Overpaying for Corporate Control: What Does the Value of Shareholder Votes Tell Us about Future Stock Returns?*

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Abstract

Firms with higher (lower) vote values have significantly lower (higher) future returns. Constructing portfolios based on an option-based measure of the value of voting rights yields average return spreads of about 80 basis points per month, and the return differences persist up to ten months. Our results cannot be explained by models of informed trading, liquidity and other factors known to affect stock prices. An alternative measure of vote value based on dual class firms generates similar results. Our findings highlight the importance of the vote component of stock prices in understanding the cross section of stock returns.

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1. Introduction

A common share of stock consists of two components – the right to future cash flows and the right to vote (Manne (1964)). Since accumulating shares in the open market can help achieve control, the observed stock price should include a vote component, as long as there is competition among parties interested in control (Zingales (1995)). The existing asset pricing studies, however, largely ignore the role of the vote component of stock prices in understanding the sources of variations in stock returns.[1] In this paper, we study whether the vote component of stock prices contains information about future stock returns.

As argued by Aghion and Bolton (1986, 1992), two important factors that make control valuable to investors are incompleteness of contracts and disagreements among investors. Voting rights give investors the right to make all the decisions that are not otherwise specified by contract (Easterbrook and Fischel (1991)),[2] and at times when disagreements arise among investors, a resolution can be found via the voting process. This makes voting rights particularly valuable before control events. Using different measures to capture the value of voting rights, Zingales (1995), and Kalay, Karakaş, and Pant (2014) show that vote value tends to increase before control events.[3]

Given the inherent uncertainty of the outcomes of future control events, when the chances of such events are high, investors interested in control may be willing to pay higher prices to accumulate stocks, and thereby voting rights, to increase their chances of winning the control

[1] On the one hand, following the tradition of Lucas (1978), simple asset pricing models assume endowment economies in which cash flows are exogenously given (i.e., shareholders take the payout process as given). On the other hand, production-based or investment-based models such as Cochrane (1991) or more broadly general equilibrium asset pricing models (e.g., Cox, Ingersoll, and Ross (1985)) presume that shareholders make both investment and payout decisions without a need for a resolution mechanism in case of a potential disagreement among shareholders.

[2] As noted by Easterbrook and Fischel (1991), the right to make all the decisions that are not otherwise specified by contract includes the right to delegate them which is what is typically observed in public corporations due to high costs of coordination among shareholders.

[3] Kalay, Karakaş, and Pant (2014) document that the market value of shareholder voting rights increases prior to special shareholder meetings, periods of hedge fund activism, and M&A events. Zingales (1995) documents that an exogenous breakdown of the controlling blocks (for example due to sudden death of the largest blockholder) leads to a significant increase in value of voting rights.

contest. In the face of competition among control contestants, dispersed shareholders free ride in selling their (voting) shares to the parties interested in control. This leads to a (partial) transfer of private benefits of control from controlling shareholders to dispersed shareholders (Grossman and Hart (1988), and Burkart, Gromb, and Panunzi (2000)).[4] Once the outcome of the control event is revealed and uncertainty is resolved, however, the voting rights are not as valuable anymore. This mean reversion in value of voting rights together with the partial transfer of private benefits due to free-riding by dispersed shareholders would imply that firms with higher value of voting rights would have lower future stock returns. We develop a simple theoretical model that generates results consistent with this prediction.[5]

To test our hypotheses, we use two measures of the value of voting rights. For our main analyses, we estimate the value of voting rights from option prices (hereafter *value-of-vote)*, following the methodology developed by Kalay, Karakaş, and Pant (2014). We define *value-of-vote* as the price difference between the underlying stock and the synthetic non-voting stock using put-call parity relation. The important insight of the method is that synthetic stocks reflect cash flows of the underlying stocks, but not the voting rights. As a robustness check, we also use an alternative measure of the value of voting rights based on the price difference between the two classes of stocks in firms with dual-class structure.[6] An important advantage of our main measure is that it enables us to estimate the value of voting rights for any firm at any time as long as there are liquid publicly traded options on the underlying stocks.

Our main finding in this paper is that firms with high *value-of-vote* earn lower returns, even after controlling for size, book-to-market, momentum, profitability, investment and other known

[4] Private benefits of control are benefits that current management or controlling shareholders obtain by keeping control of the firm, and include the ability to run the firm more efficiently compared to other control contestants.
[5] On the other hand, (marginal) investors who are not interested (and/or able) to impact the outcome of control events might be willing to buy stocks only at a discounted price in order to get compensated for the increased uncertainty prior to control events. Therefore, it is an empirical question as to which effect dominates.
[6] We follow Zingales (1995) to construct this measure of the value of voting rights for firms with dual- class stocks. Despite being a common method to compute vote values in earlier studies, one caveat of this methodology is that only about 6% of the US public corporations have dual-class structure and both classes of stocks are not always publicly traded.

predictors of stock returns such as idiosyncratic volatility, analyst forecast dispersions, liquidity, earnings surprises, and short-term reversal. The economic magnitude of these effects is large. Our results indicate that the difference in the estimated alphas between the lowest and the highest *value-of-vote* quintiles is about 80 basis points per month (an annualized return of about 10 percent). These differences are highly statistically significant, and are remarkably robust to a variety of empirical specifications.[7]. Moreover, while our results are strongest for the one-month horizon, significant return predictability of *value-of-vote* persists for up to ten months. This suggests that it is unlikely that our findings are due to liquidity or microstructure differences in stock and options markets.

Prior studies attribute apparent deviations from options put-call parity to trading activities of informed investors. If informed investors choose the option market to trade in before doing so in the stock market, option prices would deviate from what put-call parity implies in the direction of informed investors' private information (Easley, O'Hara, and Srinivas (1998)). This leads to option prices carrying information that is predictive of future stock price changes (Cremers and Weinbaum (2010), An, Ang, Bali, and Cakici (2014)). We perform extensive robustness analyses to mitigate the concern that our results might be driven by informed trading or liquidity-related issues in the option and stock markets, and find our results to not be consistent with predictions of informed trading models. This suggests that value of voting rights contains information about future stock returns distinct from informed trading or liquidity in the option and stock markets.[8]

Furthermore, we repeat our analysis for a sub-sample of dual-class firms using an alternative measure of the value of voting rights. Following Zingales (1995) we measure vote value in dual-class firms by taking the price difference between the superior and inferior voting stocks

[7] We make sure that our findings are robust to alternative specifications including: (1) alternative timings of forming portfolios, (2) different holding periods, (3) alternative out-of-sample forecasting horizons, (4) incorporating additional firm characteristics known to predict future stock returns, and (5) censoring and winsorizing negative values of *value-of-vote*.

[8] We acknowledge that it is inherently difficult to fully disentangle the effect of informed trading from that of value of voting rights on future stock prices. This is because informed trading can happen before control events precisely to accumulate voting rights (Cao, Chen, and Griffin (2005), Brav and Mathews (2011)).

normalized by their respective voting rights. Consistent with our main findings, we find that firms with higher vote value have lower future returns for superior voting stocks.[9] This further alleviates the concern that our results may be somehow driven by the preferences of the informed traders between the option and stock markets.

Moreover, our cross-sectional analyses using Fama-MacBeth (1973) regressions show that *value-of-vote* is a strong predictor of future stock returns. More specifically, we find that moving from the first quintile to the fifth quintile of *value-of-vote* decreases the expected return by 0.84% per month. Given that we control for an extensive listof firm characteristics as well as stock and option market characteristics, these results corroborate our argument that the value of voting rights contains independent information about future stock returns.

A question that might arise is why (some) investors are willing to pay higher prices at times when control becomes more important. As Grossman and Hart (1988) argue, if the controlling party enjoys private benefits, they would be willing to pay a premium in order to capture control. These private benefits include the ability to run the firm more efficiently compared to other control contestants. In addition, voting rights are especially valuable if investors feel the need to wield disciplinary pressure that improves managerial inefficiencies (see for example Manne (1964), Easterbrook and Fischel (1983), Cox and Roden (2002)). If investors are willing to pay a higher price to capture control in firms with more room for improving managerial inefficiencies, in the long run we should observe improved operating performance in firms with higher *value-of-vote*.[10] Consistent with our conjecture, we find firms in the highest *value-of-vote* quintile portfolio significantly improve their operating performance and profitability in two and three- year horizons

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[9] In fact, our option-based measure of the value of voting rights can be interpreted as synthesizing an inferior voting class of stocks with no voting rights (Kalay, Karakaş, and Pant (2014)). Hence, the common shares in firms with a single class of stocks are similar to the superior voting class stocks in dual-class firms.

[10] Since current stock prices will reflect any market expectation of future improved management, ceteris paribus, expected return for firms with higher expected improvement in managerial efficiency will be lower compared to otherwise identical firms in which the current stock prices are depressed due to managerial inefficiencies but the prospect of an improvement is slim. The expectation in improvement in managerial efficiency is reflected in the value of voting rights.

compared to those in the lowest *value-of-vote* quintile. This suggests that, consistent with the literature, control contests on average lead to improved firm performance and benefit shareholders (see *e.g.,* Barclay and Holderness (1991)).

Our findings are closely related to a literature showing that observed stock prices include a vote component that increases where and when control becomes particularly important (see *e.g.,* Lease, McConnell, and Mikkelson (1983, 1984), Barclay and Holderness (1989), Zingales (1995), Nenova (2003), Dyck and Zingales (2004), and Kalay, Karakaş, and Pant (2014)). In addition, our paper is related to a vast literature documenting the positive effect of good governance on firm value and stock market performance (see *e.g.,* Gompers, Ishii, and Metrick (2003), Bebchuk, Cohen, and Ferrell (2008), Cremers and Nair (2005), Cremers, Nair, and John (2009)). Our findings are consistent with these studies, since the value of voting rights in a well-governed company tend to be low because the potential room for improvement in managerial inefficiencies would be limited. Our lowest *value-of-vote* portfolio, therefore, would correspond to firms with best governance practices. While quality of corporate governance is clearly related to the value of the voting rights, our paper is the first to directly examine the link between the value of voting rights and future stock returns.

Our paper also joins a more recent literature documenting that option prices contain information about future stock returns (see *e.g.*, Cao, Chen, and Griffin (2005), Bali and Hovakimian (2009), Cremers and Weinbaum (2010), and Xing, Zhang, and Zhao (2010) Johnson and So (2012), and An, Ang, Bali and Cakici (2014)). By performing subsample analysis and controlling for an extensive list of firm, stock and option market characteristics, our findings suggest that the value of voting rights contains information about future stock returns distinct from informed trading or liquidity in the option and stock markets.

Finally, our paper contributes to a recent literature on the asset pricing implications of corporate control and private benefits of control. Albuquerque and Schroth (2010) estimate private benefits of control using a structural model of block trades by Burkart, Gromb, and Panunzi (2000). Albuquerque and Schroth (2015) develop a model of block trades that quantifies the illiquidity discount of controlling blocks for both blockholders and dispersed shareholders. We provide an economic model with strong empirical support to show that the market value of voting rights can help explain the cross section of stock returns. To the best of our knowledge, this is the first paper that establishes this link.

The remainder of the paper proceeds as follows. Section 2 provides an economic model to produce testable implications. Section 3 describes data, sample construction and our methodology to measure the value of voting rights. Section 4 shows the main results of our empirical analyses. Section 5 provides additional robustness checks. We conclude in section 6.

2. Theoretical Motivation

This section develops a simple theory to motivate and explain our main hypotheses. The expected stock returns by dispersed shareholders is the main focus of this model. The key departure from prototypical asset pricing models is that our model incorporates the possibility of a control event, the existence of shocks to the probability of such control event, and potential gains to dispersed shareholders from this event. To dispersed shareholders, future events related to competition between blockholders are rather exogenous and random. As we explained earlier, Kalay, Karakaş, and Pant (2014) report that stock markets assign positive values to the voting process, and different firms have different values of vote depending on the likelihood of control events and the economic gains that dispersed shareholders can obtain in this case. In addition, Albuquerque and Schroth (2015) point out that dispersed shareholders can extract the option value to sell their shares to a blockholder who can increase the firm values. Whether the firm characteristic related to control events matters to explain stock market prices is an empirical question. However, asset pricing implications in this setting are largely unknown, and our theory can provide the first set of testable hypotheses in this regard. Thus, at each point of time, firms will differ in their likelihoods of this type of event and the value of potential benefits to dispersed shareholders, and this cross-sectional variation can tell us about the future stock returns.

Time is discrete, and the model assumes rational expectation in the sense that decision makers know probability distributions of stochastic variables. The market value of a firm's equity depends on the firm's cash flows and a right associated with firm decisions in case of control events. Control event is defined as a situation in which there exists a blockholder challenging the existing controlling blockholder. We call the latter the incumbent (*I*) and the former, the rival (*R*). If a control event occurs, the incumbent and the rival players will compete and voting rights become important. In particular, firms have different likelihoods of a control event at a given point of time, and the value of vote increases as a control event is more likely to occur. To incorporate the feature, we assume that there are two firms and in each period t, both firms draw a shock that determines whether or not there exists a control event. The probability of a control event in the next period, denoted as θ, is defined as $\theta = \bar{\theta} + \varepsilon$, where $\bar{\theta}$ is a constant, and the shock ε is purely idiosyncratic in that one firm has $\varepsilon = \bar{\epsilon}$, and the other firm will have $\varepsilon = -\bar{\epsilon}$. Conditions hold such that the probability θ is between 0 and 1 $(\bar{\epsilon} > 0, \bar{\theta} + \bar{\epsilon} < 1, \bar{\theta} - \bar{\epsilon} > 0)$. For simplicity, the probability of each case is assumed to be 0.5. Thus, in the beginning of each period, ε shock realizes, and one firm has $\bar{\theta} + \bar{\epsilon}$ and the other is given with $\bar{\theta} - \bar{\epsilon}$. Because of ε shock, the probability of a control event for each firm can change every period, and the expected probability of a control event for the next period is $E(\theta) = \bar{\theta}$, implying that the expectation of each firm's likelihood of a control event is $\bar{\theta}$.

Based on the argument made in the beginning of this section, we assume that dispersed shareholders can have some additional benefits when there exists a control event, and its amount varies across firms. This results from competition between controlling block holder and the rival, because dispersed shareholders may sell their shares at premium. We denote as ϕ the amount of benefit transferred to dispersed shareholders in case of control events. Further, we denote V^I_{it+1}(V^R_{it+1}) to be the value of stock of firm i when the incumbent (rival) wins the contest, where superscripts *I* and *R* respectively refer to the incumbent and the rival shareholders.

In case of a contest, a shareholder (group) who has the higher valuation of the firm wins the contest, and the current stock price will reflect the value of winner. If there is no contest, then the incumbent's valuation continues to hold. π_{it} is the cash flow of firm *i* at time *t*. Then, the market price of equity of firm *i* at time *t*, P_{it} , is written as

$$P_{it} = \pi_{it} + \beta[\theta_{it}\{E_t\,[\max(V^I_{it+1}, V^R_{it+1})] + \phi_i\} + (1-\theta_{it})E_t(V^I_{it+1})],$$

where β is the deterministic time discount factor and between 0 and 1. E_t is the conditional expectation operator as of time *t*. The above equation states that the value of vote can be measured as the difference of the above price and the one without a control component, which is $\beta\theta_{it}\phi_i$. Interpretation is clear: the higher the likelihood of a control event (θ_{it}) and/or the larger the additional benefit of control that can be transferred to the dispersed shareholders (ϕ_i), the value of a vote reflected in the market price of a stock per share is higher, consistent with the literature such as Zingales (1995) and Kalay et al (2014), and with our empirical measure. We can write down the conditional expected return in a recursive fashion,

$$E_t P_{it+1} = E_t \pi_{it+1} + \beta[\bar{\theta} E_t(\max(V^I_{it+2}, V^R_{it+2})) + \bar{\theta}\phi_i + (1-\bar{\theta})E_t(V^I_{it+2})]$$

For simplicity, we assume that the firm cash flow process π is a martingale, or $E_t\pi_{it+1} = \pi_{it}$. Relaxing this to a more general stochastic process with temporal dependence does not affect the main messages of the model. In this case, the expected return is computed as

$$E_t P_{it+1} - P_{it} = \beta[(\bar{\theta} - \theta_{it})E_t(\max(V^I_{it+2}, V^R_{it+2})) + (\bar{\theta} - \theta_{it})\phi_i + (\theta_{it} - \bar{\theta})E_t(V^I_{it+2})].$$

To discuss asset pricing implications of the model, we assume that the time-*t* shock of control event likelihood, ε is realized, and firm 1 has the higher value of vote than firm 2 in period t. Thus, $\theta_{1t}\phi_1 > \theta_{2t}\phi_2$ holds for the period of time *t* to *t+1* based on the value of vote implied by the model. If there is a contest, either the player *R* or *I* can win the contest. If the rival block holder wins the contest, the expected return of firm 1 with the higher value of vote $(\theta_{1t}\phi_1)$

$$E_t P_{1t+1} - P_{1t} = \beta[(\bar{\theta} - \theta_{1t})\{E_t(V^R_{1t+2},) - E_t(V^I_{1t+2}) + \phi_1\}] < 0,$$

and the firm 2 with the lower value of vote has

$$E_t P_{2t+1} - P_{2t} = \beta[(\bar{\theta} - \theta_{2t})\{E_t(V^R_{2t+2},) - E_t(V^I_{2t+2}) + \phi_1\}] > 0.$$

In case that the incumbent player *I* wins the contest, the expected returns of firm 1 and 2

$$E_t P_{1t+1} - P_{1t} = \beta[-(\theta_{1t} - \bar{\theta})\phi_1] < 0,$$

$$E_t P_{2t+1} - P_{2t} = \beta[-(\theta_{2t} - \bar{\theta})\phi_1] > 0.$$

The result is simple yet surprising in that firms with the higher value of vote will have a lower expected return than the firm with the lower value of vote, whether the incumbent or rival shareholders wins. In addition, the risk-adjusted expected return of the firm with the higher value of vote (firm 1) is negative, and that of the firm with the lower value of vote (firm 2) is positive. The theoretical results mainly come from two ingredients. First, the existence of this particular type of gains from trade to dispersed shareholders is critical to have a positive value of vote. Second, it is equally important to have heterogeneity and stationarity of shocks to the likelihood of control event. In our example, this easily holds because the shock ε is constructed such that two firms will always have different shocks, and every period, firms draw a shock again. As long as chances of control event for different firms are sufficiently heterogeneous, the results carry over.

3. Data and Methodology

This section describes our data sources and the methodology used to construct two measures of the value of voting rights, and also presents summary statistics of our sample.

3.1. Data and Sample Selection

Our sample includes stocks of all public US firms in the intersection of OptionMetrics and CRSP monthly returns file between January 1996 and September 2015.[11] Some of our tests require the presence of data from other data sources to control for various firm, ownership and governance characteristics. We use Compustat for firm characteristics, I/B/E/S (Institutional Brokers' Estimate System) for data on analysts' earnings forecasts, Thomson Reuters (S34) for data on institutional holdings (13F filings), Institutional Shareholder Services (ISS) (formerly known as Riskmetrics) and GMI for data on corporate governance. We also identify firms with a control event if the firm is a target of a merger or subject to 13-D filings, or experiences a proxy contest or special shareholder meetings one-month before and after our portfolio formation period. We get this information from SDC, SEC Analytics Suite from WRDS, and ISS Voting Analytics. In addition, we hand-collect data on the relative voting power of different classes of stocks in dual-class firms by reading their proxy statements. Our sample of dual-class firms starts in 1994, before which proxy statements are relatively rare to find on EDGAR for most firms, and ends in 2016.[12]

3.2. Measuring the Value of Voting Rights

We construct our main measure of the value of voting rights (*value-of-vote*) following the method developed in Kalay, Karakaş, and Pant (2014). The main insight of the method is that one can synthesize cash flows of an underlying stock using options, but the synthetic stock does not

[11] OptionMetrics data starts from January 1996.

[12] We thank Andrew Metrick for providing the data from Gompers, Ishi and Metrick (2009) which spans from 1992 to 2002. To expand this sample, we identify dual-class firms using various data sources such as GMI and ISS, before manually verifying the accuracy of the data and collecting data on the relative voting power of different classes of stocks from firms' proxy statements.

reflect the voting rights included in the underlying stock. The measure captures the value of voting rights by subtracting the price of a synthetic non-voting stock, denoted as $\hat{S}$, from that of the underlying stock, S. In order to make the measure comparable across firms and over time, we normalize the measure by the price of the underlying stock (See equation 2 below). $\hat{S}$ is calculated using options put-call parity for an option pair with the same strike price X and maturity T, and is adjusted for the early exercise premiums of American options (EEP), and for dividends paid before options mature, denoted by DIV (See equation 1 below):

$$\hat{S} = C - P + PV(X) + adjustments\ for\ EEP\ and\ DIV, \quad (1)$$

$$Value\ of\ Vote = (S - \hat{S})\ /\ S, \quad (2)$$

where C and P are the prices of the American call and put options, respectively; X is their common strike; T is their time to maturity; and $PV(X)$ is the present value of a risk-free bond with face value X that matures at time T.[13] An important advantage of using this methodology is that it enables us to estimate the value of voting rights for any firm at any time as long as there are publicly traded options on the underlying stocks.

As a robustness check, we use an alternative measure of the value of voting rights based on the price difference between the two classes of stocks in firms with dual-class structure (adjusted for their relative voting power). Following Zingales (1995), we define the value of voting rights in dual class firms as

$$Vote\ Premium = {(P_s - P_i)}\Big/{(P_i - rP_s)}$$

where P_s and P_i are the prices of superior and inferior voting stocks, respectively, and r is the ratio of the number of votes of an inferior voting share to that of a superior voting one.

[13] In our calculations of *value-of-vote*, we use the most liquid option pair for each firm in each day defined as the option pair with the highest volume (maximum of minimum volume of call and put), closest at the money, and shortest maturity. This procedure helps minimize the impact of non-control related frictions such as liquidity or nonsynchronous trading in the option and stock markets on our measure.

This is a common method to compute vote values in the literature (*e.g.* Lease, McConnell, and Mikkelson (1983), Levy (1983), DeAngelo and DeAngelo (1985), Zingales (1994, 1995), Smith and Amoako-Adu (1995), Chung and Kim (1995), Rydqvist (1996), Cox and Roden (2002), Nenova (2003), Hauser and Lauterbach (2004), Masulis, Wang and Xie (2007)).[14] The caveat is that only about 6% of the US public firms have dual-class structure. This method is conceptually similar to our option-based methodology, since in constructing *value-of-vote* we are essentially synthesizing an inferior voting class of share with no voting rights.[15]

3.3. Summary Statistics

In this subsection, we describe the summary statistics of the sample used in our analyses. Table 1 Panel A reports the average *value-of-vote* and number of firms in our sample by the calendar year. The number of firms with publicly traded options in our sample more than doubles from 1053 in 1996 to 2164 in 2015. The average *value-of-vote* in our sample is around 0.10% of the stock price. The annual average *value-of-vote* varies over time and peaks in the period 2008-2009.

[~ Insert Table 1 here ~]

Panel B of Table 1 presents the summary statistics of *value-of-vote* and other firm characteristics for the five quintile portfolios sorted based on *value-of-vote*. To construct quintile portfolios, at the beginning of each month we sort stocks based on the median *value-of-vote* during the prior month. We rebalance our quintile portfolios every month. The time-series variations of

[14] For empirical and theoretical surveys of the literature on separation of voting rights from cash flow rights see Adams and Ferreira (2008) and Burkart and Lee (2008), respectively.

[15] Another method to measure value of voting rights takes the difference between the share price in a block trade and the prevailing market price right after the sale of the block (e.g. Barclay and Holderness (1989) and Dyck and Zingales (2004)). The limitation of this methodology is that block trades are not frequently observed. Other studies have used the equity lending market to infer about the value of voting rights. The main idea is that one can separate voting rights from cash flow rights by borrowing shares of stocks to vote without an equivalent economic interest, commonly known as empty voting. Christoffersen, Geczy, and Musto (2007) study the market for votes within the U.S. equity loan market, and find the average vote sells for zero. However, using an expanded sample, Aggarwal, Saffi, and Sturgess (2015) find that value to be positive.

average *value-of-vote* for the five quintile portfolios can be seen in Figure 1. Average *value-of-vote* is negative for quintile 1, but it is positive for quintiles 2, 3, 4 and 5. Despite *value-of-vote* taking negative values in some of our observations, it is important to emphasize that the average *value-of-vote* in our sample is positive. Negative *value-of-vote* could be due to noise, estimation errors, and potential information leakage in the option market before the stock market.[16] Kalay, Karakaş, and Pant (2014) show these frictions do not drive the changes in *value-of-vote* around important control events. Moreover, our entire analyses are robust to dropping observations with negative *value-of-vote* or replacing those negative values with zero.[17]

[~ Insert Figure 1 here ~]

Panel B of Table 1 also shows that firms with the highest *value-of-votes* appear to be smaller in size, have more dedicated institutional investors and a higher concentration of institutional investors and have higher insider ownership. In addition, changes in total institutional ownership monotonically increase as we move from the portfolio with lowest to the one with highest *value-of-votes*, which indicates that institutional investors accumulate more shares in firms with highest *value-of-votes* in the year prior to forming portfolios. Further, firms with a higher *value-of-votes* tend to show more disagreement among investors measured using dispersion in analysts' forecasts and experience more control events in the immediate time periods. As we move from lowest to highest *value-of vote* portfolios, institutional ownership by long term investors (dedicated), insider ownership and governance quality measured by modified G-Index is generally increasing.[18] These

[16] Other methods of estimating the value of voting rights also yield negative values. Barclay and Holderness (1989) find a block premium of up to 20% for the US firms but also find negative values for some firms. Applying a similar methodology to the international data Dyck and Zingales (2004) find a premium of around 14% with wide variations ranging from -4% to 65% across countries. Albuquerque and Schroth (2015) argue that depending on the costs associated with a controlling block of shares such as illiquidity, this premium can be negative as well. Using price difference in dual-class firms to measure value of voting rights Lease, McConnell, and Mikkelson (1983) also find negative vote values which they attribute to "some incremental costs borne by the holders of the class of common stock with superior voting rights that are not borne by the [others]". Applying the same methodology to the country level data, Nenova (2003) finds average value of votes in Hong Kong is negative.

[17] Our results with dropping negative *value-of-vote* firms and truncating negative values of *value-of-vote* are reported in Online Appendix Table A1 Panel A and B, respectively.

[18] These patterns become monotonic if we focus on observations with non-negative *value-of-vote*.

observed patterns are broadly consistent with prior literature stating that the value of voting rights is related to the likelihood of control events and the potential (private) benefits of control (Zingales (1995), Karakas and Mohseni (2018)).[19]

Panels C and D of Table 1 report transition matrices, which provide the empirical probabilities of a firm moving from one *value-of-vote* quintile to another for one and three-month periods, respectively. A firm in the highest quintile of *value-of-vote* in a given month is most likely to stay in the same quintile in the next one (three) month(s) with a probability of 52% (44%). The same pattern is observed for other *value-of-vote* quintiles. This suggests that while firms are more likely to stay in the same *value-of-vote* quintile than they are to move to any other quintile, there is a fair amount of transitions across quintiles. Overall, *value-of-vote* does not appear to be a firm characteristic that is as persistent over time as some other firm characteristics such as book-to-market ratio, size and profitability.

4. Empirical Analysis

In this section, we discuss the results of our empirical analysis of the links between *value-of-vote* and future stock returns.

4.1. Stock Returns on Portfolios Sorted by *Value-of-vote*

Upon formation of quantile portfolios based on *value-of-vote*, we calculate equal-weighted (EW) and value-weighted (VW) portfolio returns. Table 2 presents monthly returns on portfolios sorted based on *value-of-vote*. The average monthly returns and *t*-statistics for the quintile portfolios as well as the difference between quintile 5 (highest *value-of-vote*) and quintile 1 (lowest

[19] Online Appendix Table A2 presents the results of the panel regressions of *value-of-vote* on firm characteristics. Results are consistent with patterns emerged in our summary statistics.

value-of-vote) are reported in Panel A of Table 2. Firms in the lowest *value-of-vote* quintile portfolio earn an average EW return of 1.32% per month. Average EW return of quintile portfolios monotonically declines to 0.62% per month for firms in the highest *value-of-vote* quintile portfolio. The spread between the two is −0.70% per month, which carries a statistically significant *t*-statistic of -4.97. The spread between the VW average return of highest and lowest *value-of-vote* quintile portfolios is −0.41% per month, with a *t*-statistic of -1.81.

[~ Insert Table 2 here ~]

The last column of Panel A Table 2 present characteristics-adjusted returns of *value-of-vote* quintile portfolios. We use the method employed in Daniel, Grinblatt, Titman and Wermers (1997) to adjust individual stock returns for size, book-to-market, and momentum. Each month we first sort all firms in our sample into size quintiles (using NYSE breakpoint), and then within each size quintile we further sort firms into book-to-market quintiles. Within each of these 25 portfolios, firms are further sorted into quintiles based on the firm's past 12-month return, skipping the most recent month. Stock returns are averaged within each of these 125 portfolios to form a benchmark that is subtracted from the corresponding individual stock returns. The expected value of this excess return would be zero if size, book-to-market, and past returns completely described the cross section of expected returns. Even after adjusting for these characteristics, there is a significant spread in average returns between *value-of-vote* quantile portfolios. The average adjusted return is positive and statistically significant for the lowest *value-of-vote* quantile portfolio and monotonically decreases to negative and statistically significant for the highest *value-of-vote* quantile portfolio. The characteristic adjusted return spread for *value-of-vote* quintile portfolios is -0.66% with a *t*-statistics of -5.39.[20] This suggests that the return premium associated with *value-of-vote* is independent of those of size, book-to-market, and momentum.

[20] Online Appendix table A3 presents the results of a similar analysis for decile portfolios sorted based on *value-of-vote.* Not surprisingly, the average return spread for *value-of-vote* decile portfolios are larger in magnitude.

It is plausible that control contestability, and thereby *value-of-vote*, decreases as firm size increases. In order to examine whether firm size affects the *value-of-vote* return spread, we use dependent sorting based on market capitalization and *value-of-vote*. In panel B of Table 2 we first sort stocks based on market capitalization. Within each size quintile, we further sort stocks based on median *value-of-vote* during the prior month. For any given size quintile, we take the average spread between quintile 5 and 1 of *value-of-vote* portfolios. The average return spread is statistically significant across all size groups, except for the largest size group (size group 5). In Panel C of Table 2, we first sort stocks based on *value-of-vote* and then within each *value-of-vote* quintile we further sort stocks based on their market capitalization. Within each *value-of-vote* quintile, the average monthly return spread between smallest and largest firms (SMB) is statistically insignificant in every *value-of-vote* quintile. The results in Panels B and C of Table 2 suggest that the size effect cannot explain the return spread in *value-of-vote* portfolios, but the differences in *value-of-vote* can account for the size effect.

4.2. Adjusting for Known Pricing Factors

In this section we adjust for common risk and pricing factors to examine whether *value-of-vote* contains independent information about future stock returns. Table 3 presents monthly excess returns using three commonly used asset pricing models. Panel A of Table 3 presents the monthly estimated alphas using Fama-French (1993) model (FF3 hereafter) for the quantile portfolios as well as the alpha difference between quintile 5 and quintile 1. The FF3 alpha difference between quintile 5 and 1 is -0.77% with a *t*-statistics of -5.60.

[~ Insert Table 3 here ~]

In Panel B of Table 3 we add a momentum factor-mimicking portfolio to the Fama–French factors as in Carhart (1997) to estimate a four-factor model (FF4 hereafter). The FF4 alpha difference between quintile 5 and quintile 1 is -0.80% with a *t*-statistics of -5.73. Panel C of Table 3 uses Fama-French five factor model (FF5 hereafter) as in Fama and French (2015) which includes profitability and investment factors in addition to FF3 factors. The FF5 alpha difference between quintile 5 and quintile 1 is -0.78% with a *t*-statistics of -5.41.[21] The average returns difference between the highest and lowest *value-of-vote* quintile portfolios are very similar across different asset pricing models, and are larger than the differences in raw returns (reported in Table 2).

Moreover, to ensure what we capture by *value-of-vote* is distinct from other known pricing factors, we additionally control for five other anomaly factors: idiosyncratic volatility, analysts' forecasts dispersion, illiquidity, earnings surprise, and lottery demand. These anomalies are documented in the literature to affect stock returns. Idiosyncratic volatility factor captures firm-specific risks which can be priced in incomplete markets. Since control and voting rights are a source of firm specific volatility, we want to make sure that our results are robust to controlling for idiosyncratic volatility factor. The dispersion factor incorporates differences in opinions and heterogeneous beliefs about a stock among market participants. Since investor heterogeneities make corporate control rights more important (Aghion and Bolton (1986, 1992), and Easterbrook and Fischel (1983)), analysts' forecast dispersion may be related to the value of voting rights. . We control for the illiquidity factor for two reasons: first, to mitigate the potential concern that our main measure of the value of voting rights is contaminated with liquidity related issues (see section 4.4 for a more detailed discussion); and second, given the link between block premium/discount and illiquidity documented by Albuquerque and Schroth (2015), it is important to make sure that the effect of *value-of-vote* is independent of illiquidity factor. Later in Section 5.1, we further control for various liquidity measures related to option and stock markets. Furthermore, since Gurun and Karakaş (2016) find that vote values are negatively associated with earnings surprises, we also control for earnings surprise factor. Finally, given the existing evidence for speculative investors' high demand for lottery-like stocks (Kumar (2009), Bali, Cakici, and Whitelaw (2011), Doran, Jiang, and Peterson (2011), and Han and Kumar (2013)), we examine whether there is a connection between *value-of-vote* and lottery-like features of optionable stocks. A simple check

[21] In Online Appendix Table A3, we also present FF3, FF4 and FF5 alphas for *Value- of-vote* decile portfolios and their high-minus low (V10-V1) return differences.

would be to include a lottery demand factor in our analysis. Although some of these factors are imperfect proxies, controlling for themhelps to quantify the marginal contribution of *value-of-votes* to the cross-sectional stock return predictability.

We follow Ang, Hodrick, Xing and Zhang (2006) to calculate idiosyncratic volatility measured relative to the FF3 model; for each month we regress daily stock returns on daily market returns (value-weighted return on all NYSE, AMEX and NASDAQ stocks), size and book-to-market factor returns to get the standard deviation of residuals of the month. We follow Diether, Malloy and Scherbina (2002) to define analysts' forecast dispersion as the standard deviation of earnings forecasts divided by the absolute value of the average analysts' forecast. We use Amihud (2002)'s illiquidity measure defined as the absolute return to dollar volume averaged over the prior six months. Following Livnat and Mendenhall (2006), we define standardized unexpected earnings (SUE) as the difference between the actual earnings and the median of earnings forecasts normalized by stock price at the quarter end. Finally, we use MAX factor constructed by Bali, Brown, Murray, and Tang (2017) to control for lottery demand. MAX is calculated as the average of the 5 highest daily returns of the stock during a given month. Max factor (FMAX) is constructed using the Fama and French (1993) factor-forming technique. [22] To construct these anomaly factors, we sort stocks into five quintiles based on each anomaly factor and get the return difference between high and low quintile portfolios.

[~ Insert Table 4 here ~]

The monthly estimated alphas for the quantile portfolios as well as the alpha difference between quintile 5 and quintile 1 using modified FF3, FF4 and FF5 models are reported in Panels A, B and C of Table 4, respectively. In each panel, we modify the corresponding asset pricing model by individually adding each of the additional five anomaly factors to the model.. The alpha difference between quintile 5 and quintile 1 is highly robust to the choice of the pricing factor

[22] We thank Turan Bali for kindly sharing this data with us. See Bali, Brown, Murray, and Tang (2017) for a detailed description of the dataset.

included in the asset pricing model. This further shows that existing pricing factors do not account for the return premium associated with *value-of-votes*. [23]

4.3. Long-Term Predictability

In this section we examine whether the out-of-sample predictability of *value-of-vote* persist over longer horizons. Although Tables 3 and 4 show a robust *value-of-vote* return spread, if this predictability is very short-lived, it begs the question as to whether these results are driven by market microstructure frictions that may lead to mispricing for a short period of time.

We investigate the longer-term predictability of *value-of-vote* over the next twelve months by constructing portfolios with overlapping holding periods following Jegadeesh and Titman (1993). At the beginning of each month we sort stocks based on the median *value-of-vote* during the prior month and form five quintile portfolios based on these rankings. In a given month t, this strategy buys stocks in the highest *value-of-vote* quintile, sells stocks in the lowest *value-of-vote* quintile and hold this position for T months (i.e. closes out this position after T^{th} months). Hence, under this trading strategy, we revise the weights on $1/T$ of the stocks in the entire portfolio in any given month and carry over the remaining from the previous month (T = 1 to 12 months).

Table 5 presents the results of the long-term predictability analysis. The average raw return differences between quintile 5 and 1 of *value-of-vote* portfolios are statistically significant for the one- to three-month holding periods.[24] The magnitude of the average raw return differences, however, drops from -0.70% for one-month holding period to -0.46% for the two-month holding period and -0.36% for three-month holding period. The risk-adjusted return differences (using FF3, FF4, and FF5 models) are statistically significant for holding periods of up to ten months. The magnitude of the risk-adjusted return differences (using FF3 model) monotonically drops from -

[23] In untabulated analysis we add all the additional five anomaly factors together to the common asset pricing models and the results are very similar to those reported in Table 4. For example, when we add all five additional pricing factors to FF5, the alpha difference between quintile 5 and quintile 1 using this ten-factor model is -0.65% with a t-statistics of -4.51.

[24] We follow Harvey, Liu and Zhu (2016)'s recommendation to use a t-statistic of greater than 3.0 in claiming statistical significance for our estimated coefficients.

0.77% for the one-month holding period to -0.56% for the two-month holding period, -0.45% for the three-month holding period, all the way to -0.16% for the ten-month holding period.[25] Evidently, the return difference between quintile 5 and quintile 1 of *value-of-vote* portfolios is not a short-lived effect and persists for at least nine months despite the magnitude of the return differences declining as holding period increases. Given that most of the previous literature on lead-lag effects of option and stock markets focuses on daily and intraday frequencies (*e.g.* Manaster and Rendleman (1982), Chakravarty, Gulen, and Mayhew (2004) and Muravyev, Pearson, and Broussard (2013)), the predictability of *value-of-vote* at longer horizons further suggests that our results are not driven by microstructure differences in the option and stock markets.

[~ Insert Table 5 here ~]

4.4. Does Informed Trading Explain Our Findings?

Some existing studies attribute apparent deviations from options put-call parity, in part, to trading activity of informed investors. If informed investors choose the option market to trade first, as in the equilibrium model of Easley, O'Hara, and Srinivas (1998), option prices would deviate from what put-call parity implies in the direction of the informed investors' private information.[26] This leads to option prices carrying information that is predictive of future stock price movements. Relatedly, An, Ang, Bali and Cakici (2014) document that large increases in call (put) implied volatilities predict high (low) future returns. In a closely related study, Cremers and Weinbaum (2010) use the difference in implied volatility between call and put options (volatility spread) on the same underlying equity, with the same strike price and the same expiration date, to measure deviations from put-call parity and document that stocks with relatively expensive calls outperform

[25] Figure A1 plots the average raw return difference between High and Low *value-of-vote* portfolios as the holding period increases.
[26] Informed investors might prefer to trade in the option market rather than stock market, perhaps because of the higher leverage available in options markets (Black, 1975), or because options markets allow them to achieve better liquidity or to better hide their private information (Back (1993), Biais and Hillion (1994)).

stocks with relatively expensive puts. Both studies interpret their findings as being consistent with models of informed trading.

Since we construct our main measure of the value of voting rights using options and the underlying stock prices, our results may also be interpreted as consistent with informed trading. However, we argue that the value of voting rights contains information about future stock returns that are independent of informed trading. We provide four sets of evidence to support this argument and to distinguish our findings from those of An *et. al.* (2014) and Cremers and Weinbaum (2010). First, the model of informed trading by Easley *et. al.* (1998) indicates that when liquidity of the options market is low, informed traders prefer to mainly trade in the stock market. Consistent with this prediction, An *et. al.* (2014) and Cremers and Weinbaum (2010) both document that the degree of predictability is substantially larger when option liquidity is higher. In fact, both studies find statistically insignificant predictability in stocks with relatively illiquid options. This, however, is not the case for our findings. Following An *et. al.* (2014) and Cremers and Weinbaum (2010), we repeat our analysis for the subsamples of stocks based on different option liquidity measures. Panel A of Table 6 presents the results of our analysis for the subsamples of stocks based on options volume, open interests, and options bid-ask spreads. For example, the first two columns of Panel A of Table 6 show that the alpha difference (using FF5 model) between quintile 5 and 1 of *value-of-vote* portfolios is -0.70% (with a *t*-statistics of -4.50) and -0.87% (with a *t*-statistics of -4.60) for the subsamples of stocks with options volume below and above the median, respectively. This indicates that the predictability of *value-of-vote* is economically large, statistically significant and comparable in magnitude for both subsamples of stocks with relatively liquid and illiquid options. These findings suggest that predictability of *value-of-vote* cannot be explained by models of informed trading such as that of Easley *et. al.* (1998).

[~ Insert Table 6 here ~]

Second, we find our results to be robust to controlling for the implied volatility-based measures used in An *et. al.* (2014) and Cremers and Weinbaum (2010). Panel B of Table 6 presents the results of our analysis using double-sorted portfolios. In row (1), we first sort stocks on differences in changes of implied volatilities of put and call options, *ΔPVOL-ΔCVOL*, as used in An *et. al.* (2014). Within each quintile of *ΔPVOL-ΔCVOL*, we then form *value-of-vote* quintile portfolios. The returns of each *value-of-vote* portfolio are then averaged over the five *ΔPVOL-ΔCVOL* portfolios. Thus, they represent *value-of-vote* quintile portfolios after controlling for *ΔPVOL-ΔCVOL*. The alpha difference between quintile 5 and quintile 1 of *value-of-vote* is -0.70% with a *t*-statistics of -5.29. In row (2), we first sort stocks based on the differences between call and put implied volatilities, *CVOL-PVOL*, as used in Cremers and Weinbaum (2010). Within each quintile of *CVOL-PVOL*, we then form *value-of-vote* quintile portfolios. The five *value-of-vote* portfolios are then averaged over the five *CVOL-PVOL* portfolios. Therefore, they represent *value-of-vote* quintile portfolios after controlling for *CVOL-PVOL*. The average alpha difference between quintile 5 and quintile 1 of *value-of-vote* is -0.41% with a *t*-statistics of -3.26. Although the magnitude of *value-of-vote* return spread is smaller after controlling for volatility spread, it is still economically large and statistically significant. It is important to note that theoretically, a divergence in put and call implied volatilities could be driven by the value of voting rights. This is because one could capture voting rights without having any economic exposure to changes in stock prices by buying the common stocks and selling short the synthetic stocks (synthesized using option put-call parity). Selling short the synthetic stock, however, implies that one should buy the put and sell short the call options of the same underlying stock. The ensuing buying and selling pressures in the opposite directions could lead to the divergences of put and call implied volatilities. Thus, the above robustness checks could potentially limit our ability in capturing the return predictability of *value-of-vote*, which makes it more difficult to obtain the results. Despite this conservative approach, our empirical results hold with strong statistical significances.[27]

[27] As per An *et al.* (2014), we triple sort stocks first by *ΔPVOL,* then by *ΔCVOL* and then *value of vote*. To the extent that the results are not confined to extreme portfolios where *ΔPVOL* and *ΔCVOL* are different, our results are robust. We repeat the same exercise by first sorting stocks based on *ΔCVOL,* then *ΔPVOL* and *value of vote*. The related results are reported in Online Appendix Table A4. We also repeat the triple sort exercise using simple put and call implied volatilities. We first sort and *PVOL* and then *CVOL* and lastly *value of vote*. Also, we repeat the same thing by first sorting on *CVOL, PVOL* and *value of vote*. The results are reported in Online Appendix Table A5.

Third, even if the option market is more attractive to informed traders, option volumes (if not option prices) will convey their private information to other investors. This will lead the stock market to (perhaps partially) incorporate the informed traders' private information into prices with a delay. This suggests that the return predictability of option-based measures of An *et. al.* (2014) and Cremers and Weinbaum (2010) should largely decline if we allow for a gap between portfolio formations and return estimations. The results of replicating the analysis of An *et. al.* (2014) and Cremers and Weinbaum (2010), along with how their results change if we skip one month after portfolio formation, are presented in Panel C of Table 6.[28] In each section of Panel C of Table 6, the first row reports the baseline results (1/0/1) where there is no gap between portfolio formation and return estimation period, and the second row reports the results of skipping one month between portfolio formation and return estimation period (1/1/1). We indeed find that if we skip one month between portfolio formation (at time *t)* and observing monthly stock returns (return from *t+1* to *t+2*), the average return spread for portfolios sorted based on ΔPVOL – ΔCVOL and CVOL-PVOL will become economically smaller and statistically insignificant. In contrast, the average alpha difference between quintile 5 and 1 of *value-of-vote* portfolios, even if we skip one month after portfolio formation, still stays economically large and statistically significant at -0.61% with a *t*-statistics of -4.11.

Fourth, the findings of An *et. al.* (2014) and Cremers and Weinbaum (2010) are by definition mainly driven by stocks in which implied volatility of put and call diverge the most. Hence, if our results are robust to excluding stocks for which implied volatility of put and call options exhibit a large divergence, it would suggest that our measure of the value of voting rights indeed contains information above and beyond what is captured by the measures used in the above-mentioned two studies. We use the ratio of put to call option implied volatility, *implied volatility ratio*, to proxy for the divergence of implied volatility of put and call options, and repeat our analysis for a subsample of stocks in which *implied volatility ratio* is between 10^{th} and 90^{th} percentile of its

[28] These results are also robust to forming decile portfolios as in An *et al.* (2014). The results are in Online Appendix Table A6.

empirical distribution. This corresponds to *implied volatility ratios* between 0.91 and 1.16. Panel D of Table 6 presents the monthly estimated FF5 alphas for the quantile portfolios as well as the alpha difference between quintile 5 and 1 for the filtered sample. The monthly alpha difference between quintile 5 and quintile 1 is -0.71% with a t-statistics of -5.28, which is similar to those reported in Table 3 using the full sample, both in magnitude and statistical significance. In addition, our results are robust to the choice of the threshold used to exclude stocks with extreme divergences between implied volatility of put and call options. Repeating the same analysis, using 0.95 and 1.05 as thresholds for *implied volatility ratio,* yields similar results and is reported in the second row of Panel D of Table 6. This suggests that our results are not purely driven by stocks with extreme divergence between implied volatility of put and call options.[29]

Moreover, the literature provides some evidence against the notion that informed investors prefer the option market to trade on their private information. Muravyev, Pearson, and Broussard (2013) conclude that no economically significant price discovery occurs in the option market. Muravyev *et. al.* (2013) also argue that many of the market participants who are most likely to have valuable private information, such as hedge funds, have access to leverage anyway and do not need the synthetic leverage available in the option market. More recently, Collin-Dufresne, Fos and Muravyev (2017) study a large sample of trades from Schedule 13D filings by activist investors, who supposedly have valuable private information about the firm, and find that activists choose to trade in the stock instead of the option market in 98% of cases. They conclude that option market may not be that attractive for this class of informed traders after all. Taken together, our analyses in Table 6 suggest that the value of voting rights contains information about future stock returns that are distinct from previously documented anomalies related to informed trading.[30]

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[29] The return difference using the filtered *implied volatility ratio* for high and low value of vote portfolios are robust to adding additional anomaly factors as in Table 4. The results using two ratios with additional anomaly factors are presented in Online Appendix Tables A7 and A8.

[30] In untabulated analysis, we also examine whether the predictability of *value-of-vote* is stronger for stocks largely held by institutional investors who are more sophisticated and informed than retail investors. We find return

4.5. Fama-MacBeth Cross-Sectional Regressions with *Value-of-vote*

To further examine the relation between *value-of-vote* and average stock returns, we conduct Fama–MacBeth (FM) cross-sectional regressions of monthly stock returns on *value-of-vote* and other firm characteristics. Specifically, we run the following cross-sectional regression:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} \cdot value\ of\ vote\ + \gamma_{2,t} X_{i,t} + \varepsilon_{i,t+1,}$$

where $R_{i,t+1}$ is the realized return on stock *i* in time *t+1* and $X_{i,t}$ is a vector of control variables for stock *i* at time *t* and includes an extensive list of firm characteristics, common risk loadings, measures of option and stock market liquidity, and other option-related variables that have been shown in the literature to have cross-sectional predictability for stock returns, including changes in implied volatility and volatility spread which are used in An *et. al.* (2014) and Cremers and Weinbaum (2010), respectively. We estimate the above regression across stocks at any given time *t* and report the cross-sectional coefficients averaged across all time periods *t*. In order to correct for potential autocorrelation and heteroscedasticity in the cross-sectional coefficients, we compute Newey-West (1987) *t*-statistics on the time series of slope coefficients using standard errors computed with six lags. Table 7 presents the results of our Fama-MacBeth regressions.

[~ Insert Table 7 here ~]

In Column (1) of Table 7 we find that after controlling for firm characteristics such as size, book-to-market and leverage, and common risk loadings, *value-of-vote* has a highly significant predictive power in explaining future stock returns. The average cross-sectional regression coefficient on *value-of-vote* is -0.80, and is highly significant with a *t*-statistic of -4.82. In Column (2) of Table 7 we add asset growth, idiosyncratic volatility, analysts' forecasts dispersion, and illiquidity to the control variables, and find the average regression coefficient on *value-of-vote* becomes even larger (in absolute value) and is -0.998 and still strongly significant with a *t*-statistic

predictability of *value-of-vote* to be economically large and statistically significant in both subsamples of firms with high and low institutional ownership.

of -6.67. In Column (3) we additionally control for option and stock market liquidity measures, ratio of call to put option volume and open interest, and skewness attributes of options, namely coskewness (COSKEW) and the risk-neutral skewness (QSKEW). The average cross-sectional regression coefficient on *value-of-vote* in specifications (3) is -1.007 with *t*-statistics of -6.19. In Columns (4) and (5) we control for measures of news arrival in the option market introduced in An *et. al.* (2014) – changes in implied volatility of put and call options. In Column (4) we control for changes in implied volatility of put and call separately (ΔPVOL and ΔCVOL), while in Column (5) we control for the difference of the two (ΔPVOL-ΔCVOL). The average cross-sectional regression coefficient on *value-of-vote* in specifications (4) and (5) are -0.973 and -0.995, respectively, and both are highly significant with *t*-statistics of -6.00 and -6.09. In Column (6), instead of changes in implied volatility of put and call options, we control for volatility spread (CVOL-PVOL) which is documented by Cremers and Weinbaum (2010) to have cross-sectional return predictability. The average cross-sectional regression coefficient on *value-of-vote* is still economically large and statistically significant with a coefficient of -0.724 and a *t*-statistics of -4.48. In regression (7), we control for all of the above-mentioned characteristics. The average cross-sectional regression coefficient on *value-of-vote* is still highly significant with a coefficient of -0.742 and a *t*-statistics of -4.56.

To gauge the economic magnitude of the average slope coefficient on *value-of-vote* in Table 7, we focus on Column (7) of Table 7. Given the difference between average *value-of-vote* in the first and fifth quintile portfolios is 1.128% (reported in Table 1), if a firm were to move from the first quintile to fifth quintile of *value-of-vote,* the expected return would decrease by $-0.7416 \times 1.128\% = -0.836\%$. Given the extensive list of control variables used in our Fama-MacBeth estimation, the large economic magnitude of *value-of-vote*' cross-sectional predictability suggests that *value-of-vote* is a strong predictor of stock return.

Our results in table 7 further confirm that the effect of *value-of-vote* on the cross-section of stock returns is robust to controlling for various firm characteristics and risk factor loadings. This suggests that the *value-of-vote* effect we identify is not being driven by correlations with other determinants of expected returns, and contains independent information about the cross section of stock returns.

4.6. Dual-Class Stocks

In this section, we repeat our analysis for a subsample of firms with dual-class structure using an alternative measure of the value of voting rights. The price difference between multiple classes of stocks with different voting rights has been used in the literature as a measure of the value of voting rights and/or private benefits of control (see, *e.g.,* Lease, McConnell, and Mikkelson (1984), Zingales (1995), Nenova (2003), and Masulis, Wang and Xie (2007)). The limitation of this methodology is that the number of dual-class firms in which both classes of stocks are publicly traded in the market are limited. Another limitation of this methodology is that different classes of stocks might be different across other dimensions such as dividend rights and market liquidity (DeAngelo and DeAngelo (1985), Smart and Zutter (2003) and Kalay, Karakaş, and Pant (2014)). With these caveats in mind, at times when the uncertainty about the outcome of a future control event is high (proxied by a high value of voting rights) we expect investors to be willing to pay higher prices to accumulate superior voting shares to increase their chances of winning the control contest, which leads to lower future expected returns. Note that *voting premium* is conceptually similar to our option-based methodology, since in constructing *value-of-vote* we are essentially synthesizing an inferior voting class of share with no voting rights using options. Hence common stocks in firms with a single class of stocks are similar to the superior class of shares in dual class firms.

To construct our sample of dual-class firms, we start with a sample from Gompers, Ishi and Metrick (2009) which spans from 1992 to 2002. To expand this sample, we identify dual class firm using various data sources such as GMI and ISS before hand-collecting data on the relative voting power of different classes of stocks by reading firms' proxy statements. Because we require both classes of stocks to be publicly traded, we end up with 115 firms over the period 1994-2015. As described in section 3.2, following Zingales (1995), we measure *voting premium* in dual-class firms by taking the price difference between the superior and inferior voting stocks normalized by their respective voting rights.

We calculate *voting premium* each month using the end of month stock price, sort quintile portfolios based on *voting premium* and observe next month's return for superior voting class shares. The results of our analysis of dual-class firms are reported in Table 8. In Panel A of Table 8, we report average and median voting premium for each of the *voting premium* portfolios. Consistent with our earlier result, the lowest *voting premium* portfolio (VP1) takes negative values.

[~ Insert Table 8 here ~]

In Panel B of Table 8, we report equal-weighted, value-weighted and characteristics-adjusted returns for voting premium portfolios. Consistent with our prediction for superior voting shares, high *voting premium* stocks have lower future returns. The equal-weighted return difference between high and low *voting premium* portfolios (VP5-VP1) for superior voting shares is -1.28% per month with a t-statistics of -3.36. This is consistent with our findings in Table 2 using the option-based measure of the value of voting rights for a larger sample of firms.[31] Examining value-weighted return difference between high and low *voting premium* portfolios or adjusting stock returns for size, book-to-market and momentum following Daniel et. al. (1997) yields similar results. Overall, these findings confirm that regardless of the methodology used to measure vote value, the value of voting rights contains valuable information about future stock returns.[32]

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[31] Our findings using the dual-class subsample of firms are broadly consistent with Karakas (2009) which studies the time variation of relative prices of dual-class shares.

[32] Since holders of inferior voting shares are less likely to be influential in determining the outcome of a control contest, investors would be willing to purchase the inferior voting class only at a discounted price, which leads to higher future expected returns for this class of stocks. Consistently, for inferior voting class shares, we find that high voting premium stocks have higher future returns. The equal-weighted return difference between high and low voting premium portfolios (VP5-VP1) is 1.75% per month with a t-statistics of 4.31 (untabulated).

4.7. Long-Term Operating Performance and *Value-of-vote*

Why are (some) investors willing to pay higher prices at times when control becomes more important? There must be benefits that they receive only by having control; or more commonly known as private benefits of control. As Grossman and Hart (1988) argue, if there is competition for acquiring control, the competing investors would be willing to bid up the stock up to the minimum of what they value private benefits of control at. These private benefits include the ability to run the firm more efficiently compared to other control contestants. In addition, voting rights are especially valuable if investors feel the need to wield disciplinary pressure to improve managerial inefficiencies (see for example Manne (1964), Easterbrook and Fischel (1983), Cox and Roden (2002)). Therefore, the value of voting rights is higher in firms with more room for improving managerial inefficiencies. If investors are on average paying a higher price to capture voting rights to improve managerial inefficiencies, in the long run we should observe improved operating performance in firms with higher *value-of-vote*. On the other hand, if investors are paying higher prices to enjoy private benefits of control, we would expect the opposite. In Table 9, we report the results of analyzing measures of operating performance for *value-of-vote* portfolios for up to three years after portfolio formation. Panels A and B of Table 9 show that firms in the highest *value-of-vote* quintile, compared to those in the lowest *value-of-vote* quintile, significantly improve their operating performance and profitability, respectively. [33] The improvements in operating performance and profitability are statistically significant only in two-year or longer horizons. These findings suggest that firms with high *value-of-vote* on average experience improvement in firm operating performance.

[~ Insert Table 9 here ~]

[33] We adjust both ROA and profitability (EBITDA/AT) by industry to take out any industry-wide fixed effects. We use 3-digit SIC code for industry classifications. In Online Appendix Table A9, we provide the results of a similar analysis using Fama-French 48 industry classifications.

5. Additional Robustness Analyses

5.1. Controlling for Various Characteristics Using Double Sorts

Existing literature has documented several characteristics associated with cross-sectional differences in average stock returns. To examine whether *value-of-vote* simply captures those characteristics, we use the conventional double-sorting analysis to control for various characteristics known to affect stock return. We perform a sequential sort, by sorting first based on a given characteristic into five quintiles. Within each characteristic quintile, we further sort stocks into five quintile portfolios based on *value-of-vote*. The five *value-of-vote* portfolios are then averaged over the five characteristic portfolios. Therefore, they represent *value-of-vote* quintile portfolios controlling for the characteristic of interest. Using this approach, we can examine expected return differences between quintile 5 and 1 of *value-of-vote* after controlling for other characteristics that could affect stock returns. Table 10 reports the results of double-sorting analysis.

[~ insert Table 10 here ~]

In row (1) of Table 10, we control for size by double-sorting based on market capitalization and *value-of-vote*. The FF5 alpha difference between quintile 5 and 1 of *value-of-vote,* after controlling for market capitalization, is -0.61% with a *t*-statistic of -4.85. In row (2) of Table 10, we control for book-to-market (BTM) and still find a sizable and statistically significant alpha difference between quintile 5 and 1 *value-of-vote* (alpha difference is -0.73% with a *t*-statistic of -5.42). Row (3) of Table 10 shows that after controlling for momentum, the alpha difference between high and low (quintile 5 and quintile 1) portfolios is -0.72% with a t-statistics of -6.26. Liquidity is also an important characteristic that affects stock returns. Highly illiquid stocks, on average, have higher stock returns (Amihud (2002)). To examine whether liquidity of a stock affects predictability of our measure of the value of voting rights, we control for liquidity using Amihud (2002)'s illiquidity measure. Row (4) of Table 10 controls for illiquidity, the alpha difference between quintile 5 and 1 of *value-of-vote* is -0.61% with a *t*-statistics of -4.46, which is still economically large and statistically significant. Additionally, Ang, Hodrick, Xing and Zhang (2006) document that stocks with high idiosyncratic volatility have extremely low average returns. In order to control for the effect of idiosyncratic volatilities on stock returns, we use double sorts based on idiosyncratic volatility and *value-of-vote.* Row (5) of Table 10 shows that the alpha difference between quintile 5 and 1 of *value-of-vote*, after controlling for idiosyncratic volatility, is -0.66% with a *t*-statistics of -5.61 which suggests that *value-of-vote* return spread is distinct from idiosyncratic volatility.

As shown in the summary statistics of our sample in Panel B of Table 2, firms in quintile 5 of *value-of-vote* tend to have a high level of dispersion among analysts' earnings forecasts. Because Diether, Malloy, and Scherbina (2002) find that stocks with high dispersion in analysts' earnings forecasts have low stock returns, we want to make sure that *value-of-vote* is not isomorphic to analysts' forecasts dispersion. Row (6) of Table 10 shows that our results are not sensitive to controlling for analysts' forecasts dispersion. The alpha difference between quintile 5 and 1 of *value-of-vote*, after controlling for analysts' forecasts dispersion, is -0.74% with a *t*-statistics of -5.44. Related, Livnat and Mendenhall (2006) document that earnings surprises affect stock returns in the same directions as the earning surprise and lasts for several weeks. There is also empirical evidence that value of vote is negatively related to earnings surprises (Gurun and Karakaş 2016). If firms with high *value-of-vote* are more likely to have negative earnings surprises and thus have lower stock returns, the effect we document using *value-of-vote* might be really capturing the effect of earnings surprises. In row (7) of Table 10, we control for earnings surprises. We define surprise in earnings (SUE) by the difference of the median analysts' earnings forecasts and the actual earnings normalized by the stock price. The results show that our findings are robust to controlling for earnings surprises. The alpha difference between quintile 5 and 1 of *value-of-vote*, after controlling for earnings surprises, is -0.73% with a *t*-statistics of -5.43.

It has also been documented that stocks with high returns in the most recent month tend to have low average returns in the next month, which is referred to as short-term reversal Jegadeesh (1990)). In row (8) of Table 10, we control for the short-term reversal effect and find that the alpha difference between quintile 5 and 1 of *value-of-vote* is -0.75% per month with a *t*-statistics of -5.92. This suggests that our results are very much robust to controlling for short term reversal.

In rows (9) to (12) of Table 10 we control for additional measures of stock and option liquidity. In row (9) of Table 10 we control for stocks' bid-ask spread. We calculate bid-ask spread as the monthly average of daily bid-ask spreads for the most recent month. The results show that the alpha difference between quintile 5 and 1 of *value-of-vote* is -0.73% with a *t*-statistics of -5.42. In row (10) of Table 10 we control for another stock liquidity measure: the stocks dollar volume. Gervais, Kaniel and Mingelgrin (2001) find that stocks with high trading volume tend to have higher returns. We find that the alpha difference between quintile 5 and 1 of *value-of-vote*, after controlling for stocks dollar volume, is -0.63% with a *t*-statistics of -4.52. Moreover, in row (11) and (12) of Table 10 we control for option volume and open interest, respectively. The results show that our findings are very robust to controlling for these option liquidity measures. The alpha difference between quintiles 5 and 1 of *value-of-vote*, after controlling for option volume (open interest), is -0.82% (-0.75%) with a *t*-statistics of -5.48 (-5.28).[34]

Lastly, we control for short-sale constraint. Asquith, Pathak, and Ritter (2005) use short interest ratio to capture the demand for short-sale in the market. Short interest ratio is defined as the short interest divided by the total shares outstanding. The alpha difference between high and low *value-of-vote* portfolios, after controlling for short-interest, is reported in row (13) in Table 10. The alpha difference is -0.75% with a t-statistics of -5.56. This suggests that our results are not driven by short-sale constraints in the market.[35]

[34] We also present double sorting results using FF3 and FF4 model in Online Appendix Table A10.

[35] As an additional way to control for short-sale constraints, in untabulated analysis we use regulation SHO which introduced a shock to short-sale constraints as a quasi-natural experiment. As part of regulation SHO a random sample of US firms were selected for the pilot program in which short-selling constraints were relaxed. The pilot program was announced on July 28th 2004, implemented on May 2nd 2005 and ended on August 6th 2007. We defined treated group as firms that were randomly selected for the pilot program and control group as those that were not part of the pilot program among Russell 3000 firms. If our results were mainly driven by short-sale constraints, we expect *value-of-vote* return spread to decrease for the treaded group but not for the control group. Our difference-in-difference estimation did not show any significant difference between changes in the treated group versus those in the control

5.2. Different Formation Periods

In order to check whether our findings are robust to alternative portfolio formation periods, and in the spirit of Jegadeesh and Titman (1993) and Ang *et al.* (2006), we use L/M/N portfolio formation methodology. In a given L/M/N portfolio formation method, we use the average of the monthly medians of *value-of-vote* from previous L months to form *value-of-vote* quintile portfolios; we skip M months and then we calculate return over the next N months. The portfolio formation method used in our main analyses and described in section 4.1 can be shown as 1/0/1. Note that we do not leave a gap between portfolio formations and return estimation periods in our main analyses. While we examine longer holding periods in Table 5 (*e.g.* 1/0/1, 1/0/2, etc), in this section we vary L and M to see whether *value-of-vote* return spread is robust to alternative methods of portfolio formation. Table 11 presents the results of this analysis. Using 1/1/1 strategy, the FF5 alpha difference between high and low *value-of-vote* quintile portfolios is -0.61% per month with a t-statistics of -4.11. If we increase the gap between portfolio formation and return estimation period to two months (1/2/1 strategy), the FF5 alpha difference between high and low *value-of-vote* quintile portfolios remains statistically significant and economically large at -0.50% per month with a t-statistics of -3.36.

[~ insert Table 11 here ~]

When we use the average of the monthly medians of *value-of-vote* over the previous six months to form *value-of-vote* quintile portfolios and calculate return over the next months without a gap in between (6/0/1), we still find a significant *value-of-vote* return spread. The FF5 alpha difference in this case is -0.71% with a t-statistics of -4.87. If we skip one month between portfolio formation and return estimation period (6/1/1), we find the FF5 alpha difference to be -0.57% with

group. However, the *value-of-vote* return spread is not significant both before and after the experiment for both the treatment and control group which is likely due to the small sample size.

a t-statistics of -3.75. Using the previous 12 month to form *value-of-vote* quintile portfolios yields similar results.[36]

5.3. Using Different Subsample Periods

In order to examine whether the predictability of *value-of-vote* has changed over time, we checked whether our analysis for different sample periods. We first split our sample into two subsample periods - January 1996 to December 2006 and January 2007 to September 2015. Table 12 Panel A shows that the FF5 alpha difference between high and low *value-of-vote* quintile portfolios are economically large and highly significant in both the earlier and the later subsample periods. This contrasts with Cremers and Weinbaum (2010) who find that the degree of predictability of volatility spread (CVOL-PVOL) declined over time in their sample. Panel B of Table 12 shows that the *value-of-vote* return spread was economically large and statistically significant even during the financial crisis period of 2007-2009. [37]

[~ insert Table 12 here ~]

5.4. Other Robustness Checks

To the extent that shareholders do not incur any costs due to having voting rights, the option to vote should have a non-negative value. To mitigate potential concerns about the presence of negative values of *value-of-vote*, we repeat our analysis by replacing negative *value-of-vote* values with zero and also by excluding observations with negative *value-of-vote* (as reported in the Online Appendix Table A1). We find that our results are robust to these adjustments to our sample. As an additional robustness check, we exclude stocks with price of less than $5 and find our results are robust to this adjustment to our sample as well (Online Appendix Table A13).

[36] We present the results of a similar analysis using FF3 and FF4 models in Online Appendix Table A11.
[37] We repeat this analysis by splitting the sample into earlier and later halves excluding the financial crisis period (2007-2009). The results are robust to this choice and presented in Online Appendix Table A12.

6. Conclusion

In this paper, we show that the values of corporate voting rights significantly predict future stock returns. Stocks with high values of votes earn lower risk-adjusted returns than those with low vote values by more than 10 percent per year. Numerous robustness checks reveal that the models of informed trading and existing factors known to affect stock prices cannot explain our results. Further, we find the cross-sectional predictability persists over longer horizons suggesting that our results are not driven by microstructure differences in the option and stock markets. Moreover, we find that firms with high vote values significantly improve their operating performance and profitability over longer horizons, compared to firms with lower vote values.

An important implication of our empirical findings is that the existing asset pricing models, which heavily rely on understanding cash flow processes, cannot fully explain asset prices in part due to ignoring the vote component of stock prices. In a perfect world absent of any market frictions or failures, with no agency problems and asymmetry of information, a cash flow process should be a sufficient statistic to define an asset, provided that a proper discount factor exists and is known to investors. Outside of a perfect world and in the presence of agency problems, control rights and in particular voting rights as resolution mechanism to settle disputes and disagreements among investors, are important in better understanding the sources of variation in asset prices.

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Figure 1. Time-series of the average corporate *Value-of-Votes*

The figure plots time-series of average corporate *Value-of-Votes* across firms. At the beginning of each month we sort stocks based on the median *Value-of-Votes* during the month and assign them into five quintile portfolios based on their relative rankings. Average of *Value-of-Votes* across firms in each portfolio is then calculated. Our sample starts in January, 1996 and ends in August, 2015. Rank 1 (dashed line) indicates the lowest *Value-of-Vote* portfolio and Rank 5 (solid line) indicates the highest *Value-of-Vote* portfolio.

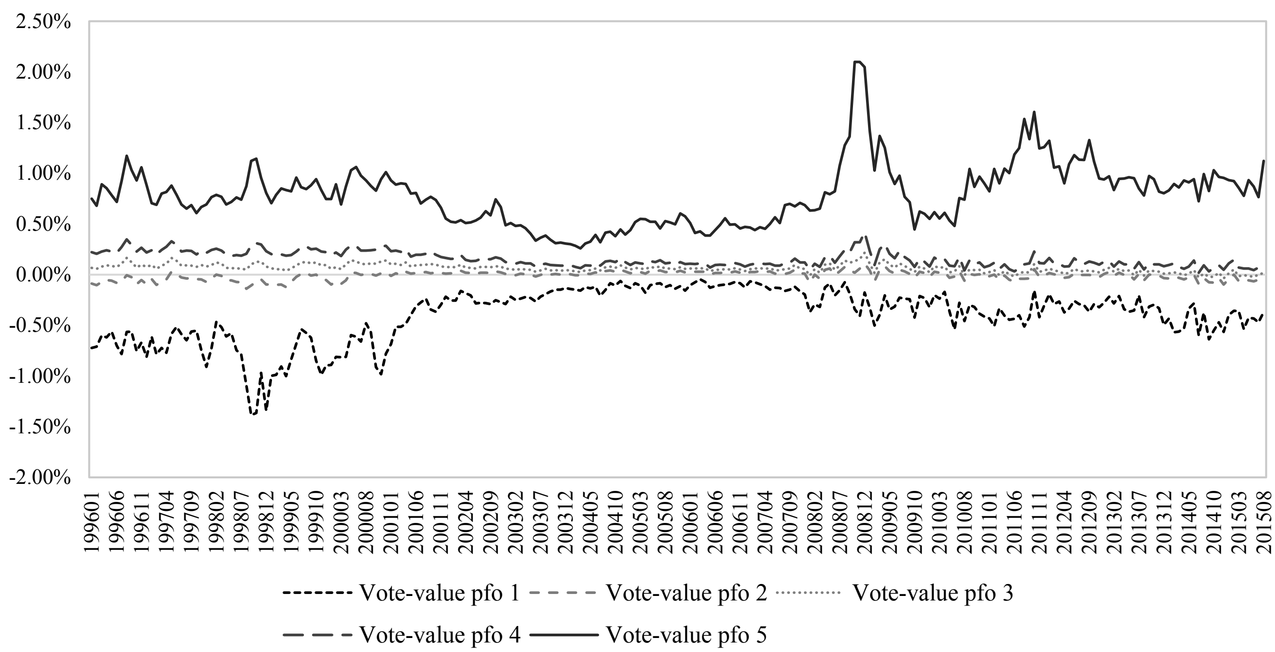

Table 1. Descriptive Statistics for *Value-of-Vote*

The table in panel A shows the average monthly *Value-of-Vote* for each year and the number of stocks per month for each year that are used in the sample. The *Value-of-Vote* is calculated from put-call parity condition explained in text. *Value-of-Vote* is the difference between observed stock price and the synthetic stock price derived from option prices standardized by its stock price. The samples covers CRSP universe that can be matched to OptionMetrics data. Panel B shows firm and ownership characteristics of portfolios sorted into quintiles by corporate *Value-of-Vote*. Size is the market capitalization measured as the stock price times the number of shares outstanding which is reported in millions of dollars. Book-to-Market (BTM) is the book value of equity over market capitalization; illiquidity (ILLIQ) is calculated using Amihud (2002)'s measure of stocks illiquidity as absolute stock return over dollar volume. Idiosyncratic volatility (IVOL) is calculated as in Ang, Hodrick, Xing and Zhang (2006), which is the monthly standard deviation of residuals from Fama-French three-factor model using the daily returns; analysts forecast dispersion (DISP) is calculated as in Diether et al. (2007), which is estimated as the standard deviation of analysts' earnings forecast divided by the absolute value of the average earnings forecasts; a firm's age is the years after the firm appeared in Compustat database, market beta is estimated using monthly returns over previous 36 to 60 months rolling window with minimum of 10 months, leverage is the total debt divided by the total asset, and prior 11-month return is the cumulative returns from month t-12 to t-2. Total institutional holding (IO_holding) is the percentage of shares held by institutional investors measured as of the recent quarter. The change in IO holding (Δ IO Holding) measures the change in institutional ownership compare to the last year's same calendar quarter. The change in the top5 institutional holdings (Δ Top5 IO Holding) is measured as the change in the top 5 institutional ownership compare to the last year's top 5 institutional ownership at the same quarter. Institutional ownership concentration (IO_HHI) is measured using Herfindahl Index based on the percentages of institutional holdings by all 13-F institutions. We also divide institutional type into three categories based on Bushee (1998)'s classification. "Dedicated" is the percentage of shares held by dedicated institutions, "Quasi-Index" is the percentage of shares held by quasi-index institution and "Transient" is the percentage of shares held by transient institutions. The managerial ownership (MGMT_own) is the shares owned by top executives available in Execucomp. G-index is the number of takeover provisions following Gompers, Ishii, and Metrick (2003). Control events is the percentage of firms in each *Value-of-vote* portfolios that experience any control events during t-1 and t+1 months of portfolio formation month t. The control events we consider are 1) a target of M&A, 2) subject to 13D-filings, 3) proxy contest, and 4) special meetings. Panel C and D report *Value-of-Vote* portfolio transition matrices. Panel C shows the probability of a firm moving from one *Value-of-Vote* quintile to another *Value-of-Vote* quintile next month. Panel D shows the probability of switching *Value-of-Vote* quintiles after three months. The sample period is from January, 1996 to August, 2015. For ownership characteristics, we use sample period from January, 1995 to December, 2013.

Panel A. Time-series average of *Value-of-Vote* and number of stocks in our sample

Year	*Value-of-Vote*	Average Number of Stocks
1996	0.10%	1053
1997	0.08%	1311
1998	0.05%	1496
1999	0.05%	1562
2000	0.09%	1436
2001	0.14%	1335
2002	0.12%	1373
2003	0.07%	1358
2004	0.08%	1446
2005	0.12%	1568
2006	0.11%	1643
2007	0.12%	1766
2008	0.22%	1782
2009	0.21%	1754
2010	0.11%	1862
2011	0.16%	1891
2012	0.19%	1876
2013	0.15%	2067
2014	0.09%	2210
2015	0.10%	2164

Panel B. Firm characteristics of *Value-of-Vote* portfolio

	Value-of-Vote portfolio				
	1 (Low Vote)	2	3	4	5 (High Vote)
Main characteristics					
Value-of-Vote	-0.388%	-0.010%	0.062%	0.150%	0.740%
Size ($ million)	$3,677.10	$11,792.13	$11,422.00	$4,701.85	$1,397.12
BTM	0.651	0.477	0.466	0.506	0.660
ILLIQ	0.035	0.008	0.007	0.012	0.044
IVOL	0.025	0.019	0.019	0.021	0.026
DISP	1.885	1.236	0.849	1.565	2.426
Age	18.820	24.263	24.790	21.776	17.390
Market Beta	1.402	1.240	1.231	1.280	1.375
Leverage	0.182	0.201	0.208	0.202	0.190
Prior 11-month return	8.96%	21.27%	23.77%	23.22%	14.10%
Ownership characteristics					
IO Holding	0.633	0.707	0.712	0.697	0.608
Δ IO Holding	0.008	0.015	0.020	0.030	0.030
Δ Top 5 IO Holding	0.004	0.004	0.005	0.008	0.012
IO_HHI	0.073	0.052	0.051	0.058	0.082
Dedicated	0.077	0.073	0.075	0.081	0.088
Quasi-Index	0.389	0.442	0.446	0.429	0.361
Transient	0.172	0.186	0.187	0.189	0.170
Insider Own.	0.040	0.031	0.030	0.036	0.046
G-Index	6.137	6.065	6.072	6.146	6.133
Control Events	0.047	0.031	0.031	0.038	0.061

Panel C. Transition matrix of *Value-of-Vote* portfolio after one month

		Value-of-Vote Portfolio at *t+1*				
		1 (Low)	2	3	4	5 (High)
Value-of-Vote portfolio *t*	1 (Low)	39.00%	17.69%	13.16%	14.74%	15.41%
	2	17.56%	31.72%	26.83%	17.24%	6.65%
	3	13.04%	27.08%	30.54%	21.51%	7.83%
	4	14.25%	17.28%	22.17%	29.41%	16.89%
	5 (High)	14.87%	7.13%	8.24%	17.85%	51.92%

Panel D. Transition matrix of *Value-of-Vote* portfolio after three months

		Value-of-Vote Portfolio at *t+3*				
		1 (Low)	2	3	4	5 (High)
Value-of-Vote portfolio *t*	1 (Low)	31.82%	17.35%	14.41%	16.99%	19.43%
	2	17.02%	29.82%	26.66%	18.13%	8.37%
	3	13.95%	26.87%	29.13%	21.11%	8.95%
	4	16.41%	18.62%	22.15%	26.09%	16.74%
	5 (High)	18.87%	9.12%	9.49%	18.62%	43.89%

Table 2. *Value-of-Vote* portfolio returns

The table reports the mean portfolio returns and their alphas sorted by *Value-of-Vote*. Stocks are sorted into five groups based on the median *Value-of-Vote* calculated each month and the mean portfolio returns for the next month are reported. In Panel A, equal-weighted (EW) portfolio returns, value-weighted (VW) returns and characteristics matched benchmark-adjusted returns are reported. In Panel A, the last column reports the characteristics matched benchmark-adjusted *Value-of-Vote* portfolio returns following Daniel, Grinblatt, Titman and Wermers (DGTW, 1997). Each stocks are matched to a portfolio of firms that have approximately the same size, book-to-market and momentum characteristics. We use 125 portfolios formed from the intersection of 5 portfolio sorted on size, 5 portfolio sorted on book-to-market and 5 portfolio sorted on momentum. Benchmark-adjusted returns are computed as the monthly *Value-of-Vote* portfolio returns in excess of the benchmarked returns of the portfolio to which a stock belongs. In Panel C, stocks are sorted into five size groups and then into five additional groups based on *Value-of-Vote* during that month. In Panel D, stocks are sorted into five groups based on *Value-of-Vote* first, then additionally sort into five groups based on size. The time period considered is from February 1996 to September, 2015. The table reports average monthly portfolio return and t-statistics are in parentheses.

Panel A. Average and benchmark-adjusted returns for *Value-of-Vote* quintile portfolio

Value-of-Vote portfolio	EW	t-statistics	VW	t-statistics	Characteristics -adjusted	t-statistics
1(Low)	1.32%	(2.76)	1.05%	(2.84)	0.40%	(3.86)
2	1.10%	(2.91)	0.87%	(2.78)	0.26%	(3.59)
3	0.95%	(2.57)	0.82%	(2.76)	0.11%	(1.69)
4	0.91%	(2.28)	0.79%	(2.41)	0.01%	(0.12)
5 (High)	0.62%	(1.34)	0.65%	(1.72)	-0.25%	(-3.29)
V5-V1 (Vote_HML)	-0.70%	(-4.97)	-0.41%	(-1.81)	-0.66%	(-5.39)

Panel B. Mean returns (EW) for double sort on size and then *Value-of-Vote* portfolio

Value-of-Vote\ Size	1 (Small)	2	3	4	5 (Large)	Mean
1 (Low)	1.41%	1.39%	1.32%	1.09%	1.02%	1.25%
2	1.31%	1.367%	1.10%	1.16%	1.04%	1.20%
3	1.16%	1.06%	0.967%	0.83%	0.80%	0.96%
4	1.12%	1.14%	0.98%	0.97%	0.84%	1.01%
5 (High)	0.44%	0.52%	0.71%	0.70%	0.81%	0.64%
V5 - V1	-0.97%	-0.87%	-0.61%	-0.38%	-0.21%	-0.61%
(Vote_HML)	(-3.07)	(-4.45)	(-3.42)	(-2.22)	(-1.32)	(-4.91)

Panel C. Mean returns (EW) for double sort on *Value-of-Vote* and then size portfolio

Size\ *Value-of-Vote*	1 (Low)	2	3	4	5 (High)	Mean
1 (Small)	1.44%	1.25%	1.27%	0.945%	0.70%	1.12%
2	1.34%	1.35%	0.88%	0.95%	0.36%	0.98%
3	1.35%	0.96%	0.89%	0.98%	0.63%	0.96%
4	1.29%	1.06%	0.91%	0.86%	0.70%	0.96%
5 (Big)	1.18%	0.88%	0.81%	0.85%	0.69%	0.88%
S1 - S5	0.26%	0.37%	0.47%	0.09%	0.01%	0.24%
(SMB)	(0.56)	(1.04)	(1.50)	(0.28)	(0.03)	(0.71)

Table 3. Time-series tests for *Value-of-Vote* quintile portfolios

This table reports estimates of Fama-French three-, four- and five-factor alphas, for monthly excess returns on the equal-weighted *Value-of-Vote* quintiles. The dependent variable is the monthly *Value-of-Vote* equal-weighted portfolio returns in excess of the one-month Treasury bill rate. Panel A reports alphas and its factor loadings using the Fama-French three factor model (FF3), which includes the market excess returns (MKTRF), the size factor (SMB) and the book-to-market factor (HML). Panel B reports alphas and its factor loadings using Fama-French four-factor model (FF4), which is the FF3 model (MKTRF, SMB, HML) plus a momentum factor (UMD), often called as Carhart (1997) model. Panel C reports alphas and its factor loadings using Fama-French five-factor (FF5) which is the FF3 factors plus a profitability factor (RMW) and an investment factor (CMA). The data on factor returns are obtained from Kenneth French website. The *Value-of-Vote* equal-weighted quintile portfolios are formed as in Table 2. The sample period is from February, 1996 to September, 2015. t-statistics are in parentheses.

Panel A. *Value-of-Vote* quintiles and FF3 model

Value-of-Vote		Factor sensitivity			
Portfolio	alpha (%)	MKTRF	SMB	HML	Adj.RSQ
1 (Low)	0.26%	1.29	0.67	0.09	86.05%
	(1.42)	(31.15)	(11.98)	(1.59)	
2	0.19%	1.12	0.45	0.07	94.74%
	(2.07)	(55.40)	(16.43)	(2.34)	
3	0.04%	1.12	0.41	0.10	96.00%
	(0.48)	(64.97)	(17.56)	(3.91)	
4	-0.07%	1.16	0.60	0.15	95.22%
	(-0.79)	(56.53)	(21.55)	(5.09)	
5 (High)	-0.51%	1.27	0.77	0.31	91.05%
	(-3.59)	(39.69)	(17.80)	(6.87)	
V5-V1	-0.77%	-0.02	0.10	0.22	9.46%
(Vote_HML)	(-5.60)	(-0.66)	(2.36)	(4.96)	

Panel B. *Value-of-Vote* quintiles and FF4 model

Value-of-Vote		Factor sensitivity				
Portfolio	alpha (%)	MKTRF	SMB	HML	UMD	Adj.RSQ
1 (Low)	0.50%	1.15	0.73	-0.01	-0.34	91.35%
	(3.41)	(33.03)	(16.40)	(-0.28)	(-11.80)	
2	0.25%	1.08	0.46	0.04	-0.09	95.31%
	(2.91)	(53.20)	(17.88)	(1.41)	(-5.33)	
3	0.090%	1.08	0.42	0.07	-0.08	96.46%
	(1.26)	(62.91)	(19.16)	(3.03)	(-5.52)	
4	0.02%	1.10	0.62	0.11	-0.14	96.40%
	(0.29)	(58.14)	(25.63)	(4.10)	(-8.68)	
5 (High)	-0.30%	1.15	0.82	0.22	-0.30	95.63%
	(-2.97)	(47.95)	(26.99)	(6.70)	(-15.41)	
V5-V1	-0.80%	-0.01	0.09	0.23	0.04	9.74%
(Vote_HML)	(-5.73)	(-0.17)	(2.20)	(5.12)	(1.30)	

Panel C. *Value-of-Vote* quintiles and FF5 model

Value-of-Vote		Factor sensitivity					
Portfolio	alpha (%)	MKTRF	SMB	HML	RMW	CMA	Adj.RSQ
1 (Low)	0.38%	1.23	0.69	0.18	-0.13	-0.33	86.77%
	(2.05)	(26.43)	(11.05)	(2.17)	(-1.44)	(-2.94)	
2	0.17%	1.12	0.50	0.03	0.08	-0.13	95.15%
	(1.89)	(50.08)	(16.80)	(0.69)	(1.79)	(-2.45)	
3	0.04%	1.11	0.45	0.07	0.05	-0.13	96.35%
	(0.48)	(58.79)	(17.84)	(2.07)	(1.41)	(-2.89)	
4	-0.04%	1.14	0.61	0.11	-0.04	-0.11	95.61%
	(-0.40)	(50.41)	(20.34)	(2.82)	(-0.85)	(-2.05)	
5 (High)	-0.40%	1.22	0.76	0.32	-0.16	-0.18	91.53%
	(-2.77)	(34.00)	(15.91)	(5.09)	(-2.25)	(-2.08)	
V5-V1	-0.78%	-0.01	0.08	0.14	-0.03	0.15	9.76%
(Vote_HML)	(-5.41)	(-0.25)	(1.57)	(2.26)	(-0.38)	(1.73)	

Table 4. Time-series tests for *Value-of-Vote* quintile portfolios with additional risk factors

This table reports estimates of the FF3, FF4 and FF5 model augmented by five additional anomaly factors for monthly excess returns on the *Value-of-Vote* quintiles. The dependent variable is the monthly equal-weighted *Value-of-Vote* portfolio returns in excess of the one-month Treasury bill rate. Each anomaly factors are constructed using the stock's anomaly rankings and by getting the high minus low portfolio returns. Panel A reports risk-adjusted returns for *Value-of-Vote* quintile portfolios, alpha, using the FF3 model (α_{FF3}) plus the following anomaly factors: idiosyncratic volatility factor ($\alpha_{FF3+IVOL}$), dispersion factor ($\alpha_{FF3+DISP}$), illiquidity factor ($\alpha_{FF3+ILLIQ}$), earnings surprise factor ($\alpha_{FF3+SUE}$), and lottery demand factor ($\alpha_{FF3+FMAX}$) which are reported in columns 1 through 5. respectively. Panel B reports the risk-adjusted returns, alpha, for *Value-of-Vote* quintile portfolios, using FF4 model (α_{FF4}) plus additional anomaly factors explained above. Panel C reports the risk-adjusted return for *Value-of-Vote* quintile portfolios, alpha, using FF5 model (α_{FF5}) plus additional anomaly factors explained above. The sample period is from February, 1996 to September, 2015. t-statistics are in parentheses.

Panel A. Risk-adjusted return using FF3 model plus additional anomaly factors

Vote portfolio	$\alpha_{FF3+IVOL}$	$\alpha_{FF3+DISP}$	$\alpha_{FF3+ILLIQ}$	$\alpha_{FF3+SUE}$	$\alpha_{FF3+FMAX}$
1 (Low)	0.43%	0.41%	0.27%	0.36%	0.21%
	(2.37)	(2.20)	(1.48)	(1.93)	(1.11)
2	0.19%	0.20%	0.18%	0.17%	0.15%
	(2.07)	(2.19)	(2.07)	(1.84)	(1.60)
3	0.05%	0.06%	0.04%	0.05%	0.02%
	(0.65)	(0.76)	(0.47)	(0.64)	(0.25)
4	-0.01%	-0.01%	-0.07%	-0.06%	-0.07%
	(-0.14)	(-0.10)	(-0.78)	(-0.64)	(-0.74)
5 (High)	-0.35%	-0.37%	-0.51%	-0.39%	-0.46%
	(-2.54)	(-2.63)	(-3.66)	(-2.76)	(-3.13)
V5-V1	-0.78%	-0.78%	-0.78%	-0.75%	-0.68%
(Vote_HML)	(-5.48)	(-5.46)	(-5.60)	(-5.29)	(-4.76)

Panel B. Risk-adjusted return using FF4 model plus additional anomaly factors

Vote portfolio	$\alpha_{FF4+IVOL}$	$\alpha_{FF4+DISP}$	$\alpha_{FF4+ILLIQ}$	$\alpha_{FF4+SUE}$	$\alpha_{FF4+ FMAX}$
1 (Low)	0.51%	0.50%	0.49%	0.44%	0.40%
	(3.40)	(3.32)	(3.38)	(2.98)	(2.65)
2	0.22%	0.23%	0.26%	0.19%	0.20%
	(2.50)	(2.62)	(3.05)	(2.31)	(2.26)
3	0.07%	0.08%	0.10%	0.07%	0.06%
	(0.98)	(1.10)	(1.36)	(0.94)	(0.83)
4	0.02%	0.03%	0.03%	-0.03%	0.00%
	(0.24)	(0.32)	(0.33)	(-0.32)	(0.02)
5 (High)	-0.28%	-0.29%	-0.300%	-0.32%	-0.30%
	(-2.74)	(-2.83)	(-3.02)	(-3.17)	(-2.91)
V5-V1	-0.79%	-0.79%	-0.80%	-0.76%	-0.70%
(Vote_HML)	(-5.55)	(-5.54)	(-5.71)	(-5.40)	(-4.92)

Panel C. Risk-adjusted returns using FF5 model plus additional anomaly factors

Vote portfolio	$\alpha_{FF5+IVOL}$	$\alpha_{FF5+DISP}$	$\alpha_{FF5+ILLIQ}$	$\alpha_{FF5+SUE}$	$\alpha_{FF5+ FMAX}$
1 (Low)	0.43%	0.41%	0.33%	0.45%	0.33%
	(2.38)	(2.22)	(1.80)	(2.40)	(1.77)
2	0.18%	0.18%	0.18%	0.16%	0.16%
	(2.01)	(2.00)	(2.02)	(1.80)	(1.81)
3	0.05%	0.04%	0.04%	0.05%	0.04%
	(0.59)	(0.60)	(0.59)	(0.65)	(0.48)
4	-0.02%	-0.02%	-0.03%	-0.03%	-0.04%
	(-0.18)	(-0.25)	(-0.39)	(-0.30)	(-0.43)
5 (High)	-0.35%	-0.37%	-0.43%	-0.31%	-0.39%
	(-2.59)	(-2.64)	(-3.07)	(-2.25)	(-2.70)
V5-V1	-0.79%	-0.78%	-0.76%	-0.76%	-0.72%
(Vote_HML)	(-5.44)	(-5.38)	(-5.29)	(-5.23)	(-5.06)

Table 5. Long-term Predictability

The table reports the *Value-of-Vote* sorted portfolio return difference by holding these portfolio for one to twelve months and rebalance them monthly. Each month, firms are sorted into quintile portfolio based on the *Value-of-Vote* during that month. The first row reports the one-month to twelve-month ahead average raw return difference between high *Value-of-Vote* portfolio (V5) and low *Value-of-Vote* portfolio (V1). The second row reports the one-month to twelve-month ahead FF3 alpha for *Value-of-Vote* portfolio (V5) and low *Value-of-Vote* portfolio (V1), the third row reports FF4 model alpha and the last row report FF5 alpha. *t*-statistics are in parentheses.

	1-month	2-month	3-month	4-month	5-month	6-month	7-month	8-month	9-month	10-month	11-month	12-month
Average return difference	-0.70%	-0.46%	-0.36%	-0.27%	-0.24%	-0.17%	-0.16%	-0.13%	-0.11%	-0.09%	-0.09%	-0.08%
	(-4.97)	(-3.72)	(-3.45)	(-2.85)	(-2.91)	(-2.23)	(-2.35)	(-2.00)	(-1.72)	(-1.62)	(-1.66)	(-1.54)
FF3 alpha	-0.77%	-0.56%	-0.45%	-0.35%	-0.32%	-0.25%	-0.23%	-0.20%	-0.18%	-0.16%	-0.15%	-0.15%
	(-5.60)	(-4.64)	(-4.55)	(-3.80)	(-4.05)	(-3.52)	(-3.74)	(-3.45)	(-3.12)	(-3.04)	(-3.05)	(-2.92)
FF4 alpha	-0.80%	-0.61%	-0.49%	-0.38%	-0.34%	-0.26%	-0.23%	-0.21%	-0.18%	-0.16%	-0.16%	-0.15%
	(-5.73)	(-5.04)	(-4.92)	(-4.09)	(-4.28)	(-3.66)	(-3.75)	(-3.46)	(-3.12)	(-2.99)	(-3.05)	(-2.88)
FF5 alpha	-0.78%	-0.58%	-0.45%	-0.34%	-0.31%	-0.24%	-0.22%	-0.20%	-0.16%	-0.14%	-0.14%	-0.13%
	(-5.41)	(-4.74)	(-4.43)	(-3.62)	(-3.83)	(-3.36)	(-3.50)	(-3.22)	(-2.79)	(-2.62)	(-2.63)	(-2.57)

Table 6. Is *Value-of-Vote* Return Spread Isomorphic to Informed Trading

The table reports results related to option trading and *Value-of-vote*. Panel A reports alphas using Fama-French five factor model (FF5 alpha) for *Value-of-vote* portfolio for different subsamples based on option market liquidity measures. The first option market liquidity measure is the option volume. The option volume is the monthly average of the sum of the daily call and put option volume. For each month, we divide the sample into above median and below median of option volume over the previous month and calculate FF5 alpha for *Value-of-vote* quintile portfolios. Second measure is option open interest. The open interest is calculated as the monthly average of the sum of daily call and put open interest. For each month, the sample is divided into above median and below median open interest over the previous month and observe FF5 alpha for *Value-of-vote* quintile portfolio. Third, we use put option bid ask spread. The put option bid/ask spread is the monthly average of the daily bid ask spread. For each month, we divide sample into above median and below median put option bid/ask spread over the previous month and calculate FF5 alpha for *Value-of-vote* quintile portfolios. Lastly, we use call option bid/ask spread. The call option bid/ask spread is the average of the call option daily bid/ask spread over the previous month. We divide sample into above and below median of call option bid/ask spread over the previous month and calculate FF5 alpha for *Value-of-vote* quintile portfolio. In Panel B, we report FF5 alphas after double sorting stocks using option implied volatilities measure documented by An et al. (2014) and Cremers and Weinbaum (2010). First we sort stocks into five quintiles on the (ΔPVOL-ΔCVOL), then within each quintile we sort stocks based on *Value-of-Vote*. The five *Value-of-Vote* portfolios are then averaged over each of the five ΔPVOL-ΔCVOL portfolios. Then each of *Value-of-Vote* portfolio would represents *Value-of-Vote* portfolios controlling for the ΔPVOL-ΔCVOL. With this average *Value-of-Vote* quintiles, we get alphas using Fama-French five-factor (FF5 alpha) model. The row (1) Control for (ΔPVOL-ΔCVOL) is the change in put and call implied volatility innovations as in An, Ang, Bali and Cikaci (2014). The last two columns reports FF5 alpha difference for high and low *Value-of-vote* quintile portfolio (V5-V1) and its t-statistics. The row (2) control for (CVOL-PVOL), we first sort stocks based on implied volatility spread (CVOL-PVOL) following Cremers and Weinbaum (2010). Then within each implied volatility spread, we further sort stocks based on *Value-of-vote*. The five *Value-of-Vote* portfolios are then averaged over each of the five CVOL-PVOL portfolios and get FF5 alpha for each of the five *Value-of-vote* portfolios. The last two columns report the difference in FF5 alpha for high and low *Value-of-vote* portfolio (V5-V1) and its t-statistics. In Panel C, we lag in observing returns to mitigate informed trading effects on stock returns. First two rows show FF5 alpha for five *Value-of-vote* portfolio for 1/0/1 strategy and 1/1/1 strategy. For 1/0/1 strategy (conventional strategy), we form quintile portfolio based on *Value-of-vote* for month t-1 and observe return at month t. For 1/1/1 strategy, we form quintile portfolio based *Value-of-vote* at month t-2, skip 1 month and observe return at month t. The last two columns report FF5 alpha difference for high and low *Value-of-vote* portfolios (V5-V1) and their t-statistics. For third and fourth rows, we form portfolios based on implied volatility innovation changes (ΔPVOL-ΔCVOL) following An et al. (2014) and report FF5 alpha for 1/0/1 and 1/1/1 strategy respectively. The last two columns report FF5 alpha difference for high and low (ΔPVOL-ΔCVOL) portfolios (A5-A1) and their t-statistics. For the last two rows in Panel C, we form portfolio based on implied volatility spread (CVOL-PVOL) and report FF5 alpha for five portfolios for 1/0/1 and 1/1/1 strategy. The last two columns report FF5 alpha difference for high and low CVOL-PVOL portfolios (C5-C1) and their t-statistics. Panel D report results for *Value-of-vote* portfolio FF5 alpha using filtered samples. We calculate *Value-of-Vote* quintile portfolios for a subsample of stocks in which ratio of put to call option implied volatility, *implied volatility ratio*, is between certain ranges. First range is the 10th and 90th percentile of its empirical distribution of *implied volatility ratio*, which corresponds to 0.91 and 1.16, respectively. The second range we use is *implied volatility ratio* between 0.95 and 1.05. With each subsample of stocks, we form *Value-of-vote* quintile portfolios and observe the FF5 alpha difference for high and low *Value-of-vote* (V5-V1) portfolios and its t-statistics are reported in the last two columns. The sample period considered is from February, 1996 to September, 2015. t-statistics are in parentheses.

Panel A. Option market liquidity and FF5 alpha for *Value-of-vote* portfolio

	Option Volume		Option Open Interest		Put option Bid/Ask spread		Call option Bid/Ask spread	
	Above	Below	Above	Below	Above	Below	Above	Below
Value-of-vote portfolio	FF5 alpha	FF5 alpha	FF5 alpha	FF5 alpha	FF5 alpha	FF5 alpha	FF5 alpha	FF5 alpha
1(Low)	0.33%	0.45%	0.32%	0.42%	0.37%	0.41%	0.28%	0.45%
	(1.77)	(2.07)	(1.54)	(2.02)	(2.17)	(1.74)	(2.25)	(1.64)
2	0.10%	0.26%	0.08%	0.29%	0.21%	0.12%	0.21%	0.19%
	(0.98)	(2.18)	(0.75)	(2.71)	(2.17)	(1.02)	(2.21)	(1.29)
3	0.05%	-0.02%	-0.01%	0.05%	0.06%	0.00%	0.10%	-0.06%
	(0.52)	(-0.17)	(-0.10)	(0.46)	(0.57)	(-0.02)	(1.06)	(-0.51)
4	0.06%	-0.13%	0.03%	-0.10%	-0.05%	-0.03%	-0.02%	-0.07%
	(0.57)	(-1.05)	(0.27)	(-0.94)	(-0.48)	(-0.25)	(-0.21)	(-0.45)
5(High)	-0.54%	-0.24%	-0.60%	-0.16%	-0.31%	-0.47%	-0.33%	-0.44%
	(-3.31)	(-1.47)	(-3.45)	(-1.08)	(-2.11)	(-2.53)	(-2.69)	(-1.96)
V5-V1	-0.87%	-0.70%	-0.91%	-0.58%	-0.68%	-0.89%	-0.61%	-0.88%
(Vote_HML)	(-4.60)	(-4.50)	(-4.75)	(-3.65)	(-4.32)	(-4.57)	(-4.22)	(-4.65)

Panel B. FF5 alpha for double-sort portfolios on factors related to informed trading and *Value-of-vote* portfolios

	Value-of-vote portfolio Rankings						
	1 (Low)	2	3	4	5 (High)	V5-V1	t-statistics
(1) Control for ΔPVOL-ΔCVOL	0.32%	0.17%	0.06%	-0.01%	-0.38%	-0.70%	(-5.29)
(2) Control for CVOL-PVOL	0.22%	0.15%	0.07%	-0.07%	-0.19%	-0.41%	(-3.26)

Panel C. FF5 alphas for portfolios formed based on factors related to informed trading and different portfolio formation periods

	Value-of-vote portfolio						
Strategies	1 (Low)	2	3	4	5 (High)	V5-V1	t-statistics
1/0/1	0.38%	0.17%	0.04%	-0.04%	-0.40%	-0.78%	(-5.41)
1/1/1	0.35%	0.09%	0.04%	0.05%	-0.27%	-0.61%	(-4.11)

	(ΔPVOL - ΔCVOL) portfolio						
Strategies	1	2	3	4	5	A5-A1	t-statistics
1/0/1	0.72%	0.33%	0.26%	0.06%	-0.21%	-0.94%	(-7.08)
1/1/1	0.17%	0.30%	0.32%	0.25%	0.18%	0.01%	(0.12)

	(CVOL-PVOL) portfolio						
Strategies	1	2	3	4	5	C5-C1	t-statistics
1/0/1	-0.50%	0.06%	0.24%	0.49%	0.86%	1.36%	(9.10)
1/1/1	0.07%	0.27%	0.32%	0.29%	0.27%	0.20%	(1.86)

Panel D. FF5 alpha excluding stocks with extreme divergence between implied volatilities of put and call options

Range of *implied volatility ratio*	*Value-of-vote* portfolio 1 (Low)	2	3	4	5 (High)	V5-V1	t-statistics
[0.91, 1.16]	0.37%	0.15%	0.00%	0.01%	-0.34%	-0.71%	(-5.28)
[0.95, 1.05]	0.29%	0.15%	0.01%	-0.08%	-0.17%	-0.45%	(-3.67)

Table 7. Fama-MacBeth regression: using individual stock returns

This table reports the estimation results from running Fama-MacBeth (1973) cross-sectional regressions of expected stock return on various firm characteristics including the *Value-of-Vote*. Each month, the cross-section of expected stock return at time t is regressed on a constant, market beta (estimated using past 250 days daily return excluding previous one-month), size (log of market capitalization at t-1), book-to-market (log of book-to-market by matching annual book value of equity (BE), which is fiscal year end accounting information, to 6 month after calendar year information such as market capitalization (ME), to form book-to-market ratio which is updated every month), previous 11 month return excluding month t-1, (Ret_t-12, t-2), previous one month return (Ret_t-1), and long-past return, previous 36 months to previous 13 months return (Ret_ t-36, t-13). These two returns are included to capture the short-term and long-run reversal effects in individual stock returns. The standard deviation of daily returns (Stdev_ret) is calculated using the last 250 days, excluding month t-1. The leverage (Lev) is the total debt divided by the total asset. Idiosyncratic volatility (IVOL) is measured as in Ang, Hodrick, Xing and Zhang (2006) which is the standard deviation of the residual from monthly regression of stock returns on Fama-French three factors (market, size and book-to-market fators) using daily returns. Illiquidity (ILLIQ) is Amihud (2002)'s measure of illiquidity, the ratio of the absolute monthly stock return to its dollar trading volume. The analysts forecast dispersion (DISP) is calculated as in Diether, Malloy and Scherbina (2002). The log asset growth (log(Asset_Growth)) is the growth in asset by the end of fiscal year t. The average daily bid-ask spread of the stock for the month (Avg_Bid-Ask_Spread (Stock)), the average daily bid-ask spread for put option (Avg_Bid-Ask_Spread (Put)) and the average daily bid-ask spread for call option (Avg_Bid-Ask_Spread (Call)) are included. We calculate daily bid-ask spread as the ask price minus bid price to get the average daily bid-ask spread for the month. For stock bid-ask spread, we scale the spread by its absolute price. C/P OI is the ratio of call and put option open interest. C/P Volume is the average call and put option volume ratio during the month. Conditional skewness (COSKEW) is calculated as in Harvey and Siddique (2000). Risk-neutral skewness (QSKEW) is defined as the difference between the out-of-money put implied volatilities and the average of the at-the money call and put implied volatilities, both using maturities of 30 days, following Xing, Zhang and Zhao (2010) and An, Ang, Bali, and Cikaci (2014). The first difference of call implied volatilities (ΔCVOL) and the first difference of put implied volatilities (ΔPVOL) are included to control for the effect of informed trading (An, Ang, Bali and Cikaci (2014)). In addition, the changes in implied volatility innovations between put and call options (ΔPVOL- ΔCVOL) is included following An, Ang, Bali and Cikaci (2014). Implied volatility spread (CVOL-PVOL) is the difference between call implied volatilities and put implied volatilities following Cremers and Weinbaum (2010). All independent variables are winsorized at the first and 99th percentile. To exclude the effect from micro-cap stocks, stocks with price less than $5 are dropped from the sample, though including those stocks barely changes the results. The sample period is from February, 1996 to September, 2015. Newey-West t-statistics are reported in parentheses. The last row reports the average adjusted R^2 values and their Newey-West t-statistics in parentheses.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Value-of-vote	**-0.8024**	**-0.9980**	**-1.0067**	**-0.9732**	**-0.9949**	**-0.7442**	**-0.7416**
	(-4.82)	**(-6.67)**	**(-6.19)**	**(-6.00)**	**(-6.09)**	**(-4.48)**	**(-4.56)**
Beta	-0.0034	-0.0004	0.0014	0.0014	0.0013	0.0012	0.0012
	(-1.06)	(-0.12)	(0.50)	(0.50)	(0.45)	(0.42)	(0.42)
log(ME)	-0.0021	-0.0007	-0.0005	-0.0004	-0.0005	-0.0005	-0.0004
	(-2.49)	(-0.96)	(-0.67)	(-0.57)	(-0.63)	(-0.65)	(-0.56)
log(B/M)	0.0024	0.0025	0.0024	0.0024	0.0024	0.0024	0.0024
	(2.18)	(2.11)	(2.07)	(2.11)	(2.10)	(2.07)	(2.06)
Ret(t-12, t-2)	-0.0072	-0.0043	-0.0035	-0.0035	-0.0036	-0.0035	-0.0035
	(-1.47)	(-0.96)	(-0.87)	(-0.86)	(-0.86)	(-0.83)	(-0.85)
Ret(t-1)	-0.0316	-0.0320	-0.0251	-0.0249	-0.0244	-0.0247	-0.0250
	(-4.18)	(-4.10)	(-3.45)	(-3.45)	(-3.39)	(-3.44)	(-3.49)
Ret(t-36, t-13)	-0.0029	-0.0014	-0.0012	-0.0011	-0.0012	-0.0012	-0.0011
	(-3.20)	(-1.73)	(-1.60)	(-1.48)	(-1.49)	(-1.52)	(-1.44)
Lev	0.0001	-0.0021	-0.0029	-0.0026	-0.0026	-0.0026	-0.0026
	(0.01)	(-0.60)	(-0.83)	(-0.72)	(-0.73)	(-0.72)	(-0.71)
stdev_ret	0.4343	0.2670	0.1985	0.2033	0.1941	0.2013	0.2032
	(3.44)	(2.14)	(1.58)	(1.61)	(1.56)	(1.63)	(1.61)
Log(Asset_Growth)		-0.0015	-0.0016	-0.0017	-0.0017	-0.0016	-0.0016
		(-3.45)	(-3.65)	(-3.85)	(-3.85)	(-3.80)	(-3.77)
DISP		0.0002	-0.0002	-0.0003	-0.0003	-0.0004	-0.0004
		(0.30)	(-0.28)	(-0.35)	(-0.36)	(-0.44)	(-0.50)
IVOL		0.0153	-0.0327	-0.0296	-0.0176	-0.0212	-0.0294
		(0.22)	(-0.45)	(-0.38)	(-0.24)	(-0.29)	(-0.39)
ILLIQ		0.2176	0.1159	0.1153	0.1138	0.1152	0.1161
		(5.47)	(2.51)	(2.51)	(2.49)	(2.51)	(2.55)
Avg_BA_spread (Stock)			3.6774	3.6102	3.5935	3.6622	3.5699
			(2.92)	(2.89)	(2.85)	(2.90)	(2.93)
Avg_BA_Spread (Put)			0.0151	0.0164	0.0163	0.0159	0.0151
			(2.37)	(2.59)	(2.53)	(2.45)	(2.36)
Avg_BA_Spread (Call)			-0.0188	-0.0206	-0.0204	-0.0202	-0.0204
			(-2.73)	(-2.87)	(-2.80)	(-2.80)	(-2.80)
C/P OI			0.0000	0.0000	0.0000	0.0000	0.0000
			(0.86)	(0.79)	(0.80)	(0.86)	(0.80)
C/P Volume			0.0002	0.0001	0.0001	0.0001	0.0001
			(1.71)	(1.40)	(1.44)	(1.41)	(1.33)
COSKEW			-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
			(-0.59)	(-0.48)	(-0.46)	(-0.45)	(-0.46)
QSKEW			-0.0576	-0.0493	-0.0517	-0.0421	-0.0397
			(-5.27)	(-5.02)	(-5.18)	(-4.57)	(-4.31)
ΔCVOL				0.0288			0.0084
				(3.23)			(0.31)
ΔPVOL				-0.025			-0.004
				(-3.27)			(-0.16)
ΔPVOL-ΔCVOL					-0.0291		-0.0035
					(-3.58)		(-0.12)
CVOL-PVOL						0.0613	0.0530
						(4.29)	(2.94)
Adj.R-square	0.0882	0.0992	0.1079	0.1099	0.1088	0.1094	0.1119
	(9.17)	(9.86)	(10.77)	(10.85)	(10.81)	(10.76)	(10.97)

Table 8. *Voting premium* portfolio using dual-class stocks

The table reports average *voting premium* and *voting premium* portfolio return calculated using dual-class stocks. *Voting premium* (VP) is calculated following Zingales (1995) and Kalay, Karakaş and Pant (2014): $VP \equiv \frac{P_S - P_I}{P_I - rP_S}$, where P_s is the stock price for superior voting share class, P_I is the price for the inferior voting share class and *r* is the relative number of votes of an inferior voting share class versus a superior voting share class. Each month, stocks are sorted into five groups based on *voting premium* calculated using the end of month stock price. In Panel A, average and median *voting premium* for each of *voting premium* portfolio is reported. In Panel B, equal-weighted (EW) portfolio returns, value-weighted (VW) portfolio returns, and the characteristics matched benchmark-adjusted *voting premium* portfolio returns (DGTW, 1997) for superior voting share class are reported. For benchmark-adjusted returns, each stock is matched to a portfolio of firms that have approximately the same size, book-to-market and momentum characteristics. We use 125 portfolios formed from the intersection of 5 portfolio sorted on size, 5 portfolio sorted on book-to-market and 5 portfolio sorted on momentum. Benchmark-adjusted returns are computed as the monthly *voting premium* portfolio returns in excess of the benchmarked returns of the portfolio to which a stock belongs. We collect dual class information from IRRC, GMI, Andrew Metrick's data and hand-collected voting share information by reading proxy statements. The time period considered is from February 1994 to December, 2015. Stocks are held for one month. The table reports average and median *voting premium* (Panel A), average monthly VP portfolio returns (Panel B), and t-statistics in parentheses.

Panel A. Mean *voting premium* for voting premium portfolio

Voting Premium Portfolio Rank	Average *Voting Premium*	Median *Voting Premium*
1 (Low)	-14.48	-0.10
2	-0.01	-0.01
3	0.01	0.01
4	0.07	0.06
5 (High)	68.10	0.33

Panel B. Mean *voting premium* portfolio return for superior voting stocks (monthly frequency)

Voting Premium Portfolio Rank	EW	VW	Characteristics-adjusted
1	1.63%	1.36%	0.58%
2	1.38%	0.73%	0.37%
3	1.23%	1.09%	0.11%
4	0.63%	1.13%	-0.34%
5	0.35%	-0.28%	-0.62%
VP_HML	-1.28%	-1.64%	-1.20%
(V5-V1)	(-3.36)	(-3.62)	(-3.18)

Table 9. Operating performance

This table reports the one-year, two-year and three-year post changes in operating performance for each of *Value-of-vote* quintile portfolios relative to the pre-portfolio formation year. For each calendar year, firms are sorted based on annual *Value-of-Vote*. The annual *Value-of-Vote* is calculated as the median of the monthly *Value-of-Vote*. Operating performance are then measured for the next one-, two-, and three- fiscal year after the portfolio formation year. Panel A reports changes in ROA (NI/AT) adjusted by the average ROA of all companies in the same SIC-3digit industry. Panel B reports changes profitability (EBITDA/AT) adjusted by the average profitability of all companies in the same SIC-3digit industry. t-statistics are reported in parentheses.

Panel A. Change in ROA for value of vote portfolio quintile

Value-of-Vote Portfolio	ΔROA (+1 yr)	ΔROA (+2 yr)	ΔROA (+3 yr)
1 (Low)	-0.01	-0.01	-0.02
2	-0.02	-0.02	-0.02
3	-0.01	-0.01	-0.02
4	-0.01	-0.02	-0.01
5 (High)	0.04	0.07	0.12
V5 - V1	0.05	0.08	0.14
(Vote_HML)	(1.61)	(1.83)	(2.21)

Panel B. Change in Profitability for value of vote quintile

Value-of-Vote Portfolio	Δ Profitability (+1 yr)	Δ Profitability (+2 yr)	Δ Profitability (+3 yr)
1 (Low)	-0.01	-0.01	-0.02
2	-0.01	-0.01	-0.02
3	-0.01	-0.01	-0.02
4	0.00	-0.01	-0.01
5 (High)	0.05	0.08	0.13
V5 - V1	0.06	0.09	0.15
(Vote_HML)	(1.67)	(1.97)	(2.32)

Table 10. Return Differences on *Value-of-Vote* Portfolios after Controlling for Other Characteristics

The table reports Fama-French five factor model alphas (FF5 alpha) after controlling for each of firm characteristics mentioned in the first column in Panel A. We perform a double sort on firm characteristics, size, book-to-market (BTM), momentum, illiquidity, dispersion, idiosyncratic volatility (IVOL), standardized unexpected earnings (SUE), short-term reversal, option volume, option open interest, and short interest ratio, respectively. First we sort stocks into five quintiles on the firm characteristic mentioned above and then within each quintile we sort stocks based on *Value-of-Vote*. The five *Value-of-Vote* portfolios are then averaged over each of the five characteristic portfolios. Then each of *Value-of-Vote* portfolio would represents *Value-of-Vote* portfolios controlling for the characteristics. With this average *Value-of-Vote* quintiles, we get alphas using Fama-French five-factor (FF5) model. The row (1), size, is the market equity measured as the stock price times shares outstanding. The row (2), book-to-market (BTM), is the ratio of total book value of assets to book value of equity. The row (3), momentum, is the past return from month t-12 to month t-2. The row (4), illiquidity, is Amihud (2002)'s measure of illiquidity which is the ratio of the absolute monthly stock return to its dollar trading volume. The row (5), idiosyncratic volatility (IVOL), is measured as in Ang, Hodrick, Xing and Zhang (2006) which is the standard deviation of the residual from monthly regression of stock returns on Fama-French three factors (market, size and book-to-market factors) using daily returns. The row (6), the analysts forecast dispersion (DISP), is calculated as in Diether, Malloy and Scherbina (2002). The row (7), standardized earnings surprise (SUE), is the difference between the actual earnings and the median of analysts' earnings forecasts normalized by the stock price. The row (8), the short-term reversal, is the return on the previous month (Ret_t-1). The row (9), the Bid-Ask spread, is the average daily bid-ask spread (scaled by the absolute stock price) over the previous month. The row (10), the stock volume, is the average daily dollar volume of a stock over the previous month. The row (11), option volume, is the average daily sum of call and put option volume over the previous month. The row (12), option open interest, is the average daily sum of call and put open interest over the previous month. The row (13), short interest ratio, is short interest divided by total shares outstanding. All portfolios are equal weighted. The sample period is from February, 1996 to September, 2015. t-statistics are reported in parentheses.

Panel A. FF5 alphas (α_{FF5})

	Value-of-vote portfolio Rankings					
	1 (Low)	2	3	4	5 (High)	V5-V1
(1) Double Sort on Size	0.28%	0.25%	-0.03%	-0.01%	-0.33%	-0.61%
	(1.86)	(2.46)	(-0.29)	(-0.13)	(-3.00)	(-4.85)
(2) Double sort on BTM	0.34%	0.19%	-0.01%	-0.08%	-0.40%	-0.73%
	(2.11)	(1.86)	(-0.10)	(-0.80)	(-3.08)	(-5.42)
(3) Double sort on Momentum	0.37%	0.19%	-0.06%	-0.11%	-0.36%	-0.72%
	(2.56)	(1.78)	(-0.54)	(-1.00)	(-2.99)	(-6.26)
(4) Double sort on Illiquidity	0.29%	0.16%	-0.02%	-0.08%	-0.32%	-0.61%
	(1.74)	(1.55)	(-0.26)	(-0.80)	(-2.58)	(-4.46)
(5) Double sort on IVOL	0.30%	0.14%	0.03%	-0.08%	-0.36%	-0.66%
	(1.87)	(1.31)	(0.29)	(-0.74)	(-3.00)	(-5.61)
(6) Double sort on Dispersion (DISP)	0.35%	0.10%	0.01%	-0.03%	-0.39%	-0.74%
	(1.93)	(1.06)	(0.05)	(-0.32)	(-2.96)	(-5.44)
(7) Double sort on SUE	0.42%	0.06%	-0.08%	-0.05%	-0.31%	-0.73%
	(2.38)	(0.65)	(-0.90)	(-0.53)	(-2.35)	(-5.43)
(8) Double sort on short-term reversal	0.36%	0.06%	0.03%	-0.01%	-0.40%	-0.75%
	(2.12)	(0.62)	(0.29)	(-0.14)	(-2.85)	(-5.92)
(9) Double sort on Stock Bid-Ask spread	0.32%	0.21%	0.02%	-0.11%	-0.41%	-0.73%
	(1.79)	(2.18)	(0.26)	(-1.08)	(-3.24)	(-5.42)
(10) Double sort on Stock Volume	0.29%	0.14%	0.03%	-0.09%	-0.34%	-0.63%
	(1.67)	(1.42)	(0.35)	(-0.94)	(-2.55)	(-4.52)
(11) Double sort on Option Volume	0.40%	0.17%	0.02%	-0.02%	-0.42%	-0.82%
	(2.17)	(1.97)	(0.30)	(-0.27)	(-2.89)	(-5.48)
(12) Double sort on Option Open Interest	0.36%	0.19%	0.03%	-0.04%	-0.42%	-0.75%
	(1.95)	(2.11)	(0.41)	(-0.48)	(-2.89)	(-5.28)
(13) Double sort on Short Interest Ratio	0.36%	0.18%	-0.03%	0.04%	-0.39%	-0.75%
	(2.06)	(1.79)	(-0.34)	(0.41)	(-2.91)	(-5.56)

Table 11. Robustness: Different portfolio formation periods (L/M/N)

The table reports Fama-French five- factor alphas (FF5 alphas) for *Value-of-Vote* quintile portfolios using various combinations of portfolio formation periods. We use L/M/N portfolio strategy as in Jegadeesh and Titman (1993) and Ang, Hodrick, Xing and Zhang (2006). At month t, we compute *Value-of-Vote* quintile portfolios using *Value-of-Vote* for that month and hold these portfolios for one month, which is 1/0/1 strategy mainly used in this paper. For L>1, we use t-L-M month to t-M month moving average *Value-of-Vote* to form quintile portfolios at month t, hold these portfolios for N months. For example, to construct 6/1/1 quintile portfolios, each month we construct equal-weighted *Value-of-Vote* quintile portfolio based on moving average of previous 6 months of *Value-of-Vote* ending in 1 month prior to the formation date, and hold these portfolios for 1 month. To construct 6/2/1 portfolios, each month we construct equal-weighted *Value-of-Vote* quintile portfolio based on the moving average of past 6 months of *Value-of-Vote* ending 2-month prior to the formation date, and hold these portfolios for one month and so on. Using various combinations of portfolio formation periods, Panel A reports Fama-French 5 factor alphas. The sample period is from February, 1995 to September, 2015. *t*-statistics are in parentheses.

	Value-of-Vote portfolio					
Strategies	1 (Low)	2	3	4	5 (High)	V5-V1 (Vote HML)
1/1/1	0.35%	0.09%	0.04%	0.05%	-0.27%	-0.61%
	(1.61)	(0.95)	(0.44)	(0.54)	(-1.76)	(-4.11)
1/2/1	0.31%	0.12%	0.04%	0.08%	-0.19%	-0.50%
	(1.52)	(1.15)	(0.47)	(0.81)	(-1.23)	(-3.36)
6/0/1	0.41%	0.15%	0.08%	0.03%	-0.30%	-0.71%
	(2.35)	(1.40)	(0.86)	(0.31)	(-2.21)	(-4.87)
6/1/1	0.43%	0.08%	0.15%	0.05%	-0.15%	-0.57%
	(2.15)	(0.73)	(1.53)	(0.47)	(-0.98)	(-3.75)
12/0/1	0.43%	0.15%	0.08%	0.10%	-0.18%	-0.61%
	(2.68)	(1.33)	(0.73)	(0.87)	(-1.39)	(-4.16)
12/1/1	0.40%	0.19%	0.13%	0.06%	-0.07%	-0.48%
	(2.34)	(1.62)	(1.17)	(0.48)	(-0.55)	(-3.06)

Table 12. Robustness: Different Subsample Periods

The table reports risk-adjusted return, alpha, for the *Value-of-Vote* quintile portfolios estimated for the subsample periods. Each month firms are sorted into five groups based on the *Value-of-Vote* that month. The dependent variable is the monthly equal-weighted *Value-of-Vote* quintile portfolio returns in excess of the one-month Treasury bill rate. In Panel A, we report risk-adjusted return, alpha, for *Value-of-Vote* quintile portfolios using FF3 model (α_{FF3}), FF4 model (α_{FF4}), and FF5 model (α_{FF5}) for the first half of the sample (1996-2006) and the second half of the sample (2007-2015), separately. Panel B reports FF3, FF4 and FF5 alphas for sub-sample, excluding financial crisis period (2007-2009 period). *t*-statistics are in parentheses.

Panel A. FF3, FF4 and FF5 alpha for subsamples

Value-of-vote portfolio	Subsample: 1996-2006			Subsample: 2007-2015		
	FF3 alpha (α_{FF3})	FF4 alpha (α_{FF4})	FF5 alpha (α_{FF5})	FF3 alpha (α_{FF3})	FF4 alpha (α_{FF4})	FF5 alpha (α_{FF5})
1 (Low)	0.16%	0.62%	0.34%	0.24%	0.25%	0.34%
	(0.52)	(2.72)	(1.09)	(1.74)	(2.18)	(2.56)
2	0.09%	0.21%	0.11%	0.16%	0.16%	0.18%
	(0.62)	(1.54)	(0.74)	(2.09)	(2.23)	(2.37)
3	-0.07%	0.01%	-0.05%	0.11%	0.11%	0.13%
	(-0.58)	(0.08)	(-0.40)	(1.29)	(1.52)	(1.56)
4	-0.26%	-0.10%	-0.19%	0.04%	0.05%	0.10%
	(-1.85)	(-0.83)	(-1.36)	(0.44)	(0.58)	(1.15)
5 (High)	-0.58%	-0.26%	-0.50%	-0.42%	-0.40%	-0.27%
	(-2.76)	(-1.79)	(-2.33)	(-2.25)	(-3.02)	(-1.56)
V5-V1	-0.75%	-0.88%	-0.84%	-0.66%	-0.65%	-0.61%
(Vote_HML)	(-3.56)	(-4.34)	(-4.03)	(-3.72)	(-3.85)	(-3.46)

Panel B. FF3, FF4 and FF5 alphas estimated excluding financial crisis period (2007-2009)

Value-of-vote portfolio	FF3 Alpha (α_{FF3})	FF4 Alpha (α_{FF4})	FF5 Alpha (α_{FF5})
1 (Low)	0.16%	0.51%	0.29%
	(0.74)	(3.24)	(1.38)
2	0.10%	0.20%	0.11%
	(0.96)	(2.07)	(1.09)
3	-0.04%	0.02%	-0.03%
	(-0.49)	(0.22)	(-0.34)
4	-0.17%	-0.04%	-0.12%
	(-1.66)	(-0.47)	(-1.23)
5 (High)	-0.57%	-0.31%	-0.48%
	(-3.71)	(-2.80)	(-3.15)
V5-V1	-0.73%	-0.82%	-0.78%
(Vote_HML)	(-4.89)	(-5.64)	(-5.16)

Online Appendix Tables

Figure A1. Holding periods and high-minus-low vote return

The figure plots the difference in returns between the highest *Value-of-Vote* portfolio (V5) and the lowest *Value-of-Vote* portfolio (V1) as the holding period is extended up to 12 months. At the end of each month, stocks are ranked into quintile portfolios based on *Value-of-Vote*. Then, the stocks are held in the portfolio for T months, with 1/T-th of each portfolio reinvested monthly. The figure plots the return difference, with the dotted line indicating the 90^{th} confidence interval (CL). Portfolios are formed in equal weights.

Panel A. High-minus-low *Value-of-Vote* portfolio return with different holding periods

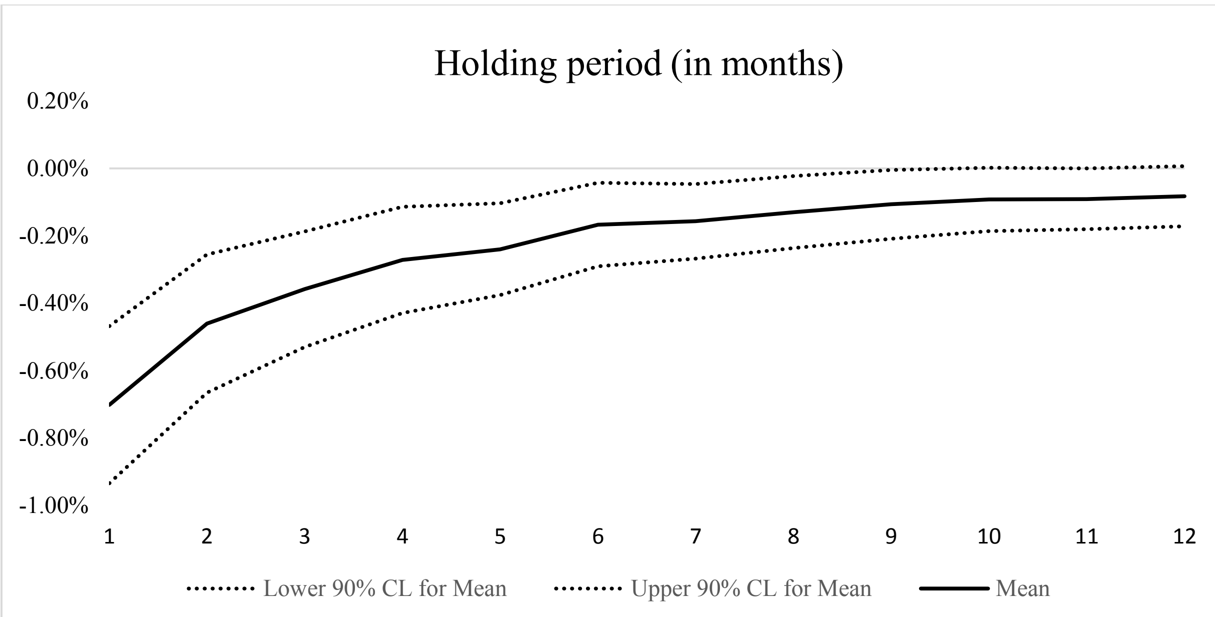

Table A1. Robustness: Risk-adjusted *Value-of-Vote* portfolios with non-negative *Value-of-Vote*

The table reports time-series test results using *Value-of-Vote* equal-weighted portfolio, where the negative *Value-of-Votes* are dropped from the sample (Panel A) and truncated at zero (Panel B). Each month firms are sorted into five groups based on the *Value-of-Vote* that month. *Value-of-Vote* is calculated from put-call parity condition explained in text. Stocks with negative *Value-of-Vote* is dropped in Panel A. Stocks with negative *Value-of-vote* is truncated at zero in Panel B. We form *Value-of-vote* quintile portfolios each month and observe FF3 alpha, FF4 alpha and FF5 alpha for each *Value-of-vote* portfolios. Also, the alpha difference between high and low *Value-of-vote* portfolio (V5-V1) are reported in the last row of each table. The sample period is from February, 1996 to September, 2015. t-statistics are in parentheses.

Panel A. FF3, FF4 and FF5 alphas for *Value-of-vote* portfolios dropping observations with negative *Value-of-vote*

Value-of-vote portfolio	FF3 Alpha ($\boldsymbol{\alpha}_{\mathbf{FF3}}$)	FF4 Alpha ($\boldsymbol{\alpha}_{\mathbf{FF4}}$)	FF5 Alpha ($\boldsymbol{\alpha}_{\mathbf{FF5}}$)
1 (Low)	0.14%	0.17%	0.13%
	(1.81)	(2.25)	(1.62)
2	-0.02%	0.03%	-0.01%
	(-0.28)	(0.36)	(-0.15)
3	-0.05%	0.03%	-0.04%
	(-0.59)	(0.33)	(-0.40)
4	-0.11%	0.01%	-0.06%
	(-1.01)	(0.05)	(-0.50)
5 (High)	-0.70%	-0.46%	-0.59%
	(-4.32)	(-3.97)	(-3.58)
V5-V1 (Vote_HML)	-0.84%	-0.63%	-0.71%
	(-5.26)	(-4.99)	(-4.39)

Panel B. FF3, FF4 and FF5 alphas for *Value-of-vote* portfolios truncating Value-of-Vote at zero

Value-of-vote portfolio	FF3 Alpha ($\boldsymbol{\alpha}_{\mathbf{FF3}}$)	FF4 Alpha ($\boldsymbol{\alpha}_{\mathbf{FF4}}$)	FF5 Alpha ($\boldsymbol{\alpha}_{\mathbf{FF5}}$)
1 (Low)	0.25%	0.50%	0.40%
	(1.39)	(3.57)	(2.20)
2	0.24%	0.33%	0.34%
	(1.27)	(1.75)	(1.66)
3	0.02%	0.09%	0.03%
	(0.25)	(1.07)	(0.32)
4	-0.14%	-0.02%	-0.09%
	(-1.35)	(-0.21)	(-0.86)
5 (High)	-0.54%	-0.28%	-0.41%
	(-3.38)	(-2.57)	(-2.48)
V5-V1 (Vote_HML)	-0.79%	-0.78%	-0.81%
	(-5.93)	(-5.79)	(-5.78)

Table A2. Panel Regression of *Value-of-Vote*

This table reports panel regressions of corporate *value-of-vote* on firm characteristics and ownership characteristics. The dependent variable is the corporate *value-of-vote*. It is measured using put-call parity condition explained in text. The managerial ownership (MGMT_own) is the shares owned by top executives available in Execucomp. Total institutional holding (IO_holding) is the percentage of shares held by institutional investors measured as of the recent quarter. Institutional ownership concentration (IO_HHI) is measured using Herfindahl Index based on the percentages of institutional holdings by all 13-F institutions. We also divide institutional type into three categories based on Bushee (1998)'s classification. "Dedicated" is the percentage of shares held by dedicated institutions, "Quasi-Index" is the percentage of shares held by quasi-index institution and "Transient" is the percentage of shares held by transient institutions. The firm characteristics include, "Size", the log of market capitalization at t-1, "BTM", the log of book-to-market, (Ret_t-12, t-2) is the previous 11-month return excluding month t-1. The leverage (LEV) is the total debt divided by the total asset. The return on asset (ROA) is the net income divided by the total asset. The previous one month return (Ret(t-1)), and long-past return, previous 36 months to previous 13 months return (Ret t-36, t-13), are included to capture the short-term and long-term stock performance. The standard deviation of daily returns (Stdev_ret) is calculated using the last 250 days, excluding month t-1. Idiosyncratic volatility (IVOL) is measured as in Ang, Hodrick, Xing and Zhang (2006). Illiquidity (ILLIQ) is Amihud (2002)'s measure of illiquidity. The analysts forecast dispersion (DISP) is calculated as in Diether, Malloy and Scherbina (2002). G-index is from IRRC. Stocks with a price less than five dollars are excluded from the sample. The sample period is from February, 1996 to January, 2014. All independent variables are winsorized at the 1% and 99% percentile. Industry (SIC) fixed effects and year fixed effects are used in columns (1) through (4). Firm fixed effect and year fixed effects are included in column (5) through (8). Standard errors are clustered at the industry level (columns 1-4), and the firm level (columns 5-8) and. t-statistics are reported in parentheses. *, **, and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MGMT_own	0.002***	0.002***	0.001*	0.001*	0.002***	0.002***	0.001	0.001
	(2.726)	(2.603)	(1.957)	(1.798)	(2.693)	(2.619)	(1.411)	(1.316)
IO_holding	0.000		0.000		0.002***		0.001***	
	(1.647)		(1.137)		(4.282)		(2.783)	
IO_HHI		0.001		0.001		-0.000		0.001
		(0.587)		(0.767)		(-0.018)		(0.978)
Dedicated		0.002***		0.002***		0.002***		0.002***
		(3.461)		(3.174)		(4.100)		(3.692)
Quasi_Index		0.000		0.000		0.002***		0.001**
		(1.396)		(0.964)		(3.638)		(2.505)
Transient		-0.000		-0.000		0.001**		0.001
		(-0.709)		(-0.848)		(2.383)		(1.321)
Size	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(-4.651)	(-5.269)	(-3.635)	(-4.054)	(-5.277)	(-5.182)	(-5.004)	(-4.760)
BTM	-0.000	-0.000	-0.000	-0.000	-0.000**	-0.000**	-0.000	-0.000*
	(-1.085)	(-1.342)	(-0.453)	(-0.630)	(-2.175)	(-2.375)	(-1.563)	(-1.702)
Ret(t-12,t-2)	-0.000*	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000
	(-1.739)	(-1.219)	(-0.772)	(-0.221)	(-1.453)	(-1.019)	(-0.268)	(0.135)
LEV	0.000*	0.000*	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(1.752)	(1.672)	(1.335)	(1.246)	(-0.057)	(-0.105)	(-0.742)	(-0.785)
ROA	0.000	0.000	-0.000	-0.000	0.000	0.000	-0.000	0.000
	(0.763)	(0.865)	(-0.088)	(-0.009)	(0.158)	(0.188)	(-0.031)	(0.030)
stdev_ret	0.021***	0.021***	0.019***	0.019***	0.025***	0.025***	0.021***	0.021***
	(4.422)	(4.491)	(3.966)	(4.079)	(6.246)	(6.292)	(6.172)	(6.247)
Ret(t-36,t-13)	-0.000***	-0.000***	-0.000**	-0.000*	-0.000*	-0.000*	-0.000	-0.000
	(-2.922)	(-2.626)	(-2.177)	(-1.817)	(-1.913)	(-1.735)	(-1.454)	(-1.187)
Ret(t-1)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(5.703)	(5.633)	(5.235)	(5.147)	(6.797)	(6.662)	(6.690)	(6.462)
IVOL	0.008*	0.008*	0.014***	0.014***	0.009**	0.009**	0.013***	0.013***
	(1.772)	(1.818)	(2.721)	(2.753)	(2.411)	(2.474)	(3.220)	(3.264)
ILLIQ	-0.004**	-0.004**	-0.003	-0.003	-0.000	-0.001	0.001	0.001
	(-2.050)	(-2.210)	(-1.368)	(-1.525)	(-0.269)	(-0.430)	(1.121)	(0.885)
DISP	0.000	0.000	0.000	0.000	0.000	0.000	-0.000	-0.000
	(1.267)	(1.222)	(0.296)	(0.191)	(0.785)	(0.763)	(-0.175)	(-0.217)
G-index			-0.000	-0.000			0.000	0.000
			(-0.974)	(-0.820)			(0.773)	(0.710)
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes
Ind(SIC) FE	Yes	Yes	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	220299	220299	188167	188167	220277	220277	188150	188150
Adj.RSQ	0.028	0.029	0.042	0.042	0.147	0.147	0.168	0.168

Table A3. *Value-of-Vote* decile portfolio

The table reports returns sorted by *Value-of-Vote* portfolios. Stocks are sorted into ten groups based on the median *Value-of-Vote* calculated each month and the risk-adjusted return for the decile portfolios for the next month are reported. In Panel A, equal-weighted (EW) portfolio returns, value-weighted (VW) returns and characteristics matched benchmark-adjusted returns are reported. The characteristics-adjusted portfolio returns report the characteristics matched benchmark-adjusted *Value-of-Vote* portfolio returns following Daniel, Grinblatt, Titman and Wermers (DGTW, 1997). Each stocks are matched to a portfolio of firms that have approximately the same size, book-to-market and momentum characteristics. We use 125 portfolios formed from the intersection of 5 portfolio sorted on size, 5 portfolio sorted on book-to-market and 5 portfolio sorted on momentum. Benchmark-adjusted returns are computed as the monthly *Value-of-Vote* portfolio returns in excess of the benchmarked returns of the portfolio to which a stock belongs. In Panel B, we report alphas (FF3 alpha, FF4 alpha and FF5 alpha) sorted by the decile portfolio of *Value-of-Vote*. The dependent variable for Panel B is the monthly *Value-of-Vote* portfolio returns in excess of the one-month Treasury bill rate. The Fama-French three factor model (FF3) alpha is estimated using FF3 model which is the excess market return (MKTRF), the size factor (SMB) and the book-to-market factor (HML). The Fama-French four factor model, is FF3 model (MKTRF, SMB, HML) plus a momentum factor (UMD), often called as Carhart (1997) model. The Fama-French five-factor (FF5) is the three factors plus a profitability factor (RMW) and an investment factor (CMA). The FF3 alpha, FF4 alpha, and FF5 alpha are reported. The time period considered is from February 1996 to September, 2015. t-statistics are in parentheses.

Panel A. Average and benchmark-adjusted returns for *Value-of-Vote* decile portfolio

Value-of-Vote portfolio	EW	t-statistics	VW	t-statistics	Characteristics-adjusted	t-statistics
1(Low)	1.37%	(2.52)	1.23%	(2.87)	0.44%	(2.58)
2	1.27%	(2.95)	1.04%	(2.80)	0.36%	(3.87)
3	1.24%	(3.13)	0.92%	(2.74)	0.39%	(4.13)
4	0.96%	(2.62)	0.88%	(2.85)	0.14%	(1.80)
5	0.95%	(2.61)	0.83%	(2.64)	0.11%	(1.58)
6	0.95%	(2.51)	0.80%	(2.71)	0.10%	(1.29)
7	0.92%	(2.32)	0.79%	(2.38)	0.00%	(-0.05)
8	0.92%	(2.21)	0.79%	(2.33)	0.02%	(0.27)
9	0.85%	(1.98)	0.79%	(2.09)	-0.07%	(-0.81)
10 (High)	0.38%	(0.75)	0.41%	(0.99)	-0.44%	(-3.67)
V10-V1 (Vote_HML)	-0.99%	(-4.90)	-0.82%	(-3.09)	-0.88%	(-4.71)

Panel B. *Value-of-vote* decile portfolio returns

Value-of-vote portfolio	FF3 Alpha	FF4 Alpha	FF5 Alpha
1(Low)	0.25%	0.61%	0.50%
	(0.96)	(3.06)	(1.92)
2	0.28%	0.40%	0.26%
	(1.85)	(2.81)	(1.72)
3	0.31%	0.38%	0.32%
	(2.68)	(3.30)	(2.74)
4	0.06%	0.12%	0.02%
	(0.64)	(1.38)	(0.20)
5	0.04%	0.07%	0.02%
	(0.54)	(0.91)	(0.22)
6	0.03%	0.11%	0.06%
	(0.32)	(1.25)	(0.58)
7	-0.05%	0.03%	-0.03%
	(-0.54)	(0.32)	(-0.30)
8	-0.09%	0.02%	-0.04%
	(-0.80)	(0.19)	(-0.38)
9	-0.23%	-0.07%	-0.15%
	(-1.73)	(-0.67)	(-1.09)
10 (High)	-0.80%	-0.53%	-0.65%
	(-4.31)	(-3.95)	(-3.48)
V10-V1	-1.05%	-1.13%	-1.15%
(Vote_HML)	(-5.21)	(-5.71)	(-5.53)

Table A4. Mean portfolio returns by ΔCVOL, ΔPVOL and *Value-of-Vote*

The table reports the mean portfolio returns sorted into three groups based on the call option implied volatility innovation (ΔCVOL), put implied volatility innovation (ΔPVOL) and *Value-of-Vote* groups at the end of the previous month. The call option implied volatility innovation and put implied volatility innovations are measured following An, Ang, Bali and Cikaci (2014). In Panel A, firms are sorted into three groups based on the ΔCVOL measured at the end of each month. Each ΔCVOL group is then sorted into three groups based on the put implied volatility innovation (ΔPVOL). Each ΔCVOL and ΔPVOL group is further sorted into three *Value-of-Vote* groups. "Low ΔPVOL" refers to an equal-weighted portfolio with the lowest implied put volatility innovations and "High ΔPVOL" refers to an equal-weighted portfolio with the highest ΔPVOL (the top 33%). The *Value-of-Vote* is calculated using put-call parity condition explained in text. Stocks are held for one month. In Panel B, firms are sorted into three groups based on the ΔPVOL measured at the end of each month. Each ΔPVOL group is then sorted into three groups based on the call implied volatility innovation (ΔCVOL). Each ΔPVOL and ΔCVOL group is further sorted into three *Value-of-Vote* groups. "Low ΔCVOL" refers to an equal-weighted portfolio with the lowest implied call volatility innovations and "High ΔCVOL" refers to an equal-weighted portfolio with the highest ΔCVOL (the top 33%). Panel C reports benchmark adjusted return using characteristics match following (DGTW, 1997) for the triple sort approach explained in Panel A. Each stocks are matched to a portfolio of firms that have approximately the same size, book-to-market and momentum characteristics. We use 125 portfolios formed from the intersection of 5 portfolio sorted on size, 5 portfolio sorted on book-to-market and 5 portfolio sorted on momentum. Benchmark-adjusted returns are computed as the monthly *Value-of-Vote* portfolio returns in excess of the benchmarked returns of the portfolio to which a stock belongs. Panel D reports benchmark adjusted return for triple sort approach explained in Panel B. The sample period is from February, 1996 to September, 2015. *t*-statistics are in parentheses.

Panel A. Mean portfolio return sorted by ΔCVOL, ΔPVOL and *Value-of-Vote*

	Low ΔPVOL			Med ΔPVOL			High ΔPVOL		
Value-of-Vote portfolio	Low ΔCVOL	Med ΔCVOL	High ΔCVOL	Low ΔCVOL	Med ΔCVOL	High ΔCVOL	Low ΔCVOL	Med ΔCVOL	High ΔCVOL
Low	1.01%	1.22%	1.90%	0.91%	1.31%	1.43%	0.72%	1.14%	1.38%
Medium	0.74%	1.03%	1.44%	0.72%	0.94%	1.16%	0.45%	1.02%	1.06%
High	0.90%	0.87%	1.09%	0.56%	0.83%	0.99%	0.25%	0.60%	0.69%
V3 - V1 (Vote_HML)	-0.11%	-0.35%	-0.80%	-0.35%	-0.48%	-0.44%	-0.47%	-0.54%	-0.68%
	(-0.49)	(-2.02)	(-3.80)	(-1.79)	(-3.11)	(-1.96)	(-2.60)	(-3.39)	(-2.47)

Panel B. Mean portfolio return sorted by ΔPVOL, ΔCVOL, and *Value-of-Vote*

	Low ΔCVOL			Med ΔCVOL			High ΔCVOL		
Value-of-Vote portfolio	Low ΔPVOL	Med ΔPVOL	High ΔPVOL	Low ΔPVOL	Med ΔPVOL	High ΔPVOL	Low ΔPVOL	Med ΔPVOL	High ΔPVOL
Low	0.81%	1.02%	0.78%	1.16%	1.30%	1.13%	1.63%	1.75%	1.57%
Medium	0.65%	0.69%	0.70%	0.78%	0.92%	1.06%	1.22%	1.09%	1.19%
High	0.70%	0.59%	0.09%	0.81%	0.92%	0.82%	0.86%	1.22%	0.89%
V3 - V1	-0.10%	-0.44%	-0.68%	-0.35%	-0.39%	-0.31%	-0.78%	-0.53%	-0.68%
(Vote_HML)	(-0.46)	(-2.69)	(-3.28)	(-1.91)	(-2.46)	(-1.56)	(-3.80)	(-2.87)	(-2.37)

Panel C. Characteristics adjusted (DGTW, 1997) portfolio return sorted by ΔCVOL, ΔPVOL and *Value-of-Vote*

	Low ΔPVOL			Med ΔPVOL			High ΔPVOL		
Value-of-Vote portfolio	Low ΔCVOL	Med ΔCVOL	High ΔCVOL	Low ΔCVOL	Med ΔCVOL	High ΔCVOL	Low ΔCVOL	Med ΔCVOL	High ΔCVOL
Low	0.15%	0.25%	0.89%	0.08%	0.40%	0.61%	0.02%	0.26%	0.51%
Medium	-0.17%	0.12%	0.51%	-0.08%	0.09%	0.29%	-0.23%	0.16%	0.14%
High	0.11%	-0.03%	0.17%	-0.29%	-0.01%	0.12%	-0.66%	-0.25%	-0.16%
	-0.04%	-0.27%	-0.73%	-0.37%	-0.41%	-0.50%	-0.69%	-0.51%	-0.66%
V3 - V1 (Vote_HML)	(-0.17)	(-1.64)	(-3.61)	(-2.15)	(-2.92)	(-2.37)	(-4.02)	(-3.30)	(-2.44)

Panel D. Characteristics adjusted (DGTW, 1997) portfolio return sorted by ΔPVOL, ΔCVOL, and *Value-of-Vote*

	Low ΔCVOL			Med ΔPVOL			High ΔCVOL		
Value-of-Vote portfolio	Low ΔPVOL	Med ΔPVOL	High ΔPVOL	Low ΔPVOL	Med ΔPVOL	High ΔPVOL	Low ΔPVOL	Med ΔPVOL	High ΔPVOL
Low	-0.07%	0.19%	0.03%	0.36%	0.40%	0.28%	0.60%	0.77%	0.69%
Medium	-0.25%	-0.12%	-0.06%	-0.01%	0.12%	0.19%	0.30%	0.19%	0.26%
High	-0.08%	-0.34%	-0.67%	-0.11%	0.04%	-0.03%	-0.02%	0.23%	0.06%
V3 - V1	-0.01%	-0.54%	-0.70%	-0.47%	-0.36%	-0.31%	-0.61%	-0.54%	-0.63%
(Vote_HML)	(-0.03)	(-3.68)	(-3.37)	(-2.68)	(-2.39)	(-1.69)	(-3.11)	(-2.99)	(-2.29)

Table A5. Mean portfolio returns by CVOL, PVOL and *Value-of-Vote*

The table reports the mean portfolio returns sorted into three groups based on the call option implied volatility (CVOL), put implied volatility (PVOL) and *Value-of-Vote* groups at the end of the previous month. The call option implied volatility and put implied volatility are from OptionMetrics. In Panel A, firms are sorted into three groups based on the CVOL measured at the end of each month. Each CVOL group is then sorted into three groups based on the PVOL. Each CVOL and PVOL group is further sorted into three *Value-of-Vote* groups. “Low PVOL” refers to an equal-weighted portfolio with the lowest implied put volatilities and “High PVOL” refers to an equal-weighted portfolio with the highest put implied volatilities (the top 33%). The *Value-of-Vote* is calculated using put-call parity condition explained in text. Stocks are held for one month. In Panel B, firms are sorted into three groups based on the PVOL measured at the end of each month. Each PVOL group is then sorted into three groups based on the call implied volatility (CVOL). Each PVOL and CVOL group is further sorted into three *Value-of-Vote* groups. “Low CVOL” refers to an equal-weighted portfolio with the lowest implied call volatilities and “High CVOL” refers to an equal-weighted portfolio with the highest CVOL (the top 33%). Panel C reports benchmark adjusted return using characteristics match following (DGTW, 1997) for the triple sort approach explained in Panel A. Each stocks are matched to a portfolio of firms that have approximately the same size, book-to-market and momentum characteristics. We use 125 portfolios formed from the intersection of 5 portfolio sorted on size, 5 portfolio sorted on book-to-market and 5 portfolio sorted on momentum. Benchmark-adjusted returns are computed as the monthly *Value-of-Vote* portfolio returns in excess of the benchmarked returns of the portfolio to which a stock belongs. Panel D reports benchmark adjusted return for triple sort approach explained in Panel B. The sample period is from February, 1996 to September, 2015. *t*-statistics are in parentheses.

Panel A. Mean portfolio return sorted by CVOL, PVOL and *Value-of-Vote*

	Low PVOL			Med PVOL			High PVOL		
Value-of-Vote	Low CVOL	Med CVOL	High CVOL	Low CVOL	Med CVOL	High CVOL	Low CVOL	Med CVOL	High CVOL
Low	1.06%	1.58%	1.75%	1.17%	1.48%	1.11%	0.90%	0.87%	1.04%
Medium	0.80%	1.32%	1.31%	0.87%	0.96%	0.87%	0.80%	0.78%	0.98%
High	0.83%	1.01%	1.30%	0.86%	1.07%	0.79%	0.76%	0.13%	-0.04%
V3 - V1	-0.24%	-0.57%	-0.45%	-0.31%	-0.40%	-0.32%	-0.13%	-0.73%	-1.07%
(Vote_HML)	-2.72	-4.46	-2.25	-3.34	-2.71	-1.13	-1.27	-3.91	-3.37

Panel B. Mean portfolio return sorted by PVOL, CVOL, and *Value-of-Vote*

	Low CVOL			Med CVOL			High CVOL		
Value-of-Vote	Low PVOL	Med PVOL	High PVOL	Low PVOL	Med PVOL	High PVOL	Low PVOL	Med PVOL	High PVOL
Low	1.06%	1.58%	1.75%	1.17%	1.48%	1.11%	0.90%	0.87%	1.04%
Medium	0.80%	1.32%	1.31%	0.87%	0.96%	0.87%	0.80%	0.78%	0.98%
High	0.83%	1.01%	1.30%	0.86%	1.07%	0.79%	0.76%	0.13%	-0.04%
V3 - V1	-0.24%	-0.36%	-0.81%	-0.25%	-0.52%	-0.90%	-0.18%	-0.64%	-0.73%
(Vote_HML)	-2.71	-2.74	-4.02	-2.62	-3.50	-3.42	-1.61	-3.34	-2.43

Panel C. Characteristics adjusted (DGTW, 1997) portfolio return sorted by CVOL, PVOL and *Value-of-Vote*

	Low PVOL			Med PVOL			High PVOL		
Value-of-Vote	Low CVOL	Med CVOL	High CVOL	Low CVOL	Med CVOL	High CVOL	Low CVOL	Med CVOL	High CVOL
Low	0.18%	0.56%	0.89%	0.24%	0.54%	0.34%	-0.06%	0.07%	0.20%
Medium	0.02%	0.29%	0.50%	-0.02%	0.17%	0.01%	-0.13%	-0.04%	0.09%
High	0.01%	0.09%	0.45%	-0.07%	0.18%	-0.04%	-0.15%	-0.68%	-0.63%
V3 - V1	-0.17%	-0.47%	-0.44%	-0.31%	-0.36%	-0.38%	-0.10%	-0.75%	-0.82%
(Vote_HML)	-1.81	-3.64	-2.18	-3.28	-2.39	-1.41	-0.87	-4.19	-2.28

Panel D. Characteristics adjusted (DGTW, 1997) portfolio return sorted by PVOL, CVOL, and *Value-of-Vote*

	Low CVOL			Med CVOL			High CVOL		
Value-of-Vote	Low PVOL	Med PVOL	High PVOL	Low PVOL	Med PVOL	High PVOL	Low PVOL	Med PVOL	High PVOL
Low	0.10%	0.14%	0.30%	0.22%	0.46%	0.53%	0.28%	0.68%	0.47%
Medium	-0.09%	0.01%	-0.14%	0.08%	0.21%	0.17%	0.11%	0.43%	0.06%
High	-0.08%	-0.13%	-0.58%	-0.06%	0.07%	-0.31%	0.13%	0.03%	-0.05%
V3 - V1	-0.19%	-0.27%	-0.88%	-0.28%	-0.38%	-0.84%	-0.15%	-0.65%	-0.52%
(Vote_HML)	-2.04	-2.03	-4.45	-2.84	-2.64	-3.26	-1.34	-3.57	-1.53

Table A6. 1/1/1 strategy for informed trading effects

This table reports 1/0/1 (conventional strategy) and 1/1/1 strategies for *Value-of-vote* portfolios and two other informed trading effects on stock returns documented by An et al. (2014) and Cremers and Weinbaum (2010). In Panel A (the first table), we for decile portfolio based on *value-of-vote*. Then, we calculate return difference between the tenth decile and the first decile for 1/0/1 strategy and 1/1/1/ strategy, respectively. For 1/0/1 strategy, we form decile portfolio in month t-1 and observe return at month t (conventional strategy). For 1/1/1/ strategy, we form (ΔPVOL – ΔCVOL) decile portfolio at month t-2, skip one month and observe return at month t. The return difference between the high and low value of vote portfolio (V10-V1) and its associated t-statistics are reported in the last two columns. In the second table in Panel A, we form decile portfolio based on put and call implied volatility innovations difference (ΔPVOL – ΔCVOL) following An et al. (2014). At the end of each month t-1 we form decile portfolio on ΔPVOL – ΔCVOL and observe return at month t (1/0/1 strategy). For 1/1/1 strategy, we form implied volatility innovations change portfolios at month t-2, skip 1 month and observe return at month t. The return differences for high and low ΔPVOL – ΔCVOL portfolio (A10-A1) and its t-statistics are reported in the last two columns. The third table in Panel A, we form decile portfolio based on call and put implied volatility spread (CVOL-PVOL) following Cremers and Weinbaum (2010). At the end of each month t-1, we form decile portfolio based in implied volatility spread and observe return at month t (1/0/1 strategy). For 1/1/1 strategy, we form decile implied volatility spread portfolio at the end of month t-2, skip one month and observe return at month t. The return difference for high and low CVOL-PVOL portfolio (C10-C1) and its statistics are reported in the last two columns. In Panel B, we observe FF5 alpha differences for decile portfolios sorted based on value of vote, (ΔPVOL – ΔCVOL) and (CVOL-PVOL). The FF5 alpha difference for the high and low value of vote portfolios (V10-V1) for 1/0/1 and 1/1/1 strategies are reported in the last two columns in the first table in Panel B, respectively. The FF5 alpha differences between high and low ΔPVOL – ΔCVOL portfolio (A10-A1) and its t-statistics are reported in the last column for each 1/0/1 and 1/1/1 strategy explained above. The third table in Panel B reports FF5 alpha using CVOL-PVOL portfolio. The FF5 alpha difference for CVOL-PVOL high and low portfolios (C10-C1) and its associated t-statistics are reported in the last two columns for each 1/0/1 and 1/1/1 strategy explained above. The sample period considered is from February, 1996 to September, 2015. t-statistics are in parentheses.

Panel A. Average portfolio returns for informed trading related portfolios

	Value-of-vote portfolios											
Strategies	1	2	3	4	5	6	7	8	9	10	V10-V1	t-statistics
1/0/1	1.37%	1.27%	1.24%	0.96%	0.95%	0.95%	0.92%	0.92%	0.85%	0.38%	-0.99%	(-4.90)
1/1/1	1.36%	1.17%	1.00%	0.98%	0.96%	1.05%	0.94%	1.13%	1.05%	0.60%	-0.76%	(-3.45)
	ΔPVOL – ΔCVOL Portfolios											
Strategies	1	2	3	4	5	6	7	8	9	10	A10-A1	t-statistics
1/0/1	1.56%	1.34%	1.18%	0.99%	1.00%	0.98%	0.92%	0.71%	0.70%	0.37%	-1.19%	(-6.85)
1/1/1	0.89%	0.95%	0.97%	1.10%	1.01%	1.14%	0.93%	1.09%	1.02%	0.97%	0.07%	(0.60)
	CVOL-PVOL portfolios											
Strategies	1	2	3	4	5	6	7	8	9	10	C10-C1	t-statistics
1/0/1	0.00%	0.57%	0.65%	0.90%	0.87%	1.01%	1.18%	1.26%	1.46%	1.85%	1.84%	(9.13)
1/1/1	0.80%	0.95%	1.09%	0.90%	1.08%	1.04%	1.10%	1.03%	1.04%	1.03%	0.23%	(1.42)

Panel B. FF5 alpha for informed trading related portfolios

	Value-of-vote portfolio											
Strategies	1	2	3	4	5	6	7	8	9	10	V10-V1	t-statistics
1/0/1	0.50%	0.26%	0.32%	0.02%	0.02%	0.06%	-0.03%	-0.04%	-0.15%	-0.65%	-1.15%	(-4.90)
1/1/1	0.50%	0.18%	0.08%	0.10%	-0.02%	0.10%	0.06%	0.19%	0.00%	-0.54%	-1.04%	(-5.53)
	ΔPVOL – ΔCVOL portfolios											
Strategies	1	2	3	4	5	6	7	8	9	10	A10-A1	t-statistics
1/0/1	0.82%	0.62%	0.43%	0.23%	0.28%	0.23%	0.19%	-0.07%	-0.04%	-0.39%	-1.21%	(-6.48)
1/1/1	0.13%	0.20%	0.21%	0.40%	0.23%	0.40%	0.17%	0.34%	0.19%	0.17%	0.04%	(0.27)
	CVOL-PVOL portfolios											
Strategies	1	2	3	4	5	6	7	8	9	10	C10-C1	t-statistics
1/0/1	-0.78%	-0.22%	-0.09%	0.21%	0.21%	0.27%	0.45%	0.53%	0.66%	1.07%	1.85%	(8.78)
1/1/1	0.01%	0.13%	0.35%	0.18%	0.35%	0.29%	0.33%	0.26%	0.25%	0.30%	0.29%	(1.72)

Table A7. Time-series tests of *Value-of-Vote* quintile portfolios excluding stocks with extreme divergence between implied volatilities of put and call options

This table reports estimates of Fama-French three-, four- and five-factor alphas, for monthly excess returns on the equal-weighted *Value-of-Vote* quintile portfolios for a subsample of stocks in which ratio of put to call option implied volatility, *implied volatility ratio*, is between 10th and 90th percentile of its empirical distribution, which corresponds to 0.91 and 1.16, respectively. Each month firms are sorted into five groups based on the filtered *Value-of-Vote* that month. The dependent variable is the monthly *Value-of-Vote* quintile portfolio returns in excess of the one-month Treasury bill rate. Each anomaly factors are constructed using the stock's anomaly rankings and by getting the high minus low portfolio returns. Panel A reports risk-adjusted returns for *Value-of-Vote* quintile portfolios, alpha, using FF3 model plus anomaly factors such as idiosyncratic volatility factor ($\boldsymbol{\alpha}_{\mathbf{FF3+IVOL}}$), dispersion factor ($\boldsymbol{\alpha}_{\mathbf{FF5+DISP}}$), illiquidity factor ($\boldsymbol{\alpha}_{\mathbf{FF3+ILLIQ}}$), earnings surprise factor ($\boldsymbol{\alpha}_{\mathbf{FF3+SUE}}$), which are reported in each column, respectively. The last column reports the risk-adjusted return using FF3 model plus all anomaly factors mentioned above included at the same time ($\boldsymbol{\alpha}_{\mathbf{FF3+ALL}}$). Panels B and C report the same results for FF4 models ($\boldsymbol{\alpha}_{\mathbf{FF4+anomaly}}$) and FF5 models ($\boldsymbol{\alpha}_{\mathbf{FF5+anomaly}}$) respectively. Firms are held for one month. The sample period is from February, 1996 to September, 2015. *t*-statistics are in parentheses.

Panel A. Risk-adjusted return for FF3 model plus additional anomaly factors

Vote portfolio	$\boldsymbol{\alpha}_{\mathbf{FF3+IVOL}}$	$\boldsymbol{\alpha}_{\mathbf{FF3+DISP}}$	$\boldsymbol{\alpha}_{\mathbf{FF3+ILLIQ}}$	$\boldsymbol{\alpha}_{\mathbf{FF3+SUE}}$	$\boldsymbol{\alpha}_{\mathbf{FF3+ALL}}$
1 (Low)	0.42%	0.40%	0.27%	0.34%	0.42%
	(2.49)	(2.28)	(1.56)	(1.93)	(2.45)
2	0.18%	0.19%	0.19%	0.17%	0.20%
	(2.13)	(2.18)	(2.21)	(2.00)	(2.24)
3	0.00%	0.02%	0.00%	0.01%	0.02%
	(-0.04)	(0.30)	(-0.02)	(0.09)	(0.30)
4	0.05%	0.04%	-0.02%	0.00%	0.06%
	(0.46)	(0.44)	(-0.16)	(0.03)	(0.62)
5 (High)	-0.30%	-0.33%	-0.49%	-0.36%	-0.27%
	(-2.18)	(-2.26)	(-3.44)	(-2.46)	(-1.98)
V5-V1	-0.73%	-0.72%	-0.75%	-0.69%	-0.70%
(Vote_HML)	(-5.43)	(-5.39)	(-5.78)	(-5.24)	(-5.14)

Panel B. Risk-adjusted return for FF4 model plus additional anomaly factors

Vote portfolio	$\boldsymbol{\alpha}_{\mathbf{FF4+IVOL}}$	$\boldsymbol{\alpha}_{\mathbf{FF4+DISP}}$	$\boldsymbol{\alpha}_{\mathbf{FF4+ILLIQ}}$	$\boldsymbol{\alpha}_{\mathbf{FF4+SUE}}$	$\boldsymbol{\alpha}_{\mathbf{FF4+ALL}}$
1 (Low)	0.49%	0.48%	0.48%	0.41%	0.43%
	(3.48)	(3.37)	(3.43)	(2.97)	(3.05)
2	0.20%	0.21%	0.24%	0.19%	0.20%
	(2.48)	(2.53)	(3.02)	(2.37)	(2.44)
3	0.02%	0.05%	0.06%	0.03%	0.03%
	(0.31)	(0.66)	(0.90)	(0.41)	(0.37)
4	0.08%	0.08%	0.09%	0.04%	0.06%
	(0.91)	(0.94)	(1.06)	(0.46)	(0.76)
5 (High)	-0.23%	-0.24%	-0.27%	-0.29%	-0.27%
	(-2.29)	(-2.37)	(-2.73)	(-2.81)	(-2.62)
V5-V1	-0.72%	-0.72%	-0.75%	-0.70%	-0.70%
(Vote_HML)	(-5.41)	(-5.36)	(-5.67)	(-5.25)	(-5.14)

Panel C. Risk-adjusted return for FF5 model plus additional anomaly factors

Vote portfolio	$\boldsymbol{\alpha}_{\mathbf{FF4+IVOL}}$	$\boldsymbol{\alpha}_{\mathbf{FF4+DISP}}$	$\boldsymbol{\alpha}_{\mathbf{FF4+ILLIQ}}$	$\boldsymbol{\alpha}_{\mathbf{FF4+SUE}}$	$\boldsymbol{\alpha}_{\mathbf{FF4+ALL}}$
1 (Low)	0.42%	0.39%	0.33%	0.42%	0.40%
	(2.47)	(2.30)	(1.90)	(2.39)	(2.35)
2	0.16%	0.16%	0.16%	0.15%	0.17%
	(1.90)	(1.92)	(1.97)	(1.78)	(2.00)
3	0.01%	0.01%	0.00%	0.01%	0.02%
	(0.08)	(0.11)	(0.04)	(0.13)	(0.26)
4	0.03%	0.03%	0.01%	0.03%	0.04%
	(0.34)	(0.27)	(0.14)	(0.26)	(0.42)
5 (high)	-0.29%	-0.31%	-0.39%	-0.25%	-0.28%
	(-2.11)	(-2.18)	(-2.68)	(-1.77)	(-2.05)
V5-V1	-0.71%	-0.70%	-0.71%	-0.67%	-0.69%
(Vote_HML)	(-5.26)	(-5.23)	(-5.28)	(-4.97)	(-5.00)

Table A8: Time-series tests of *Value-of-Vote* quintile portfolios excluding stocks with extreme divergence between implied volatilities of put and call options

The table reports risk-adjusted returns using *Value-of-Vote* calculated using a filter to account for extreme put-call parity deviations. The *Value-of-Vote* is calculated using only samples where ratio of put implied volatilities and call implied volatilities is between 0.95 and 1.05. Each month firms are sorted into five groups based on the filtered *Value-of-Vote* during that month. The dependent variable is the monthly *Value-of-Vote* quintile portfolio returns in excess of the one-month Treasury bill rate. Each anomaly factors are constructed using the stock's anomaly rankings and by getting the high minus low portfolio returns. Panel A reports risk-adjusted returns for *Value-of-Vote* quintile portfolios, alpha, using FF3 model plus anomaly factors such as idiosyncratic volatility factor ($\boldsymbol{\alpha}_{\mathbf{FF3+IVOL}}$), dispersion factor ($\boldsymbol{\alpha}_{\mathbf{FF5+DISP}}$), illiquidity factor ($\boldsymbol{\alpha}_{\mathbf{FF3+ILLIQ}}$), earnings surprise factor ($\boldsymbol{\alpha}_{\mathbf{FF3+SUE}}$), which are reported in each column, respectively. The last column reports the risk-adjusted return using FF3 model plus all anomaly factors mentioned above included at the same time ($\boldsymbol{\alpha}_{\mathbf{FF3+ALL}}$). Panel B reports the risk-adjusted returns for *Value-of-Vote* quintile portfolios, alpha, using FF4 model plus additional anomaly factors explained above ($\boldsymbol{\alpha}_{\mathbf{FF4+anomaly}}$). Panel C reports the risk-adjusted return for *Value-of-Vote* quintile portfolios, alpha, using FF5 model plus additional anomaly factors explained above ($\boldsymbol{\alpha}_{\mathbf{FF5+anomaly}}$). Firms are held for one month. The sample period is from February, 1996 to September, 2015. t-statistics are in parentheses.

Panel A. Risk-adjusted return for FF3 model plus additional anomaly factors

Vote portfolio	$\boldsymbol{\alpha}_{\mathbf{FF3+IVOL}}$	$\boldsymbol{\alpha}_{\mathbf{FF3+DISP}}$	$\boldsymbol{\alpha}_{\mathbf{FF3+ILLIQ}}$	$\boldsymbol{\alpha}_{\mathbf{FF3+SUE}}$	$\boldsymbol{\alpha}_{\mathbf{FF3+ALL}}$
1 (Low)	0.35%	0.31%	0.20%	0.28%	0.35%
	(2.16)	(1.91)	(1.22)	(1.71)	(2.17)
2	0.19%	0.20%	0.18%	0.18%	0.20%
	(1.88)	(1.94)	(1.77)	(1.73)	(1.91)
3	0.01%	0.03%	0.04%	0.03%	0.02%
	(0.11)	(0.42)	(0.54)	(0.33)	(0.27)
4	-0.08%	-0.07%	-0.10%	-0.10%	-0.07%
	(-0.93)	(-0.85)	(-1.18)	(-1.11)	(-0.80)
5 (high)	-0.12%	-0.14%	-0.35%	-0.21%	-0.07%
	(-0.93)	(-1.05)	(-2.55)	(-1.54)	(-0.53)
V5-V1	-0.46%	-0.45%	-0.55%	-0.49%	-0.42%
(Vote_HML)	(-3.85)	(-3.76)	(-4.56)	(-4.06)	(-3.44)

Panel B. Risk-adjusted return for FF4 model plus additional anomaly factors

Vote portfolio	$\boldsymbol{\alpha}_{\mathbf{FF4+IVOL}}$	$\boldsymbol{\alpha}_{\mathbf{FF4+DISP}}$	$\boldsymbol{\alpha}_{\mathbf{FF4+ILLIQ}}$	$\boldsymbol{\alpha}_{\mathbf{FF4+SUE}}$	$\boldsymbol{\alpha}_{\mathbf{FF4+ALL}}$
1 (Low)	0.42%	0.40%	0.41%	0.35%	0.36%
	(3.26)	(3.09)	(3.25)	(2.81)	(2.80)
2	0.23%	0.24%	0.28%	0.22%	0.21%
	(2.55)	(2.62)	(3.09)	(2.42)	(2.29)
3	0.03%	0.05%	0.08%	0.04%	0.02%
	(0.34)	(0.63)	(1.04)	(0.53)	(0.30)
4	-0.05%	-0.05%	-0.03%	-0.07%	-0.07%
	(-0.69)	(-0.58)	(-0.37)	(-0.90)	(-0.85)
5 (high)	-0.05%	-0.06%	-0.14%	-0.15%	-0.06%
	(-0.59)	(-0.67)	(-1.45)	(-1.50)	(-0.65)
V5-V1	-0.47%	-0.46%	-0.55%	-0.50%	-0.42%
(Vote_HML)	(-3.94)	(-3.83)	(-4.52)	(-4.11)	(-3.48)

Panel C. Risk-adjusted return for FF5 model plus additional anomaly factors

Vote portfolio	$\boldsymbol{\alpha}_{\mathbf{FF5+IVOL}}$	$\boldsymbol{\alpha}_{\mathbf{FF5+DISP}}$	$\boldsymbol{\alpha}_{\mathbf{FF5+ILLIQ}}$	$\boldsymbol{\alpha}_{\mathbf{FF5+SUE}}$	$\boldsymbol{\alpha}_{\mathbf{FF5+ALL}}$
1 (Low)	0.34%	0.31%	0.25%	0.35%	0.34%
	(2.12)	(1.91)	(1.54)	(2.11)	(2.09)
2	0.16%	0.16%	0.14%	0.15%	0.16%
	(1.57)	(1.59)	(1.43)	(1.52)	(1.55)
3	0.01%	0.01%	0.02%	0.01%	0.02%
	(0.14)	(0.19)	(0.23)	(0.08)	(0.20)
4	-0.07%	-0.07%	-0.08%	-0.07%	-0.06%
	(-0.79)	(-0.83)	(-0.91)	(-0.84)	(-0.73)
5 (high)	-0.11%	-0.13%	-0.20%	-0.08%	-0.09%
	(-0.88)	(-0.95)	(-1.42)	(-0.58)	(-0.70)
V5-V1	-0.45%	-0.44%	-0.45%	-0.43%	-0.43%
(Vote_HML)	(-3.68)	(-3.57)	(-3.61)	(-3.42)	(-3.43)

Table A9. Accounting performance using alternative industry classification (FF48)

This table reports the one-year, two-year and three-year post operating performance for each of *Value-of-vote* quintile portfolios, and the one-year, two-year and three-year post changes in operating performance for each of *Value-of-vote* quintile portfolios relative to the pre-portfolio formation year. For each calendar year, firms are sorted based on annual *Value-of-vote*. The annual *Value-of-vote* is calculated as the median value of monthly *Value-of-Vote* for each year. Panel A reports ROA (NI/AT) adjusted by the average ROA of all companies in the same Fama-French 48 industry. Panel B reports profitability (EBITDA/AT) adjusted by the average profitability of all companies in the same Fama-French 48 industry. . Panel C reports changes in ROA (NI/AT) adjusted by the average ROA of all companies in the same Fama-French 48 industry. Panel D reports changes profitability (EBITDA/AT) adjusted by the average profitability of all companies in the same Fama-French 48 industry. The changes in performances are calculated for one- (1 yr), two- (2 yr) and three- years (3 yr) post to portfolio formation year relative to the prior to portfolio formation year (-1yr). t-statistics are reported in parentheses.

Panel A. Industry Adjusted (FF48) ROA

Value-of-vote Quintiles	ROA (+1 yr)	ROA (+2 yr)	ROA (+3 yr)
1 (Low)	0.02	0.03	0.03
2	0.06	0.06	0.06
3	0.04	0.04	0.04
4	0.03	0.03	0.03
5 (High)	0.17	0.19	0.24
V5 - V1	0.15	0.17	0.21
(Vote_HML)	(3.10)	(2.98)	(2.97)

Panel B. Industry Adjusted (FF48) Profitability (EBITDA/Asset)

Value-of-vote Quintiles	Profitability (+1 yr)	Profitability (+2 yr)	Profitability (+3 yr)
1 (Low)	0.02	0.02	0.02
2	0.06	0.06	0.06
3	0.05	0.05	0.05
4	0.04	0.04	0.04
5 (High)	0.18	0.20	0.25
V5 - V1	0.16	0.18	0.23
(Vote_HML)	(3.20)	(3.06)	(3.09)

Panel C. Change in ROA for *Value-of-vote* portfolio quintile

Value-of-vote Quintiles	ΔROA (+1 yr)	ΔROA (+2 yr)	ΔROA (+3 yr)
1 (Low)	-0.01	-0.01	-0.02
2	-0.02	-0.02	-0.02
3	-0.02	-0.02	-0.02
4	-0.01	-0.02	-0.02
5 (High)	0.04	0.07	0.12
V5 - V1	1.22	0.08	0.14
(Vote_HML)	(1.63)	(1.86)	(2.20)

Panel D. Change in Profitability for *Value-of-vote* portfolio quintile

Value-of-vote Quintiles	Δ Profitability (+1 yr)	Δ Profitability (+2 yr)	Δ Profitability (+3 yr)
1 (Low)	-0.01	-0.02	-0.02
2	-0.01	-0.01	-0.02
3	-0.01	-0.02	-0.02
4	-0.01	-0.01	-0.01
5 (High)	0.04	0.08	0.13
V5 - V1	0.06	0.10	0.15
(Vote_HML)	(1.65)	(1.94)	(2.28)

Table A10. FF3 and FF4 Alphas of double-sorting portfolios

The table reports FF3 alpha and FF4 alpha after controlling for each of firm characteristics mentioned in the first column in Panel A and B, respectively. We perform a double sort on firm characteristics, ΔPVOL-ΔCVOL, CVOL-PVOL, size, momentum, book-to-market (BTM), illiquidity, dispersion, idiosyncratic volatility (IVOL), standardized unexpected earnings (SUE), short-term reversal, option volume, option open interest and short interest ratio. First we sort stocks into five quintiles on the firm characteristic and then within each quintile we sort stocks based on *Value-of-vote*. The five value-of-vote portfolios are then averaged over each of the five characteristic portfolios. Then each of value-of-vote portfolio would represents *Value-of-vote* portfolios controlling for the characteristics. With this average *Value-of-vote* quintiles, we get alphas using Fama-French five-factor (FF5) model. (ΔPVOL-ΔCVOL) is the change in put and call implied volatility innovations as in An, Ang, Bali and Cikaci (2014). (CVOL-PVOL) is the implied volatility spread measured as in Cremers and Weinbaum (2010). Size is the market equity measured as the stock price times shares outstanding. Book-to-market (BTM) is the ratio of total book value of assets to book value of equity. Momentum is the past return from month t-12 to month t-2. Illiquidity is Amihud (2002)'s measure of illiquidity which is the ratio of the absolute monthly stock return to its dollar trading volume. The analysts forecast dispersion (DISP) is calculated as in Diether, Malloy and Scherbina (2002). Idiosyncratic volatility (IVOL) is measured as in Ang, Hodrick, Xing and Zhang (2006) which is the standard deviation of the residual from monthly regression of stock returns on Fama-French three factors (market, size and book-to-market factors) using daily returns. Standardized earnings surprise (SUE) is the difference between the actual earnings and the median of analysts' earnings forecasts normalized by the stock price. The short-term reversal is the return on the previous month (Ret_t-1). The Bid-Ask spread is the average daily bid-ask spread over the previous month. The (dollar) volume is the average daily dollar volume over the previous month. Option volume is the average daily call and put option volume over the previous month. Option open interest is the average daily call and put open interest over the previous month. Short interest ratio is the short interest divided by the total shares outstanding. All portfolios are equal weighted. The sample period is from February, 1996 to September, 2015. t-statistics are reported in parentheses.

Panel A. FF3 alphas (α_{FF3})	*Value-of-vote* portfolio					
	1 (Low)	2	3	4	5 (High)	V5-V1
Control for ΔPVOL-ΔCVOL	0.23%	0.19%	0.03%	-0.06%	-0.44%	-0.67%
	(1.34)	(2.01)	(0.31)	(-0.71)	(-3.59)	(-5.25)
Control for CVOL-PVOL	0.11%	0.15%	0.04%	-0.12%	-0.25%	-0.36%
	(0.71)	(1.56)	(0.52)	(-1.23)	(-2.00)	(-2.94)
Double Sort on Size	0.20%	0.24%	-0.05%	-0.07%	-0.42%	-0.62%
	(1.34)	(2.43)	(-0.53)	(-0.71)	(-3.75)	(-5.10)
Double sort on BTM	0.21%	0.23%	0.01%	-0.10%	-0.49%	-0.70%
	(1.34)	(2.17)	(0.12)	(-0.95)	(-3.82)	(-5.39)
Double sort on Momentum	0.29%	0.17%	-0.04%	-0.15%	-0.41%	-0.71%
	(2.07)	(1.58)	(-0.34)	(-1.41)	(-3.48)	(-6.40)
Double sort on Illiquidity	0.21%	0.18%	-0.02%	-0.12%	-0.40%	-0.61%
	(1.26)	(1.79)	(-0.21)	(-1.28)	(-3.22)	(-4.60)
Double sort on IVOL	0.24%	0.16%	-0.02%	-0.09%	-0.43%	-0.67%
	(1.51)	(1.48)	(-0.17)	(-0.89)	(-3.62)	(-5.99)
Double sort on Dispersion	0.27%	0.13%	-0.02%	-0.05%	-0.46%	-0.73%
	(1.49)	(1.37)	(-0.27)	(-0.51)	(-3.54)	(-5.59)
Double sort on SUE	0.33%	0.08%	-0.09%	-0.09%	-0.37%	-0.70%
	(1.91)	(0.85)	(-0.99)	(-0.90)	(-2.81)	(-5.42)
Double sort on short-term reversal	0.27%	0.10%	0.01%	-0.03%	-0.49%	-0.76%
	(1.60)	(0.96)	(0.13)	(-0.28)	(-3.54)	(-6.21)
Double sort on Stock Bid-Ask spread	0.18%	0.27%	0.06%	-0.13%	-0.52%	-0.70%
	(1.03)	(2.68)	(0.58)	(-1.27)	(-4.10)	(-5.38)
Double sort on Stock Volume	0.18%	0.19%	0.06%	-0.11%	-0.47%	-0.65%
	(1.04)	(1.99)	(0.64)	(-1.20)	(-3.52)	(-4.79)
Double sort on Option Volume	0.25%	0.22%	0.04%	-0.05%	-0.56%	-0.82%
	(1.38)	(2.48)	(0.54)	(-0.55)	(-3.89)	(-5.64)
Double sort on Option Open Interest	0.23%	0.22%	0.04%	-0.08%	-0.52%	-0.75%
	(1.25)	(2.48)	(0.50)	(-0.88)	(-3.52)	(-5.47)
Double sort on Short Interest Ratio	0.25%	0.22%	-0.05%	-0.03%	-0.48%	-0.73%
	(1.42)	(2.15)	(-0.58)	(-0.36)	(-3.60)	(-5.64)

Panel B. FF4 alphas ($\boldsymbol{\alpha}_{\mathbf{FF4}}$)	*Value-of-vote* portfolio					
	1 (Low)	2	3	4	5 (High)	V5-V1
Control for ΔPVOL-ΔCVOL	0.45%	0.26%	0.10%	0.04%	-0.27%	-0.71%
	(3.34)	(2.93)	(1.28)	(0.55)	(-2.93)	(-5.61)
Control for CVOL-PVOL	0.31%	0.23%	0.12%	-0.01%	-0.07%	-0.39%
	(2.40)	(2.62)	(1.60)	(-0.09)	(-0.79)	(-3.12)
Double Sort on Size	0.39%	0.34%	0.05%	0.05%	-0.26%	-0.65%
	(3.23)	(3.77)	(0.52)	(0.67)	(-3.16)	(-5.30)
Double sort on BTM	0.41%	0.32%	0.12%	0.01%	-0.31%	-0.72%
	(3.19)	(3.30)	(1.43)	(0.13)	(-3.23)	(-5.47)
Double sort on Momentum	0.46%	0.28%	0.09%	-0.02%	-0.27%	-0.73%
	(3.93)	(3.08)	(1.08)	(-0.19)	(-2.76)	(-6.59)
Double sort on Illiquidity	0.43%	0.28%	0.07%	-0.02%	-0.22%	-0.64%
	(3.20)	(2.94)	(0.85)	(-0.20)	(-2.44)	(-4.85)
Double sort on IVOL	0.46%	0.26%	0.08%	0.01%	-0.26%	-0.72%
	(3.72)	(2.63)	(0.94)	(0.16)	(-2.97)	(-6.46)
Double sort on Dispersion	0.51%	0.20%	0.06%	0.05%	-0.28%	-0.79%
	(3.68)	(2.23)	(0.78)	(0.62)	(-2.86)	(-6.11)
Double sort on SUE	0.56%	0.16%	0.00%	0.02%	-0.19%	-0.75%
	(4.11)	(1.79)	(0.00)	(0.22)	(-1.90)	(-5.81)
Double sort on short-term reversal	0.50%	0.18%	0.09%	0.08%	-0.29%	-0.80%
	(3.97)	(1.85)	(1.07)	(0.89)	(-2.86)	(-6.52)
Double sort on Stock Bid-Ask spread	0.42%	0.34%	0.15%	-0.01%	-0.34%	-0.77%
	(3.05)	(3.51)	(1.70)	(-0.15)	(-3.60)	(-5.93)
Double sort on Stock Volume	0.41%	0.27%	0.15%	-0.01%	-0.27%	-0.67%
	(2.95)	(2.95)	1.70	(-0.14)	(-2.87)	(-4.96)
Double sort on Option Volume	0.50%	0.27%	0.10%	0.04%	-0.34%	-0.84%
	(3.43)	(3.15)	(1.38)	(0.50)	(-3.42)	(-5.73)
Double sort on Option Open Interest	0.48%	0.28%	0.10%	0.01%	-0.29%	-0.77%
	(3.27)	(3.16)	(1.36)	(0.10)	(-2.89)	(-5.57)
Double sort on Short Interest Ratio	0.47%	0.29%	0.02%	0.07%	-0.29%	-0.76%
	(3.48)	(3.08)	(0.27)	(0.90)	(-2.98)	(-5.86)

Table A11. Different portfolio formation periods

The table reports Fama-French three- and four- factor alphas for *Value-of-vote* quintile portfolios using various combinations of portfolio formation periods. We use L/M/N portfolio strategy as in Jegadeesh and Titman (1993) and Ang, Hodrick, Xing and Zhang (2006). We use t-L-M month to t-M month moving average *Value-of-vote* to form quintile portfolios at month t, hold these portfolios for N months. At month t, we compute *Value-of-vote* quintile portfolios using *Value-of-vote* for that month and hold these portfolios for one month, which is 1/0/1 strategy. For example, to construct 6/1/1 quintile portfolios, each month we construct equal-weighted *Value-of-vote* quintile portfolio based on moving average of previous 6 months of *Value-of-vote* ending in 1 month prior to the formation date, and hold these portfolios. To construct 12/1/1 portfolios, each month we construct equal-weighted *Value-of-vote* quintile portfolio based on the moving average of past 12 months of *Value-of-vote* ending 1-month prior to the formation date, and hold these portfolios for 1 month and so on. Using various combinations of portfolio formation periods, Panel A reports Fama-French 3 factor alphas and Panel B reports Fama-French 4 factor alpha. The sample period is from February, 1995 to September, 2015. t-statistics are in parentheses.

Panel A. FF3 alphas ($\boldsymbol{\alpha_{FF3}}$)

strategies	*Value-of-vote* portfolio Rankings					
	1 (Low)	2	3	4	5 (High)	V5-V1
1/1/1	0.22%	0.05%	0.07%	0.05%	-0.34%	-0.57%
	(1.04)	(0.51)	(0.76)	(0.54)	(-2.26)	(-3.84)
1/2/1	0.20%	0.11%	0.03%	0.03%	-0.31%	-0.51%
	(1.00)	(1.05)	(0.31)	(0.27)	(-1.95)	(-3.51)
6/0/1	0.28%	0.16%	0.07%	0.04%	-0.37%	-0.64%
	(1.60)	(1.49)	(0.75)	(0.38)	(-2.69)	(-4.51)
6/1/1	0.32%	0.07%	0.15%	0.04%	-0.21%	-0.53%
	(1.62)	(0.65)	(1.51)	(0.43)	(-1.44)	(-3.59)
12/0/1	0.38%	0.15%	0.12%	0.10%	-0.20%	-0.58%
	(2.40)	(1.31)	(1.16)	(0.93)	(-1.53)	(-4.05)
12/1/1	0.35%	0.21%	0.14%	0.06%	-0.08%	-0.44%
	(2.05)	(1.82)	(1.33)	(0.54)	(-0.62)	(-2.85)

Panel B. FF4 alphas ($\boldsymbol{\alpha_{FF4}}$)

strategies	*Value-of-vote* portfolio Rankings					
	1 (Low)	2	3	4	5 (High)	V5-V1
1/1/1	0.52%	0.15%	0.11%	0.13%	-0.12%	-0.64%
	(3.31)	(1.69)	(1.32)	(1.62)	(-1.08)	(-4.42)
1/2/1	0.49%	0.23%	0.11%	0.13%	-0.07%	-0.57%
	(3.30)	(2.57)	(1.29)	(1.44)	(-0.65)	(-3.92)
6/0/1	0.52%	0.28%	0.14%	0.14%	-0.18%	-0.70%
	(4.04)	(2.82)	(1.61)	(1.60)	(-1.72)	(-4.95)
6/1/1	0.60%	0.19%	0.23%	0.15%	0.00%	-0.60%
	(4.03)	(2.02)	(2.63)	(1.75)	(0.00)	(-4.06)
12/0/1	0.59%	0.26%	0.22%	0.23%	-0.05%	-0.64%
	(4.71)	(2.63)	(2.34)	(2.53)	(-0.49)	(-4.50)
12/1/1	0.56%	0.33%	0.25%	0.20%	0.06%	-0.50%
	(4.15)	(3.27)	(2.77)	(2.07)	(0.55)	(-3.29)

Table A12. Subsample Analysis

The table reports risk-adjusted return, alpha, for the *value-of-vote* quintile portfolios estimated for the subsample periods. Each month firms are sorted into five groups based on the *value-of-vote* that month. The dependent variable is the monthly equal-weighted *value-of-vote* quintile portfolio returns in excess of the one-month Treasury bill rate. In each panel, the six columns from the left report results using the first half of the sample period which is from year 1996 to 2006. The six columns from the right report results using the second half of the sample period which is from year 2009 to 2015. We observe pre- and post- sample of financial crisis period (2007-2009) excluding the period. The Panel A reports risk-adjusted returns for value-of-vote quintile portfolios, α (alpha), using the FF3 model (α_{FF3}) only, FF3 model plus anomaly factors such as idiosyncratic volatility factor ($\alpha_{FF3+IVOL}$), dispersion factor ($\alpha_{FF3+DISP}$), illiquidity factor ($\alpha_{FF3+ILLIQ}$), earnings surprise factor ($\alpha_{FF3+SUE}$), which are reported in each column, respectively. The last columns within each subsample period report the risk-adjusted return using FF3 model plus all anomaly factors mentioned above included at the same time ($\alpha_{FF3+ALL}$). Each anomaly factors are constructed using the stock's anomaly rankings and by getting the high minus low portfolio returns. Panel B reports the risk-adjusted returns for *value-of-vote* quintile portfolios, α (alpha), using FF4 model (α_{FF4}) only, FF4 model plus additional anomaly factors explained above ($\alpha_{FF4+Anomaly}$). Panel C reports the risk-adjusted return for *value-of-vote* quintile portfolios, α (alpha), using FF5 model (α_{FF5}) only, FF5 model plus additional anomaly factors explained above ($\alpha_{FF5+Anomaly}$). t-statistics are in parentheses.

Panel A. Risk-adjusted return using FF3 factor model plus other additional anomaly factors

Value-of-Vote	Subsample: 1996-2006						Subsample: 2009-2015					
portfolio	α_{FF3}	$\alpha_{FF3+IVOL}$	$\alpha_{FF3+DISP}$	$\alpha_{FF3+ILLIQ}$	$\alpha_{FF3+SUE}$	$\alpha_{FF3+ALL}$	α_{FF3}	$\alpha_{FF3+IVOL}$	$\alpha_{FF3+DISP}$	$\alpha_{FF3+ILLIQ}$	$\alpha_{FF3+SUE}$	$\alpha_{FF3+ALL}$
1 (Low)	0.160%	0.390%	0.270%	0.120%	0.240%	0.340%	0.310%	0.320%	0.420%	0.210%	0.330%	0.290%
	(0.52)	(1.28)	(0.87)	(0.38)	(0.78)	(1.14)	(2.01)	(2.32)	(3.03)	(1.56)	(2.15)	(2.25)
2	0.090%	0.110%	0.110%	0.110%	0.090%	0.140%	0.090%	0.090%	0.130%	0.090%	0.090%	0.150%
	(0.62)	(0.71)	(0.72)	(0.72)	(0.63)	(0.94)	(0.93)	(0.97)	(1.49)	(0.94)	(0.94)	(1.63)
3	-0.070%	-0.060%	-0.050%	-0.060%	-0.060%	-0.030%	0.100%	0.110%	0.150%	0.090%	0.120%	0.130%
	(-0.58)	(-0.49)	(-0.42)	(-0.50)	(-0.49)	(-0.24)	(1.03)	(1.16)	(1.57)	(0.90)	(1.28)	(1.34)
4	-0.260%	-0.190%	-0.220%	-0.260%	-0.250%	-0.170%	0.060%	0.070%	0.150%	0.020%	0.110%	0.100%
	(-1.85)	(-1.37)	(-1.58)	(-1.82)	(-1.75)	(-1.23)	(0.53)	(0.68)	(1.43)	(0.18)	(0.99)	(1.05)
5 (High)	-0.580%	-0.460%	-0.530%	-0.610%	-0.530%	-0.480%	-0.270%	-0.260%	-0.070%	-0.380%	-0.150%	-0.180%
	(-2.76)	(-2.22)	(-2.54)	(-2.97)	(-2.55)	(-2.34)	(-1.13)	(-1.50)	(-0.35)	(-1.66)	(-0.75)	(-1.15)
V5-V1	-0.750%	-0.840%	-0.790%	-0.730%	-0.770%	-0.830%	-0.580%	-0.570%	-0.480%	-0.590%	-0.480%	-0.470%
(Vote_HML)	(-3.56)	(-4.06)	(-3.83)	(-3.50)	(-3.67)	(-3.92)	(-2.85)	(-3.12)	(-2.49)	(-2.84)	(-2.78)	(-2.65)

Panel B. Risk-adjusted return using FF4 factor model plus other additional anomaly factors

Value-of-Vote portfolio	Subsample: 1996-2006						Subsample: 2009-2015					
	α_{FF4}	$\alpha_{FF4+IVOL}$	$\alpha_{FF4+DISP}$	$\alpha_{FF4+ILLIQ}$	$\alpha_{FF4+SUE}$	$\alpha_{FF4+ALL}$	α_{FF4}	$\alpha_{FF4+IVOL}$	$\alpha_{FF4+DISP}$	$\alpha_{FF4+ILLIQ}$	$\alpha_{FF4+SUE}$	$\alpha_{FF4+ALL}$
1 (Low)	0.620%	0.650%	0.630%	0.610%	0.610%	0.640%	0.280%	0.290%	0.340%	0.200%	0.230%	0.200%
	(2.72)	(2.84)	(2.75)	(2.64)	(2.68)	(2.72)	(2.18)	(2.27)	(2.63)	(1.78)	(1.84)	(1.75)
2	0.210%	0.190%	0.210%	0.270%	0.200%	0.250%	0.070%	0.070%	0.100%	0.080%	0.040%	0.100%
	(1.54)	(1.37)	(1.51)	(2.06)	(1.47)	(1.90)	(0.85)	(0.83)	(1.16)	(0.95)	(0.47)	(1.17)
3	0.010%	-0.010%	0.010%	0.050%	0.010%	0.040%	0.080%	0.090%	0.090%	0.080%	0.070%	0.080%
	(0.08)	(-0.05)	(0.09)	(0.44)	(0.06)	(0.35)	(0.97)	(1.02)	(1.05)	(0.95)	(0.83)	(0.86)
4	-0.100%	-0.100%	-0.100%	-0.060%	-0.110%	-0.050%	0.030%	0.040%	0.070%	0.010%	0.040%	0.040%
	(-0.83)	(-0.79)	(-0.78)	(-0.49)	(-0.92)	(-0.43)	(0.36)	(0.46)	(0.78)	(0.11)	(0.41)	(0.49)
5 (High)	-0.260%	-0.260%	-0.260%	-0.260%	-0.270%	-0.260%	-0.340%	-0.320%	-0.250%	-0.400%	-0.310%	-0.310%
	(-1.79)	(-1.78)	(-1.81)	(-1.76)	(-1.84)	(-1.76)	(-2.46)	(-2.47)	(-1.87)	(-3.08)	(-2.19)	(-2.39)
V5-V1	-0.880%	-0.910%	-0.890%	-0.870%	-0.880%	-0.900%	-0.620%	-0.610%	-0.590%	-0.600%	-0.530%	-0.510%
(Vote_HML)	(-4.34)	(-4.48)	(-4.40)	(-4.23)	(-4.32)	(-4.33)	(-3.50)	(-3.46)	(-3.24)	(-3.37)	(-3.16)	(-2.86)

Panel C. Risk-adjusted return using FF5 factor model plus other additional anomaly factors

Value-of-Vote portfolio	Subsample: 1996-2006						Subsample: 2009-2015					
	α_{FF5}	$\alpha_{FF5+IVOL}$	$\alpha_{FF5+DISP}$	$\alpha_{FF5+ILLIQ}$	$\alpha_{FF5+SUE}$	$\alpha_{FF5+ALL}$	α_{FF5}	$\alpha_{FF5+IVOL}$	$\alpha_{FF5+DISP}$	$\alpha_{FF5+ILLIQ}$	$\alpha_{FF5+SUE}$	$\alpha_{FF5+ALL}$
1 (Low)	0.34%	0.39%	0.26%	0.24%	0.39%	0.28%	0.34%	0.36%	0.37%	0.22%	0.36%	0.29%
	(1.09)	(1.29)	(0.83)	(0.76)	(1.26)	(0.94)	(2.36)	(2.73)	(2.83)	(1.61)	(2.52)	(2.31)
2	0.11%	0.12%	0.08%	0.14%	0.12%	0.12%	0.11%	0.14%	0.12%	0.13%	0.11%	0.19%
	(0.74)	(0.78)	(0.53)	(0.93)	(0.78)	(0.81)	(1.27)	(1.58)	(1.44)	(1.50)	(1.24)	(2.17)
3	-0.05%	-0.04%	-0.08%	-0.03%	-0.04%	-0.04%	0.11%	0.11%	0.13%	0.10%	0.12%	0.12%
	(-0.40)	(-0.37)	(-0.66)	(-0.22)	(-0.32)	(-0.36)	(1.21)	(1.19)	(1.39)	(1.03)	(1.32)	(1.26)
4	-0.19%	-0.18%	-0.23%	-0.18%	-0.19%	-0.20%	0.09%	0.09%	0.11%	0.04%	0.12%	0.10%
	(-1.36)	(-1.29)	(-1.67)	(-1.25)	(-1.31)	(-1.39)	(0.82)	(0.91)	(1.18)	(0.37)	(1.15)	(1.02)
5 (High)	-0.50%	-0.47%	-0.54%	-0.56%	-0.47%	-0.52%	-0.11%	-0.18%	-0.06%	-0.25%	-0.04%	-0.19%
	(-2.33)	(-2.29)	(-2.56)	(-2.63)	(-2.22)	(-2.51)	(-0.54)	(-1.06)	(-0.33)	(-1.23)	(-0.25)	(-1.22)
V5-V1	-0.84%	-0.86%	-0.80%	-0.79%	-0.86%	-0.80%	-0.46%	-0.54%	-0.43%	-0.47%	-0.41%	-0.48%
(Vote_HML)	(-4.03)	(-4.22)	(-3.86)	(-3.81)	(-4.13)	(-3.87)	(-2.41)	(-3.00)	(-2.36)	(-2.41)	(-2.34)	(-2.74)

Table A13. Risk-adjusted return using Value-of-Vote portfolios without stock price less than $5

The table reports time-series test results using *Value-of-Vote* equal-weighted portfolio, where the sample only includes stock price higher than $5. Each month firms are sorted into five groups based on the *Value-of-Vote* that month. *Value-of-Vote* is calculated from put-call parity condition explained in text. Panel A reports risk-adjusted returns for *Value-of-Vote* quintile portfolios, alpha, using the FF3 model ($\boldsymbol{\alpha_{FF3}}$) only, FF3 model plus anomaly factors such as idiosyncratic volatility factor ($\boldsymbol{\alpha_{FF3+IVOL}}$), dispersion factor ($\boldsymbol{\alpha_{FF3+DISP}}$), illiquidity factor ($\boldsymbol{\alpha_{FF3+ILLIQ}}$), earnings surprise factor ($\boldsymbol{\alpha_{FF3+SUE}}$), which are reported in each column, respectively. The last column reports the risk-adjusted return using FF3 model plus all anomaly factors mentioned above included at the same time ($\boldsymbol{\alpha_{FF3+ALL}}$). Each anomaly factors are constructed using the stock's anomaly rankings and by getting the high minus low portfolio returns. Panel B reports the risk-adjusted returns for *Value-of-Vote* quintile portfolios, alpha, using FF4 model ($\boldsymbol{\alpha_{FF4}}$) only, FF4 model plus additional anomaly factors explained above ($\boldsymbol{\alpha_{FF4+anomaly}}$). Panel C reports the risk-adjusted return for *Value-of-Vote* quintile portfolios, alpha, using FF5 model ($\boldsymbol{\alpha_{FF5}}$) only, FF5 model plus additional anomaly factors explained above ($\boldsymbol{\alpha_{FF5+anomaly}}$). Firms are held for one month. The sample period is from February, 1996 to September, 2015. t-statistics are in parentheses.

Panel A. Risk-adjusted return using FF3 model plus additional anomaly factors

Vote portfolio	α_{FF3}	$\alpha_{FF3+IVOL}$	$\alpha_{FF3+DISP}$	$\alpha_{FF3+ILLIQ}$	$\alpha_{FF3+SUE}$	$\alpha_{FF3+ALL}$
1 (Low)	0.16%	0.23%	0.21%	0.16%	0.20%	0.23%
	(1.13)	(1.61)	(1.43)	(1.14)	(1.37)	(1.55)
2	0.12%	0.12%	0.12%	0.12%	0.10%	0.12%
	(1.42)	(1.41)	(1.32)	(1.42)	(1.10)	(1.36)
3	-0.01%	-0.01%	0.01%	-0.01%	0.00%	0.01%
	(-0.07)	(-0.08)	(0.12)	(-0.08)	(-0.06)	(0.20)
4	-0.12%	-0.09%	-0.09%	-0.12%	-0.14%	-0.09%
	(-1.43)	(-1.06)	(-0.99)	(-1.42)	(-1.53)	(-1.04)
5 (High)	-0.62%	-0.54%	-0.56%	-0.61%	-0.56%	-0.53%
	(-5.49)	(-4.80)	(-4.87)	(-5.52)	(-4.92)	(-4.64)
V5-V1	-0.78%	-0.77%	-0.76%	-0.78%	-0.76%	-0.76%
(Vote_HML)	(-6.66)	(-6.46)	(-6.37)	(-6.65)	(-6.35)	(-6.21)

Panel B. Risk-adjusted return using FF4 model plus additional anomaly factors

Vote portfolio	α_{FF4}	$\alpha_{FF4+IVOL}$	$\alpha_{FF4+DISP}$	$\alpha_{FF4+ILLIQ}$	$\alpha_{FF4+SUE}$	$\alpha_{FF4+ALL}$
1 (Low)	0.30%	0.28%	0.26%	0.30%	0.25%	0.23%
	(2.37)	(2.18)	(2.05)	(2.37)	(1.94)	(1.80)
2	0.17%	0.15%	0.14%	0.18%	0.12%	0.12%
	(2.09)	(1.72)	(1.66)	(2.21)	(1.46)	(1.51)
3	0.03%	0.01%	0.02%	0.04%	0.01%	0.02%
	(0.44)	(0.12)	(0.32)	(0.51)	(0.13)	(0.23)
4	-0.06%	-0.07%	-0.06%	-0.05%	-0.11%	-0.09%
	(-0.69)	(-0.84)	(-0.75)	(-0.66)	(-1.36)	(-1.12)
5 (High)	-0.48%	-0.49%	-0.50%	-0.48%	-0.51%	-0.53%
	(-5.20)	(-5.28)	(-5.35)	(-5.20)	(-5.55)	(-5.55)
V5-V1	-0.78%	-0.77%	-0.77%	-0.78%	-0.76%	-0.76%
(Vote_HML)	(-6.61)	(-6.46)	(-6.37)	(-6.61)	(-6.36)	(-6.20)

Panel C. Risk-adjusted return using FF5 model plus additional anomaly factors

Vote portfolio	α_{FF5}	$\alpha_{FF5+IVOL}$	$\alpha_{FF5+DISP}$	$\alpha_{FF5+ILLIQ}$	$\alpha_{FF5+SUE}$	$\alpha_{FF5+ALL}$
1 (Low)	0.18%	0.21%	0.19%	0.16%	0.21%	0.20%
	(1.24)	(1.45)	(1.32)	(1.11)	(1.44)	(1.41)
2	0.09%	0.11%	0.10%	0.10%	0.08%	0.11%
	(1.09)	(1.21)	(1.13)	(1.22)	(0.95)	(1.22)
3	0.00%	0.00%	0.00%	0.01%	0.00%	0.02%
	(-0.03)	(0.02)	(0.04)	(0.09)	(0.01)	(0.22)
4	-0.09%	-0.08%	-0.09%	-0.09%	-0.10%	-0.09%
	(-1.08)	(-0.92)	(-1.00)	(-1.05)	(-1.17)	(-0.99)
5 (High)	-0.55%	-0.54%	-0.54%	-0.56%	-0.51%	-0.53%
	(-4.89)	(-4.82)	(-4.80)	(-5.03)	(-4.53)	(-4.69)
V5-V1	-0.72%	-0.74%	-0.72%	-0.72%	-0.71%	-0.73%
(Vote_HML)	(-5.96)	(-6.07)	(-5.93)	(-5.91)	(-5.81)	(-5.87)