$ , respectively.

	$\Delta \log (m)$									
	Baseline	Placebo	Realized uncertainty	Anal. for. dispersion	Outc. against man.	Pred. uncertainty	Special meeting	Merger vote	6 disag. measures	4 disag. measures
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant ( $a_0$ )	0.036*** (6.746)	0.027*** (7.757)	0.030*** (3.432)	0.054*** (3.934)	0.025*** (4.621)	0.039*** (7.119)	0.019*** (3.692)	0.027*** (5.190)	0.047*** (3.155)	0.026*** (2.945)
$\Delta \log (\sigma) (a_1)$	0.584*** (22.397)	0.657*** (34.947)	0.611*** (15.070)	0.460*** (6.206)	0.621*** (22.900)	0.580*** (21.192)	0.626*** (23.531)	0.617*** (23.720)	0.454*** (6.045)	0.624*** (15.926)
Realized uncertainty ( $b_0$ )			0.001 (.005)						-0.109 (-0.755)	-0.03 (-0.203)
Realized uncertainty * $\Delta \log (\sigma) (b_1)$			-0.221 (-0.347)						0.854 (1.456)	0.168 (.269)
Anal. for. dispersion ( $b_0$ )				-0.045*** (-2.687)					-0.042*** (-2.580)	
Anal. for. dispersion * $\Delta \log (\sigma) (b_1)$				0.254*** (2.775)					0.272*** (3.182)	
Outc. against man. ( $b_0$ )					0.055*** (3.087)				0.003 (.144)	-0.002 (-0.078)
Outc. against man. * $\Delta \log (\sigma) (b_1)$					-0.205** (-2.473)				0.073 (1.026)	0.065 (.832)
Pred. uncertainty ( $b_0$ )						-0.065*** (-3.181)			-0.055*** (-2.624)	-0.050** (-2.065)
Pred. uncertainty * $\Delta \log (\sigma) (b_1)$						0.09 (1.463)			-0.031 (-0.507)	0.001 (.008)
Special meeting ( $b_0$ )							0.302*** (7.116)		0.187*** (3.388)	
Special meeting * $\Delta \log (\sigma) (b_1)$							-0.379*** (-2.996)		-0.181 (-0.954)	
Merger vote ( $b_0$ )								0.265*** (4.836)	0.085 (1.030)	0.272*** (4.801)
Merger vote * $\Delta \log (\sigma) (b_1)$								-0.471*** (-3.151)	-0.629** (-2.427)	-0.538*** (-3.245)
R-squared	0.1430	0.1820	0.1500	0.1740	0.1490	0.1440	0.1640	0.1550	0.2000	0.1640
N	9,440	18,508	9,300	8,746	9,373	9,440	9,373	9,440	8,639	9,300

**Table 5: Volume, Volatility and Volume Autocorrelation after Meeting**

This table tests part (i) of Hypothesis 5 by running panel regressions in equations (4) and (6) using all trading days from 45 days before the meeting to 45 days after the meeting for meetings held during the February 28, 2010-June 30, 2013 period. The dependent variable of columns (1) and (3) is the abnormal volume  $m_t$ , and that of column (2) is the abnormal volatility  $\sigma_t$ .  $D_t^{[1,10]}$  and  $D_{t-1}^{[1,10]}$  are dummy variables equal one for post-event days from 1 to 10, and  $m_{t-1}$  is the lagged abnormal volume. In all regressions, we include meeting and calendar-month fixed effects, and cluster standard errors by meeting. T-statistics are reported in parentheses. \*, \*\*, and \*\*\* indicate  $p < .10$ ,  $p < .05$ , and  $p < .01$ , respectively.

	$m_t$	$\sigma_t$	$m_t$
	(1)	(2)	(3)
$D_t^{[1,10]}$	0.04** (2.340)	0.01*** (3.560)	
$m_{t-1}$			0.22*** (15.610)
$D_{t-1}^{[1,10]} * m_{t-1}$			0.16 (1.210)
R-squared	0.17	0.298	0.224
N	801,062	801,062	801,062

**Table 6: Returns to Marginal Voting Outcomes**

This table tests Hypothesis 6 by reporting abnormal returns around shareholder meetings. The analysis is conducted at the meeting level and includes meetings held during the February 28, 2010-June 30, 2013 period. Daily abnormal returns (in percent) are calculated using the Fama-French-Carhart four-factor model. *0-day return* denotes the abnormal return on meeting date, and *[0,4] return* denotes the cumulative 5-day abnormal return from meeting date to four days after the meeting. *At least one proposal received 50%-52%(50%-55%, or 50%-60%) support rate* is a dummy variable equal to one if at least one of the proposals received 50%-52%(50%-55%, or 50%-60%) support rate. *Market capitalization* is the market capitalization of a company in millions. *Number of proposals at meeting* is the total number of proposals voted upon at the meeting. In all regressions, we cluster standard errors on the company level. T-statistics are reported in parentheses. \*, \*\*, and \*\*\* indicate  $p < .10$ ,  $p < .05$ , and  $p < .01$ , respectively.

	0-day return	[0,4] return	0-day return	[0,4] return	0-day return	[0,4] return
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.034 (.667)	0.259** (2.349)	0.033 (.632)	0.251** (2.278)	0.035 (.672)	0.255** (2.308)
At least one proposal received 50%-52% support rate	.197 (.866)	.053 (.125)				
At least one proposal received 50%-55% support rate			0.170 (1.373)	0.439* (1.672)		
At least one proposal received 50%-60% support rate					0.021 (.252)	0.089 (.502)
Market capitalization	-0.000 (-0.672)	-0.000 (-1.570)	-0.000 (-0.720)	-0.000 (-1.624)	-0.000 (-0.696)	-0.000 (-1.598)
Number of proposals at meeting	-0.000 (-0.000)	-0.018 (-1.632)	-0.000 (-0.019)	-0.018* (-1.676)	0.000 (.014)	-0.018 (-1.641)
R-squared	0.000	0.000	0.000	0.001	0.000	0.000
N	9,537	9,537	9,537	9,537	9,537	9,537

F Online Appendix

**Table A 1: Returns to Marginal Voting Outcomes including Controls**

This table tests Hypothesis 6 by reporting abnormal returns around shareholder meetings including controls. The analysis is conducted at the meeting level and includes meetings held during the February 28, 2010-June 30, 2013 period. Daily abnormal returns (in percentage) are calculated using the Fama-French-Carhart four-factor model. *0-day return* denotes the abnormal return on meeting date, and *[0,4] return* denotes the cumulative 5-day abnormal return from meeting date to four days after the meeting. *At least one proposal received 50%-52%(55%, 60%) support rate* is a dummy variable equal to one if at least one of the proposals received 50%-52%(55%, 60%) support rate. *Market capitalization* is the market capitalization of a company in millions. *Number of proposals at meeting* is the total number of proposals voted upon at the meeting. *Say-on-pay proposal held* is a dummy variable equal to one if a say-on-pay proposal was held at the meeting. *Merger vote held* is a dummy variable equal to one if a merger vote was held at the meeting. *At least one proposal submitted by a shareholder* is a dummy variable equal to one if at least one of the proposals was submitted by a shareholder. *Number of votes that failed* captures the number of proposals that failed. *Special meeting* is a dummy variable equal to one if the meeting is with “meetingtype” different from “annual” according to ISS Voting Analytics. In all regressions, we cluster standard errors on the company level. T-statistics are reported in parentheses. \*, \*\*, and \*\*\* indicate p<.10, p<.05, and p<.01, respectively.

	0-day return (7)	[0,4] return (8)	0-day return (9)	[0,4] return (10)	0-day return (11)	[0,4] return (12)
Constant	0.072 (1.198)	0.413*** (3.119)	0.069 (1.163)	0.403*** (3.039)	0.073 (1.220)	0.410*** (3.081)
At least one proposal received 50%-52% support rate	0.178 (.776)	0.021 (.049)				
At least one proposal received 50%-55% support rate			0.153 (1.228)	0.417 (1.578)		
At least one proposal received 50%-60% support rate					0.006 (.069)	0.07 (.389)
Market capitalization	-0.000 (-0.965)	-0.000* (-1.834)	-0.000 (-0.954)	-0.000* (-1.761)	-0.000 (-1.014)	-0.000* (-1.824)
Number of proposals at meeting	-0.002 (-0.331)	-0.022* (-1.832)	-0.002 (-0.328)	-0.022* (-1.834)	-0.002 (-0.326)	-0.022* (-1.830)
Say-on-pay proposal held	-0.034 (-0.673)	-0.155 (-1.373)	-0.034 (-0.674)	-0.153 (-1.361)	-0.035 (-0.685)	-0.155 (-1.375)
Merger vote held	0.089 (.491)	0.058 (.125)	0.089 (.490)	0.057 (.125)	0.089 (.491)	0.056 (.123)
At least one proposal submitted by a shareholder	0.081 (1.013)	0.022 (.140)	0.076 (.953)	-0.004 (-0.028)	0.085 (1.060)	0.014 (.091)
Number of votes that failed	-0.003 (-0.077)	0.061 (.873)	-0.003 (-0.084)	0.058 (.845)	-0.002 (-0.061)	0.061 (.873)
Special meeting	-0.198 (-1.276)	-0.632 (-1.403)	-0.197 (-1.270)	-0.629 (-1.396)	-0.198 (-1.277)	-0.63 (-1.399)
R-squared	0.000	0.001	0.000	0.001	0.000	0.001
N	9,537	9,537	9,537	9,537	9,537	9,537

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