

UNIVERSITY OF MICHIGAN

# Funds of a feather: Influencing corporate elections by voting together

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## Abstract

I analyze the role of shareholders' portfolio / ownership structure on voting participation in director elections. I find that portfolio composition matters for how mutual funds vote. Funds with more similar portfolios are more likely to cast identical votes. An increase in within-group similarity of mutual funds' portfolios leads to an increase in the number of broker "Non-Votes". Thus, highly diversified horizontal shareholding causes lower participation ("rational apathy") among other shareholders. This effect gives widely diversified cohorts of mutual funds, shareholders of the firm, a higher marginal influence at director elections than their plain share of ownership would suggest.

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# 1 Introduction

The dramatic rise of institutional equity ownership over the last few decades warrants greater scrutiny over the effects it may have on corporate governance of the U.S. public firms.<sup>1</sup> Close attention in the literature is placed on the role of the “Big Three” (BlackRock, Vanguard, and State Street) as they command substantial shares in the largest U.S. companies and frequently populate the lists of top beneficiaries of respective companies.<sup>2</sup> Studies have shown that individual mutual funds within a mutual fund family tend to exhibit similar voting behavior at corporate elections.<sup>3</sup> By voting in a lockstep, a group of shareholders might exercise greater influence on company’s governance. While literature views mutual fund families as blockholders, much less attention is devoted to study correlated voting behavior among non-related investors, e.g., individual mutual funds belonging to different families.

In this article, I explore the factors that are associated with higher chances that a pair of shareholders makes the same voting decision at corporate elections. I do this by observing votes of individual mutual funds at director elections. Then, I study how one such factor, similarity of shareholders’ portfolios, affects shareholder participation.

I find a positive relationship between portfolio similarity of a pair of mutual funds and probability of their voting decisions being the same. I show that greater portfolio similarity among mutual funds leads to lower participation of other shareholders in director elections.

Theoretical literature provides a classical result, Fisher separation theorem (Fisher, 1930), that shareholders with heterogeneous portfolios should unanimously agree on actions that maximize a firm’s profit under the necessary assumption that firms are price-takers (Milne, 1974; Hart, 1979; DeAngelo, 1981). Therefore, we should not observe heterogeneity in shareholders’ voting decisions that is based on differences in their portfolios. The observed correlation between portfolio structure and voting decisions suggests that the price taking assumption is most likely violated (and shareholders no longer unanimously want to maximize the firm’s profits).<sup>4</sup> In the absence

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<sup>1</sup>Backus et al. (2019b); Baig et al. (2018)

<sup>2</sup>Bebchuk & Hirst (2019); Coates (2018)

<sup>3</sup>Fichtner et al. (2017)

<sup>4</sup>The other possible explanations might include limited ability of shareholders to collect and process information, thus differences in portfolio structures may correlate with differences in opinions of what is best for profit maximization.

of perfect competition, profit maximization is less likely to be a firm’s objective (Hansen & Lott, 1996; Gordon, 2003). Contemporaneous literature suggests that maximization of a weighted sum of profits of shareholders’ portfolios might be a reasonable alternative objective (Salop & O’Brien (2000); Azar (2017); Brito et al. (2018), see also Schmalz (2018) for a detailed review). Thus, a shareholder who wants to maximize the value of her portfolio may want to account for the effects of between-firms externalities when setting the firm’s objective through voting at corporate elections.

Mutual funds’ investment advisers have a fiduciary duty to vote proxies “in a manner consistent with the best interest of the fund and its shareholders” (SEC, 2003). This ensures high turnout by mutual funds at corporate elections and, in conjunction with imperfect competition, provides a testable hypothesis about their voting patterns. Under imperfect competition governance decisions at one firm may affect the financial outcomes of other firms. Therefore, a mutual fund, which strives to maximize its portfolio profit,<sup>5</sup> must internalize the effect of a voting outcome at one firm on the value of other firms in its portfolio. I reject the hypothesis that mutual funds’ voting decisions are not related to their portfolios by observing a positive correlation between portfolio similarity and voting decisions.

This work contributes to the literature in three main ways. First, I study the voting behavior of individual mutual funds. Iliev & Lowry (2015) find that funds, that have higher net benefits of voting, more often vote independently of Institutional Shareholder Services (ISS) recommendation.<sup>6</sup> Fichtner et al. (2017) demonstrate that the “Big Three” families of mutual funds utilize coordinated voting strategies. Schwartz-Ziv & Wermers (2019) observe that institutional investors, when making voting decisions, account for firm’s weight in their portfolio and their fraction-of-company investments. In contrast to the existing literature, I study how differences in characteristics of mutual funds affect the probability of them making the same voting decisions. I find that a mutual fund’s family has a significant impact on the fund’s voting behavior. This result goes in line with Fichtner et al. (2017), as funds from the same family tend to agree on voting decisions. I then discover that funds with more similar portfolios tend to cast identical votes more often. This find-

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<sup>5</sup>In a more realistic scenario a mutual fund would want to maximize profit of its portfolio subject to a variance constraint. Since between-firm externalities shape the joint distribution of fund’s holdings’ payoffs, the fund should internalize the effect of voting outcome at one firm on this joint distribution of payoffs. This would require mutual fund to account for its entire portfolio composition when voting at a single firm.

<sup>6</sup>Institutional Shareholder Services (ISS) is the largest proxy advisory firm. It routinely issues voting recommendations regarding how investors should vote on corporate questions.

ing provides evidence that individual mutual fund’s portfolio structure is taken into account by the decision-making body. Unlike [Schwartz-Ziv & Wermers \(2019\)](#), I find that portfolio structure at the individual fund level explains the fund’s voting behavior better than portfolio structure of its mutual fund family.<sup>7</sup> I also find that favorable ISS recommendation reduces chances of disagreement between the funds. This result adds to the literature of mutual funds’ reliance on Institutional Shareholder Services (ISS) and management recommendations on voting decisions ([Choi et al., 2009, 2010](#); [Iliev & Lowry, 2015](#); [Malenko & Shen, 2016](#); [Malenko & Malenko, 2019](#)).

Second, I investigate how highly diversified horizontal shareholders<sup>8</sup> affect a company’s governance process. My analysis shows that portfolio structure affects both: individual mutual funds’ voting decisions and participation at directors elections as a whole. This contributes to the literature on the effects of horizontal shareholding and cross-ownership ([Backus et al., 2019a](#); [Elhauge, 2019a,b,c](#); [Morton & Hovenkamp, 2018](#); [Brito et al., 2019](#); [He et al., 2019](#)). I establish that higher portfolio similarity of mutual funds causes lower turnout at director elections by other shareholders. This adds to the literature on rational apathy of investors ([Jill E. Fisch, 2017](#); [Nili & Kastiel, 2016](#)), network effects on voting ([Enriques & Romano, 2018](#)), and shareholder free-riding ([Lafarre, 2017](#); [Cvijanovic et al., 2019](#)). Third, I extend the cosine portfolio similarity measure ([Bohlin & Rosvall, 2014](#); [Sias et al., 2013](#); [Getmansky et al., 2018](#); [Backus et al., 2019b](#)) to evaluate portfolio similarity within sets of more than two shareholders.

This paper also provides a bridge between the literature examining the growth of large index fund families ([Bebchuk & Hirst, 2019](#); [Coates, 2018](#)) and the literature on horizontal shareholding ([Elhauge, 2019a,b,c](#); [Morton & Hovenkamp, 2018](#); [Brito et al., 2019](#); [He et al., 2019](#)). The former focuses on the power of small groups of exceptionally large mutual funds families in influencing corporate decision making, while the latter considers investors, not necessarily large ones, that hold multiple competitors in the same product market simultaneously. I observe that a mutual fund family is not the only source of power centralization. Since an increase in portfolio similarity tends to correlate with probability of different individual mutual funds making the same voting decisions, I infer that the boundaries between different mutual fund families might be blurred by the disperse

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<sup>7</sup>In an unreported regression, I study how similarity of mutual fund families’ portfolios affect the probability that funds from different families make identical voting decisions. After conditioning on the same mutual funds’ and their families’ characteristics I do not find a statistically significant relationship.

<sup>8</sup>[Elhauge \(2019a\)](#) defines horizontal shareholding as an overlap of leading shareholders of horizontal competitors.

nature of their funds' portfolios. Therefore, not only the number and size of the top mutual fund families matter for concentration of decision making power, but also their, and other shareholders, degree of portfolio similarity, which is driven up by diversification and horizontal shareholding.<sup>9</sup>

Free-riding is a possible explanation for lower turnout of shareholders at elections with high portfolio similarity among mutual funds. Retail shareholders may expect mutual funds votes to be aligned with their position (Cvijanovic et al., 2019); as well as shareholders may decide not to vote if they are less informed and want more informed voters to participate instead (Feddersen & Pesendorfer, 1996).

Alternative possible channels might include shareholders' rational apathy. In the previous chapter, I establish a firm's objective function and find that a firm pays greater attention to shareholders with correlated voting decisions than to the ones with no or negative correlation. Then, a reasonable explanation for the causal effect of portfolio similarity on shareholder turnout might be the perception of other shareholders that mutual funds are more likely to vote the same way as a block. Thus, other shareholders might perceive themselves to have a smaller impact on the election outcome and hence rationally decide to not take part in the elections. Literature attributes rational apathy to a lack of sufficient stake, a lack of ability to make an informed decision, and to the dispersion of ownership (Jill E. Fisch, 2017; Nili & Kastiel, 2016).

Following the literature, I define portfolio similarity measure as a dot product of corresponding portfolio vectors for a pair of mutual funds (Getmansky et al., 2018; Sias et al., 2013; Bohlin & Rosvall, 2014). This measure is also known as cosine similarity. I extend this measure to group similarity measure with a help of a two-step procedure. In the first step, using mutual funds' shares in the company, I compute the weighted average portfolio of a group of mutual funds. In the second step, I compute a weighted average of similarity measures between this average portfolio and mutual funds' portfolio vectors. Thus, groups with closely related portfolios receive larger similarity measure values than groups with highly heterogeneous portfolios.

I study the effects of portfolio similarity at two different scales. First, I investigate at the level of individual funds by observing the relationship between portfolio similarity of a pair of mutual

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<sup>9</sup>Horizontal shareholding and diversification do not increase portfolio similarity measure if two investors diversify/hold competitors in two non-overlapping sets of companies. Since investors choose their holdings from the same universe of companies, these sets almost always overlap.

funds and probability that the pair casts the same votes. For every director election,<sup>10</sup> I select a small number of fund pairs at random from the pool of participating mutual funds.<sup>11</sup> This is a necessary data reduction step as considering every possible pair combination is not feasible for computation. I find a positive and statistically significant relationship.

Second, I investigate at the level of all mutual funds present at director elections. Using the portfolio similarity measure for groups, I find that mutual funds groups with more homogeneous portfolios cause the share<sup>12</sup> of votes “For” to drop and the share of “Non-votes” to rise.

Mutual funds with overlapping portfolios might be involved in self-selection into companies with more passive retail shareholders. At the same time, some retail shareholders might seek companies with more homogeneous institutional investor portfolios, so they can free ride on mutual funds’ efforts in supporting good directors. Thus, I believe that my OLS results for the effect of mutual funds portfolio similarity on election participation might be biased.

I use reconstitution of Russell 1000/2000 indices ([FTSE Russell, 2019](#)) to establish causality for the effect of mutual funds portfolio similarity on shareholders’ voting decisions. Using instrumental variable approach, I attempt to capture exogenous variation in the degree of within group portfolio similarity and the level of passive ownership. I instrument both variables in order to disentangle the effects of portfolio structure from the effects of ownership by index funds.

Since 2007, annual reconstitution of Russell 1000/2000 indices involves a banding procedure. Firms with market capitalization within a vicinity of the 1000th largest firm’s market capitalization, do not switch the index.<sup>13</sup> I exploit both the inclusion of a firm in a certain index and its banded status to construct my instrumental variables. I use inclusion in Russell 2000 dummy, its lagged version, banded state dummy, and an interaction between banded state and inclusion in Russell 2000 as instrumental variables.

The weak instrument hypothesis is rejected using a test proposed by [Sanderson & Windmeijer \(2016\)](#). This test is specifically designed for the case of multiple endogenous variables. Conditional

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<sup>10</sup>I concentrate on the sample of director elections because it is relatively homogeneous and abundant: most firms hold annual director elections with a number of positions to fill in.

<sup>11</sup>The possible bias from not choosing the non-participating funds should be small as mutual funds exercise their fiduciary duty by voting and the participation rate for institutional investors is very high ([Jill E. Fisch, 2017](#); [Nili & Kastiel, 2016](#)).

<sup>12</sup>To be able to see the redistribution of shareholders’ votes, I measure the share of particular voting option out of the total shares outstanding and eligible to vote during the meeting.

<sup>13</sup>The 1000th largest firm would be the threshold firm if sharp selection rule was used. The bandwidth is 5% of cumulative market capitalization of Russell 3000E.

F-test statistics substantially exceed the 5% significance level's critical values for both endogenous variables.

The results of the instrumental variable approach largely confirm the main result of the OLS approach: more homogeneous groups of mutual funds, holding shares at a firm, reduce shareholder participation in director elections.

## 2 Data

The paper relies on three main kinds of data: portfolios of mutual funds, their voting decisions at corporate elections, and aggregate results of these elections. Additionally, I use data on characteristics of mutual funds and companies, and data on Russell 1000/2000 indices. As datasets come from a multitude of sources, I employ non-trivial automatic and manual matching that I describe in detail in this section and later in the Appendix.

My primary data source of mutual funds' voting decisions is the ISS's Voting Analytics database. This database provides individual mutual fund's votes that come from from N-PX filings, available on the EDGAR website. Since 2003, mutual funds have been required to publicly disclose their votes on all shares they hold. Along with mutual fund's vote, the Voting Analytics database attributes each mutual fund to a family of mutual funds and, starting in 2006, provides a link to the N-PX file that voting data was sourced from. The Voting Analytics database does not link its proprietary fund identifiers to these in other datasets, thus the links to underlying N-PX filings are very helpful in connecting the datasets.

The ISS's Voting Analytics database also contains aggregate voting data for Russell 3000 Index companies. Along with the company's CUSIP, numbers of votes "For," "Abstain," "Against/Withhold," and "Broker Non-votes," it also provides proposal's description, shareholder meeting date, management and ISS recommendations, sponsor information, number of shares outstanding, and the Pass/Fail outcome. Each proposal has a unique ID that allows to connect it to the votes of individual mutual funds.

The mutual funds' characteristics and portfolio data come from the CRSP Mutual Funds database. The portfolio composition data has quarterly frequency. For a mutual fund, which has voted at a corporate election, I use the holdings report that is nearest in terms of the ab-

solute difference between the report date and shareholder meeting date (but no more than 183 days apart).<sup>14</sup> To ensure that result is not driven by artifacts of the CRSP MFDB dataset, I repeat the study with data from Thomson Reuters S12 dataset and get very similar results. Firm’s characteristics are obtained from Compustat quarterly dataset.

Russell 1000 and 2000 indices constituents, their “free float” share numbers, and the relevant stock prices are obtained from Bloomberg. I then compute the index weights and impute the ranks of index constituents.

Figure 1 presents a diagram of the links that I use to connect the datasets together. The most complicated step was to connect ISS Voting Analytics mutual funds voting dataset to CRSP Mutual Funds database. I follow the procedure outlined in [Schwartz-Ziv & Wermers \(2019\)](#); [Matvos & Ostrovsky \(2008\)](#) and [Iliev & Lowry \(2015\)](#). Figure 2 shows the match rate between the votes of mutual funds at director elections obtained from ISS Voting Analytics database and the mutual funds’ records from CRSP Mutual Fund database. For years 2009 to 2016 I get a match of around 80% which motivates my choice of the time interval. I present the details of the match procedure in the Appendix.

### 3 Similarity measure

To compute the portfolio similarity measure for a pair of mutual funds I take a dot product of normalized vectors that represent the respective portfolios. In the literature this measure is known as cosine similarity. For groups of mutual funds I first compute a weighted-average portfolio vector and then evaluate the weighted-average similarity measure between the average portfolio and individual funds’ portfolios.

To formally define the measure consider two mutual funds,  $i$  and  $j$ . Let vectors  $\beta_i$  and  $\beta_j$  represent the respective portfolio allocations. Then the portfolio similarity measure is

$$\text{Pair Similarity} = \mathbb{S}(\beta_i, \beta_j) = \frac{\langle \beta_i, \beta_j \rangle}{\|\beta_i\| \|\beta_j\|}, \quad (1)$$

where  $\|\cdot\|$  is a L2-norm.

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<sup>14</sup>In some cases, for a mutual fund, which participated in a firm’s shareholder meeting, there is no information on its share in the firm available in the selected CRSP MFDB’s holdings report. In these cases I use adjacent holdings report for this fund to retrieve its approximate share in the firm.



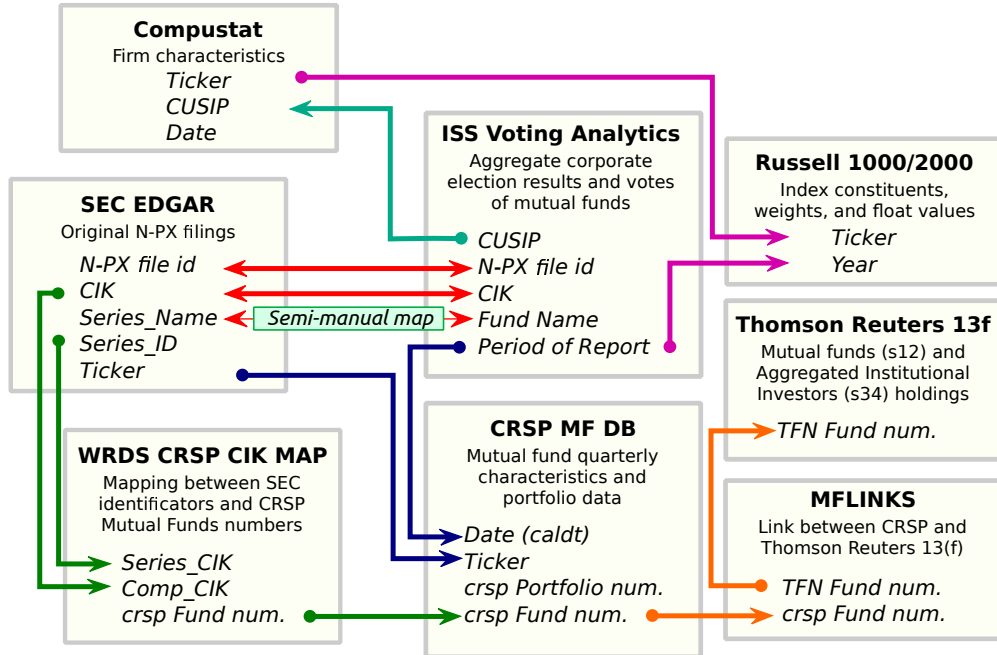


Figure 1: The datasets and the links between them. ISS Voting Analytics dataset provides aggregate corporate election results (numbers of votes “For,” “Against/Abstain,” “Withhold,” “Broker Non-votes”) along with short proposal description, ISS and management recommendations, and other vote-related information. I link it to Compustat by *CUSIP* and election date, and to Russell indices’ constituents by the period of report and company’s ticker, retrieved from Compustat. Linking ISS Voting Analytics dataset to CRSP Mutual Fund database of funds’ characteristics and portfolios is done in two steps. First, I retrieve the original SEC N-PX filings from EDGAR web database for every mutual fund’s vote in the ISS dataset. Since a N-PX form may contain voting data for more than one mutual fund, I match *Series\_Name* to *Fund Name* from the ISS dataset. This allows me to associate a mutual fund from ISS dataset to its *Series\_ID* and Ticker from SEC data. Second, I use mutual fund’s ticker and date of the N-PX report to link the fund to its records in CRSP Mutual Fund database. There is also an alternative route that uses WRDS CRSP CIK MAP dataset that links pairs of *CIK* and *Series\_ID* (*Comp\_CIK*) to fund’s records in CRSP Mutual Fund database. Both paths give very similar match results. Lastly, I match mutual fund records from CRSP Mutual Fund database to Thomson Reuters 13f (s12) database using MFLINKS dataset.

This measure has a clear geometrical representation. Consider a unit-sphere in a  $N$ -dimensional space, where  $N$  is the number of assets. Any portfolio, less of its scale, has a corresponding dot on the sphere. The normalized portfolio vector points from the origin to the point on the sphere. The dot product of a pair of such vectors is equal to the cosine of the angle between them. Smaller angles correspond to larger cosine values and portfolios’ points being in a small vicinity of each other.

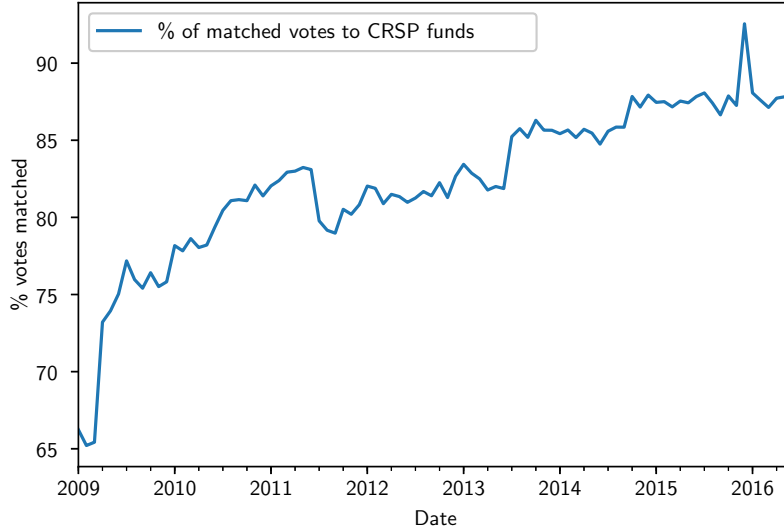


Figure 2: The average (monthly) match rate between the votes of mutual funds at director elections obtained from ISS Voting Analytics database and the mutual funds’ portfolio identifiers from CRSP Mutual Fund database. For every director election in the ISS database, I retrieve all mutual funds that held shares of the respective company at the time of the election and reported these holdings in their N-PX filings. Then, for each such mutual fund, I attempt to find *crsp\_fundno*, an identifier of respective mutual fund in the CRSP MF database, and *crsp\_portno*, a portfolio identifier of the respective mutual fund in CRSP MF database. The matching procedure is described in the data section and in the Appendix. To find the match rate for a single director election, I divide the number of funds for which I was able to find corresponding portfolio identifier in CRSP MF database, *crsp\_portno*, by the number of funds present in the ISS dataset for this director election. Then, I compute an average match rate for all director elections that happened within a calendar month and plot the figure above.

Theoretically, this measure spans from  $-1$  (funds with completely opposite portfolios) to  $+1$  (funds with identical up-to-scale portfolios), while in practice the range is  $[0, 1]$  as short positions are not observed. Figure 3 illustrates the distribution of the measure values for a pair of mutual funds chosen at random. While most pairs have modest values, the distribution has a heavy tail and few pairs have values close to 1.

Cosine similarity measure is widely known in the literature. The measure is used in portfolio analysis (Getmansky et al., 2018; Sias et al., 2013; Bohlin & Rosvall, 2014) and in text similarity analysis (Hanley & Hoberg, 2010, 2012).<sup>15</sup>

<sup>15</sup>Cha (2007) provides a survey of similarity measures. See Kwon & Lee (2003) and Sebastiani (2002) on usage of cosine similarity in text classification problems.

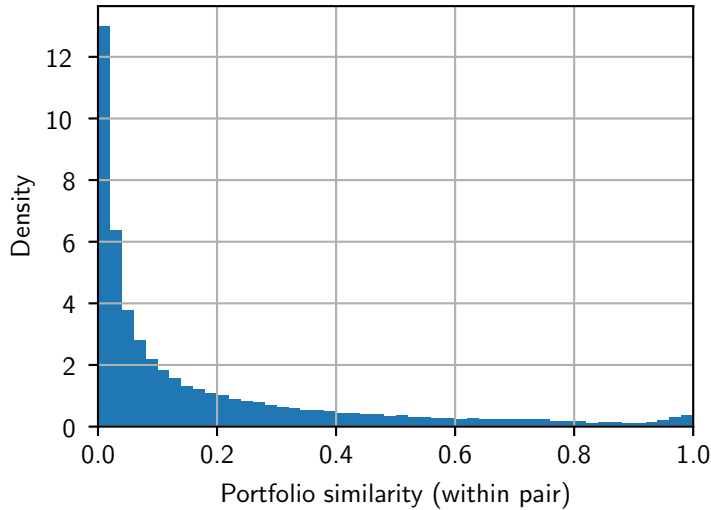


Figure 3: Distribution of portfolio similarity measure’s (cosine similarity) values computed for 459507 random pairs of mutual funds at corporate elections from 2009 to 2016. For every director election between 2009 and 2016, I sample 3 random pairs (without return) of mutual funds. For every fund in a pair I retrieve portfolio data from CRSP MF database if I am able to match that fund to the respective portfolio. All pairs where one or more mutual funds miss portfolio data are discarded. Then, I compute the cosine similarity measure between the portfolios of funds in a pair.

### 3.1 Similarity in groups

Cosine similarity measure accommodates the case of two mutual funds but it does not cover the case of many. I adapt the measure by computing a weighted average similarity between the weighted mean group portfolio and funds’ portfolios.

The goal is to measure how diverse the group’s portfolios are. When most shareholders have analogous portfolios, the mean portfolio will not be far from these. On the contrary, shareholders with heterogeneous portfolios will form a mean portfolio that is quite unlike theirs. By measuring how similar their portfolios to the mean, I get an idea of how homogeneous the shareholders’ portfolios are in the group.

I use shareholders’ holdings at the company as the weights in this procedure. This ensures that many small shareholders of the company will not change the averages too much. To find the weighted mean portfolio of the group I weigh the shareholders’ portfolios allocations (portfolio vectors with L1-norm being 1) by their shares at the company. Hence, the absolute size of share-

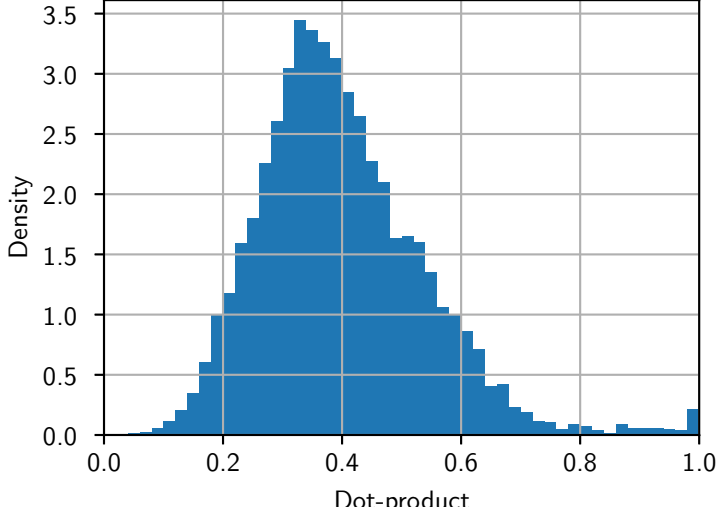


Figure 4: Distribution of group portfolio similarity measure’s (group cosine similarity) values computed for mutual funds at corporate elections from 2009 to 2016. For every corporate election, I form a group of mutual funds which held shares of the respective company at the time of the election and reported these holdings in their N-PX filings. I match these mutual funds to their respective portfolios in the CRSP MF database. I use the mutual fund’s share of the company normalized by the share owned by all mutual funds as the mutual fund’s weight in the group similarity measure. In cases where the fund’s most recent portfolio does not include shares owned in the company of interest, I use preceding or succeeding quarters of portfolio data to proxy for fund’s holdings. Funds with missing portfolio data and funds with missing data on their holdings in the firm of interest are excluded from the group. Then, I compute the portfolio similarity measure among the funds remaining in the group.

holder’s portfolio does not matter. Next, I use the same weights to compute the weighted average similarity measure for a group.

Consider a group of  $N$  shareholders, enumerated by  $i$ , with portfolio vectors  $\beta_i$ , where each element represents the dollar value allocated to shares of the respective company. Let  $\mathbb{A}$  be the weighted mean group portfolio vector at the company  $n$

$$\mathbb{A} = \frac{\sum_{i=1}^N \beta_{in} * \bar{\beta}_i}{\sum_{i=1}^N \beta_{in}}, \quad (2)$$

where  $\bar{\beta}_i = \frac{\beta_i}{\|\beta_i\|_1}$  and  $\|\cdot\|_1$  is L1-norm. Then the group similarity measure is

$$\text{Group Similarity} = \frac{\sum_{i=1}^N \beta_{in} \langle \mathbb{A}, \beta_i \rangle}{\sum_{i=1}^N \beta_{in}}, \quad (3)$$

where  $\mathbb{S}$  is pair similarity measure defined above.<sup>16</sup>

Figure 4 illustrates how often we find a company where mutual funds, who are shareholders in that company, have certain level of portfolio similarity. Overall, this is a unimodal distribution with some outliers at the right tail.<sup>17</sup>

## 4 Similar portfolios and voting decisions

The voting outcome at corporate elections arises from decisions of many participants. While each of them might be too small to significantly affect the result, multiple participants following the same voting strategies may sway the election outcome. In this section I document that, among other factors, higher portfolio similarity in pairs of mutual funds is associated with greater probability of both funds making the same voting decision. This suggests that portfolio structure is likely related to the voting strategies of mutual funds in particular, and institutional investors in general.

To investigate what may affect shareholders' voting decisions I focus on votes of randomly chosen pairs of mutual funds that hold shares and vote at corporate elections.<sup>18</sup> For each fund in a pair, I collect fund characteristics, fund's share in a firm, and portfolio data. As a pair of funds does not have any order, both funds are equal participants in a pair. Thus, I do not directly use funds' characteristics and instead I construct averages and absolute differences. Using funds' portfolio data I compute the value of portfolio similarity measure. For each pair I also retrieve firm's characteristics.

Shareholders may choose to vote "for," "against," "abstain," and "withhold." I consider two views on votes being the same: exact match and aggregation of "against," "abstain," and "withhold" votes. In the first approach, both funds in a pair must submit identical vote to count these

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<sup>16</sup>Another way to define group similarity measure could be the weighted average of pair similarity measure for all investor pairs. This would change the weighted mean group portfolio vector computation. That is, L1-norm will be replaced by L2-norm with all the rest being the same. Advantage of this approach is a more straightforward generalization from the 2 investors case, while the disadvantage is a more complicated definition of the group mean portfolio vector. In results I use the first approach. I've also implemented the second approach with results being very close to what the first approach yields.

<sup>17</sup>The value of zero is unattainable in the absence of short positions. The firms in the left tail of the distribution have mutual fund shareholders with almost non-overlapping portfolios.

<sup>18</sup>Typically, the number of mutual funds participating in a corporate election is relatively large: from 50 to 500 funds (see fig. 5). Thus, the number of possible funds pairs is in the range of hundreds to hundreds of thousands. Since I combine data from multiple election issues and multiple elections, the approach of looking at every possible pair quickly becomes infeasible. Instead, I randomly select mutual funds into a pair without return which drastically reduces the number of pairs that could be drawn. As this adversely affects the randomness of further pairs drawn, I only draw up to three pairs per election issue and in most cases I draw just one.

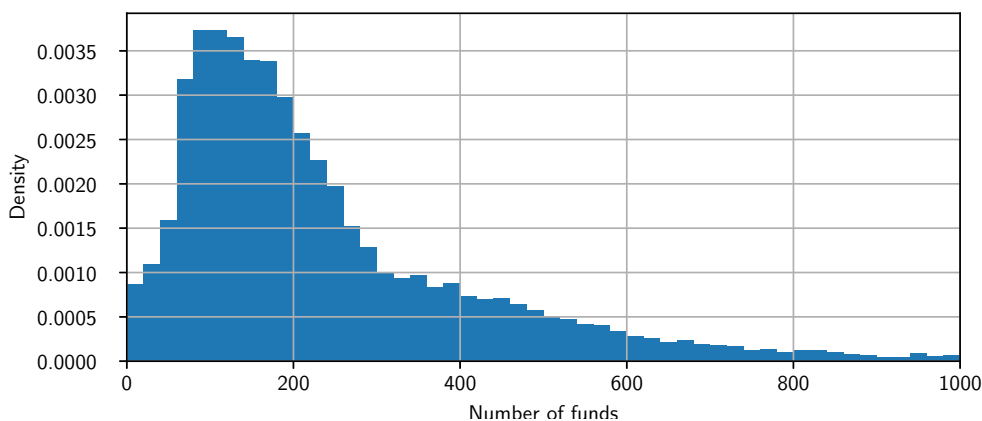


Figure 5: Distribution of the number of mutual funds participating in corporate elections from 2009 to 2016. Since I study all possible actions (including “Non-votes”) a fund can take, I define participation as holding company’s shares and reporting its vote (or “Non-vote”) in an N-PX form by the mutual fund.

as being the same. The second approach relaxes this condition a little bit: votes are considered the same as long as both funds submit votes from a single set, where sets are {For} and {Against, Abstain, Withhold}. To test whether the second approach is reasonable, I also consider a placebo definition where I use sets {Against} and {For, Abstain, Withhold}.

Corporate elections bring up a wide range of agendas: director elections, auditors ratification, compensation matters and say on pay votes, and proposals on governance matters. I concentrate my attention on director elections. The benefits involve the sample being quite homogeneous and abundant: almost every firm holds annual directors elections with multiple positions to fill in. The overwhelming majority of these directors run unopposed and are management-proposed.

For director elections from 2010 to 2016 I draw a single random pair of participating mutual funds. I use logistic regression to explain the relationship between the binary dependent variable, pair voted the same way, and the explanatory variables. I partially follow [Iliev & Lowry \(2015\)](#) in my selection of explanatory variables.

Table 1 presents the logistic regression results. Both, strict (1) and permissive (2) specifications yield statistically significant positive coefficient. For a logistic regression interpretation comes in a form of an odds ratio: the ratio of probability that funds make the same voting decision over the probability of making different decisions is about 41% higher with identical portfolios in comparison to a case of non-overlapping portfolios keeping other things fixed.

Table 1: Logistic regression: relationship between making the same voting decision and portfolio similarity for a randomly chosen pair of mutual funds. The dependent variable is dummy equal to 1 when votes are the same, and 0 otherwise. First specification requires votes to be exactly the same. Second relaxes the first by treating votes {Against, Abstain, Withhold} as being the same. Third specification is a placebo that treats votes {For, Abstain, Withhold} as being the same.

	Same vote (strict)	Same vote	For/Abs/Wth as a group
	(1)	(2)	(3)
Similarity measure (pair)	0.349*** (0.053)	0.348*** (0.053)	0.064 (0.104)
Same family	3.007*** (0.219)	3.084*** (0.225)	3.004*** (0.564)
1 index fund	0.057 (0.036)	0.056 (0.036)	-0.065 (0.073)
2 index funds	0.059 (0.050)	0.053 (0.050)	-0.214** (0.103)
Same MSA	-0.092 (0.059)	-0.098* (0.059)	-0.196* (0.109)
<b>Geometric Averages of Funds Characteristics</b>			
Expense ratio (geom. av.)	0.528*** (0.076)	0.531*** (0.076)	-0.067 (0.142)
Management fee (geom. av.)	0.125 (0.089)	0.123 (0.089)	0.044 (0.180)
Fund turnover ratio (geom. av.)	0.016 (0.037)	0.016 (0.038)	0.205*** (0.080)
Total net assets (log(geom. av.))	-0.023** (0.012)	-0.023* (0.012)	-0.004 (0.022)
Family size (log(geom. av.))	0.224*** (0.011)	0.223*** (0.011)	0.115*** (0.020)
% of Total net assets (geom. av.)	0.025 (0.041)	0.029 (0.041)	0.139** (0.060)
% of Total Equity (geom. av.)	0.002 (0.017)	0.002 (0.017)	0.049 (0.051)
Ratio of expense ratios	0.013*** (0.003)	0.013*** (0.003)	0.001 (0.006)
<b>Absolute Differences of Funds Characteristics</b>			
Management fee (abs. diff.)	0.170*** (0.038)	0.172*** (0.038)	0.002 (0.069)
Fund turnover ratio (abs. diff.)	0.027** (0.011)	0.026** (0.011)	0.063** (0.026)

Table 1, continued

	(1)	(2)	(3)
Total net assets (log(abs. diff.))	0.018** (0.009)	0.019** (0.009)	0.016 (0.017)
Family size (log(abs. diff.))	-0.041*** (0.009)	-0.043*** (0.009)	-0.023 (0.017)
% of Total net assets (abs. diff.)	-0.030** (0.015)	-0.031** (0.015)	-0.036 (0.024)
% of Total Equity (abs. diff.)	0.012** (0.005)	0.012** (0.005)	-0.008** (0.003)
<b>Firm characteristics and ISS Recommendations</b>			
S&P 500	0.115** (0.047)	0.110** (0.047)	-0.496*** (0.089)
ISS Against another item	-0.377*** (0.030)	-0.380*** (0.030)	-0.106* (0.062)
ISS “For” recommendation	2.493*** (0.034)	2.474*** (0.034)	1.884*** (0.074)
log(Total assets)	0.102*** (0.011)	0.103*** (0.011)	-0.221*** (0.022)
Return on assets	-0.001 (0.001)	-0.001 (0.001)	-0.008* (0.004)
Book to market ratio	-0.116*** (0.023)	-0.111*** (0.023)	0.041 (0.068)
Leverage	-0.018 (0.012)	-0.019 (0.012)	0.047* (0.025)
Constant	-2.799*** (0.167)	-2.770*** (0.167)	3.352*** (0.320)
Observations	85099	85099	85099

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ 

A pair of funds coming from the same mutual fund family is enormously more likely to vote the same way than a pair of funds from different families. This is consistent with literature that provides evidence of centralized voting behavior among the Big Three<sup>19</sup> mutual funds families (Fichtner et al., 2017).

The second most prominent effect comes from the ISS recommendation. A “For” recommendation from the ISS is associated with significantly higher chances of voting the same way. This is coherent with the literature on the role of the ISS and correlation between its recommendations and shareholders’ votes (Choi et al., 2010; Iliev & Lowry, 2015; Malenko & Shen, 2016). Notably,

<sup>19</sup>Big Three are BlackRock, Vanguard and State Street mutual fund families.



an ISS recommendation against another item is linked to reduced chances of vote unanimity within the mutual funds pair.

Funds with higher expense ratios and from bigger mutual fund families tend to cast similar votes. Firms in S&P 500 and larger firms in general receive a more homogeneous treatment from mutual funds, whereas firms with higher book to market ratio are more likely to receive different votes.

The placebo specification which combines “For,” “Abstain,” and “Withhold” votes performs largely as expected. Portfolio similarity has no significant association with unanimity in pair’s votes. Same family and ISS recommendation dummies retain relatively large albeit less significant coefficients. This is likely due to their resolute power between “For” and “Against” votes even when “Abstained” and “Withhold” votes somewhat scramble the pair’s outcomes.

## **5 Similar portfolios and shareholder participation**

As individual pairs of mutual funds more likely to cast same votes having analogous portfolios, the same effect should scale to groups of many mutual funds. With higher probability of them voting the same way, other shareholders may re-evaluate their decision to participate in elections. I find that at elections where mutual funds, as a group, have more similar portfolios, other shareholders decide to not submit their votes. This shrinks the pool of votes cast, which in turn may enhance the power of those who vote.

To see the relationship between portfolio similarity and shareholder participation I investigate how portfolio similarity is related to aggregate characteristics of elections’ outcomes. As in the previous section, I focus on director elections to benefit from abundance and homogeneity of these as well as to maintain consistency within the paper.

### **5.1 Voting standards**

The corporate governance process through shareholder voting is covered with a patchwork regulatory framework composed of federal and state corporate and securities laws, stock exchange requirements and company bylaws. Director elections are usually governed by a state law default

if company’s bylaw provides no other standard (Stokdyk & Trotter, 2016). The two most used standards are majority voting and plurality voting.

Shareholders have a variety of options at director elections. They can support the candidate by voting “For,” disapprove the candidate by voting “Against” (or “Withhold” under plurality voting standard), or be more neutral and vote “Abstain.” Another option is to do nothing and do not vote at all.<sup>20</sup> This would result in a “Non-Vote,” an outcome that covers the case not covered by the options above. Depending on the voting standard, the voting options have different effect on the election outcome.

Under a plurality voting standard, director candidate who receives the highest number of votes “For” wins the seat. Notably, if candidate is running unopposed, a single vote “For” is enough to get elected. Shareholders may wish to vote “Withhold” if they are not happy with the candidate. While high number of withhold votes does not prevent such candidate from being elected, the board of director may adjust its director nomination practices (The Office of Investor Education and Advocacy, 2012).

Under a majority voting standard, director nominee needs to secure enough “For” votes to satisfy a majority voting requirement. The requirement typically describes a threshold that the share of “For” votes needs to pass. Table 2 shows the subsets of votes used to calculate the share of “For” votes under different standards. These serve as denominator in a formula used to compute the support rate. The ISS Voting Analytics dataset suggests that less than 1% of director elections use majority of outstanding shares as base. GMI Ratings (2013) report that 94% of companies in both S&P 500 and Russell 1000 exclude broker non-votes for shareholder proposals.

Majority voting standard does not preclude unpopular directors from getting elected. This standard has been on the rise since 2004 and by 2007 approximately two-thirds of S&P 500 firms used some form of majority voting (Allen, 2007). The adoption was not uniform; at the early stages firms were also introducing a “plurality plus” standard which required elected candidate to resign, pending an approval of resignation from board of directors, if he or she fails to win under a majority vote standard. Cai et al. (2013) claims that majority voting standard is a paper tiger, instituted to appease shareholders, which has little teeth to affect director elections. Cai et al. (2009) finds

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<sup>20</sup>“Abstain” vote is an affirmative choice of a shareholder, represented at the meeting (by proxy or in person), to not vote “For” or “Against” particular candidate. Abstentions may or may not be considered “vote cast.” See Schnell & Chen (2019).

Table 2: Types of votes forming the base that is used to compute the share of votes “For” under different majority voting standards.

	For	Against	Abstain	Broker Non- Vote	Other Non- Vote
Standard					
Majority of votes cast	✓	✓			
Majority of shares present and entitled to vote on the subject matter (Default in Delaware)	✓	✓	✓		
Majority of shares present and entitled to vote at the meeting	✓	✓	✓	✓	
Majority of outstanding shares	✓	✓	✓	✓	✓

that even at poorly performing firms with bad governance badly performing directors consistently receive more than 90% of votes “For”; the exceptions are negative ISS recommendation with 19% fewer votes and directors attending less than 75% of board meetings who receive 14% fewer votes. Hence, in virtually every case even an unpopular director receives more than 50% of votes “For” which brings him above the usual threshold in majority voting elections. [Cai et al. \(2013\)](#) find that from 2004 to 2010 from 105445 directors only 294 directors at 153 firms received less than 50% of “For” votes; among these 153 firms only 14 firms had adopted a version of majority voting standard and all except 3 of 22 directors that failed elections at these firms secured a seat on the board. Thus, majority voting standard is not much different from plurality voting standard in the case of director elections.

While elections do not weed out unpopular candidates, dissent votes convey a credible signal of shareholder displeasure to board of directors and management. [Yermack \(2010\)](#) argues that this signal may pressure management to change the composition of the board, dismantle takeover defenses, and to revise executive compensation packages. [Cai et al. \(2009\)](#) estimate that a 1% decrease in support of compensation committee member tends to reduce unexplained CEO compensation by \$143,000 in the following year. They also find that CEO turnover is more likely when independent directors receive lower votes. [Iliev et al. \(2015\)](#) show an association between low percentages of “For” votes and a higher number of directors leaving the board over the next year. So even if

director elections have no immediate effect, there is an evidence of delayed action taken by the board and firm management.

Thus I do not make a distinction between the two voting standards as in both cases shareholders have a way to display their dissent and the majority voting standard poses no substantial barriers for directors to get on the board. At the same time election results matter for the corporate governance in the long run: low percentages of “For” votes nudge management and the board into taking shareholder appeasing actions.

## 5.2 Data sample

The ISS Voting Analytics dataset provides vote results for corporate elections that include vote outcome, number of outstanding shares, number of votes “For,” “Abstain,” “Against”/“Withhold,”<sup>21</sup> and number of broker non-votes<sup>22</sup> along with individual votes of mutual funds and other election information.

For every director election happened between 2009 and 2016 I collect its aggregate voting outcomes together with the individual votes of mutual funds from ISS Voting Analytics dataset. Using the numbers of votes cast I construct the number of “Non-votes” which is the difference between “Shares Outstanding” and total number of votes cast. The number of “Non-votes” is then split into “Broker non-votes,” reported by the ISS, and “Other non-votes.” I drop election issues where number of votes cast exceeds the reported number of shares outstanding.

Using CRSP Mutual Funds database and Thomson Reuters S12 database I retrieve mutual fund portfolios as well as their shares in the firms that they vote at.<sup>23</sup> Next, I evaluate the group portfolio similarity measure for mutual funds participating in director elections. The firm characteristics are then pulled from Compustat. Finally, I aggregate votes of mutual funds to evaluate their input into the aggregate voting election results. Table 3 provides summary statistics for the constructed sample.

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<sup>21</sup>ISS does not provide a separate number of “Withhold” votes for records starting 2006; instead it reports this number in the “Against” column.

<sup>22</sup>A broker non-vote happens when a beneficial owner does not submit voting instructions to a broker through which she holds shares. Brokers, in general, are permitted to vote on behalf of beneficial owners on “routine” matters without explicit instructions from beneficial shareholders but director elections are not considered “routine.”

<sup>23</sup>The portfolio data is updated quarterly so for some mutual funds I can not directly observe its holdings at the firm of interest. In such cases I use adjacent quarters data to proxy for the missing number.

Table 3: Director elections sample’s summary statistics. Sample contains 95543 election datapoints after removing outliers and records with missing values.

Variable	Min	Max	Mean	Median	std.
“For” votes, %	3.000	99.782	74.694	77.022	12.810
“Against”/“Withhold” votes, %	0.000	71.375	3.330	1.370	5.667
“Abstain” votes, %	0.000	39.112	0.146	0.000	0.785
Broker “Non-Votes”, %	0.000	69.596	9.733	7.953	7.715
Other “Non-Votes”, %	0.000	96.989	12.098	10.657	8.347
Similarity measure	0.151	0.794	0.397	0.375	0.113
log(Total assets)	2.615	14.637	7.973	7.909	1.942
Return on assets, %	-49.985	49.844	3.122	3.134	9.264
Book to market ratio	0.001	16.544	0.567	0.479	0.477
Leverage	0.000	9.880	0.870	0.516	1.200
% owned by index funds	0.000	68.362	7.872	7.519	4.302
% owned by non-index funds	0.000	95.818	16.274	15.907	9.479
ISS “For” recommendation	0.000	1.000	0.923	1.000	0.266

### 5.3 Results

Mutual funds portfolio similarity has a sizable association with directors election outcomes. Firms where mutual funds, as shareholders, have more similar portfolios are more likely to see lower shareholder participation in director elections. Fewer votes “Against”/“Withhold” and substantially fewer “For” votes being cast, while shareholders increase the share of “Non-Votes” by not submitting their voting instructions.

To explore the relationship between portfolio similarity and election outcomes I regress the numbers of votes “For,” “Against,” “Abstain,” and “Non-votes,” normalized by the shares outstanding, on similarity measure, shares of index and non-index mutual funds, ISS recommendation, and firm controls. The normalization used allows me to see how shareholders dispose their votes across all possible options. Table 4 presents the OLS regression results.

The percentage of votes “For,” measured as a share of shares outstanding, changes the most in relation to portfolio similarity. As these five dependent variables cover the entire set of possible outcomes<sup>24</sup>, a drop in “For” votes should be accompanied with a hike in other categories. The

<sup>24</sup>ISS uses “Against” column to report “Withhold” votes when needed and I follow this practice here.

share of “Against” votes decreases as well,<sup>25</sup> thus the missing “For” and “Against” votes end up as “Non-Votes” as shareholders reduce their involvement in the election process. As both “Broker Non-Votes” and “Other Non-Votes” have substantial positive coefficients for portfolio similarity, I can conclude that both retail and institutional investors’ decisions are at play.

More homogeneous groups of mutual funds, that hold shares in a firm, thereby decrease<sup>26</sup> shareholder turnout. [Jill E. Fisch \(2017\)](#) argues that low turnout among retail shareholders leads institutional investors to dominate election results; she reports that while 90% of institutional shares are voted, retail investors turnout averages at less than 30% (see also [Matt Egan \(2014\)](#)). [Nili & Kastiel \(2016\)](#) claim that retail investors have rational apathy which stems from the dispersion of ownership and diversification of investor portfolios, and cite vote outcome distortion, limitation of shareholders’ ability to initiate governance changes, and dead-lock situations where low shareholder turnout prevents issues from passing as the direct costs of investors’ apathy.

Election outcome is also responsive to the share of a firm owned by mutual funds. Using the CRSP Mutual Funds database, I’m able to disentangle the input of index mutual funds<sup>27</sup> and non-index mutual funds. Higher share, owned by index mutual funds, reduces observed number of votes “For” and increases the number of votes “Against” as shareholders tend to not vote their shares. Quite the opposite happens when non-index mutual funds hold bigger share: shareholders, institutional and not, tend to vote more often.

ISS issues a favorable recommendation for director elections in more than 90% of the cases. A lack of favorable ISS recommendation has an expected relationship to the election outcome: a sharp decrease in the number of votes “For” coming from an increase of even bigger magnitude in number of votes “Against.” Part of these votes “Against” come from previously passive shareholders as can be seen from a decrease in the numbers of non-votes.

Larger firms attract more retail shareholder attention. Higher return on assets is associated with better shareholder participation, while high leverage is associated with lower.

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<sup>25</sup>While the coefficient is about an order of magnitude smaller, the effect on “Against” votes is still substantial as the average number of votes “Against” is also more than a magnitude smaller than the number of votes “For.” See [table 3](#) for a detailed summary statistics.

<sup>26</sup>Here I will talk about possible causal effects that a lower shareholder turnout may have. I leave the discussion of whether portfolio similarity causes shareholder turnout to drop for a separate section.

<sup>27</sup>I consider a mutual fund as an index fund if it has flag “D” in the `findex_fund_flag` field of CRSP Mutual Fund database.

Table 4: The relationship between mutual funds portfolio similarity and election outcome at director elections. Dependent variables normalized by the shares outstanding. Standard errors are robust to cluster correlation (clustered by meetings).

	% For	% Against	% Abstain	% Broker Non-Vote	% Other Non-Vote
	(1)	(2)	(3)	(4)	(5)
Similarity measure	-14.151*** (1.086)	-2.448*** (0.359)	0.124** (0.063)	7.218*** (0.674)	14.892*** (0.713)
% owned by index funds	-0.489*** (0.032)	0.149*** (0.011)	0.001 (0.002)	0.265*** (0.020)	0.127*** (0.020)
% owned by non-index funds	0.417*** (0.012)	0.050*** (0.004)	-0.000 (0.001)	-0.228*** (0.008)	-0.213*** (0.007)
ISS "For" recommendation	10.404*** (0.405)	-14.372*** (0.250)	-0.083*** (0.032)	2.159*** (0.174)	3.668*** (0.215)
log(Total assets)	0.264*** (0.063)	-0.018 (0.019)	0.028*** (0.005)	-0.474*** (0.041)	0.464*** (0.042)
Return on assets, %	0.194*** (0.012)	-0.005 (0.004)	-0.001 (0.001)	-0.085*** (0.008)	-0.113*** (0.008)
Book to market ratio	-0.007*** (0.000)	0.001*** (0.000)	-0.000* (0.000)	0.006*** (0.000)	0.001*** (0.000)
Leverage	-0.185* (0.106)	-0.108*** (0.026)	0.008 (0.011)	0.520*** (0.076)	-0.238*** (0.062)
Year controls	Yes	Yes	Yes	Yes	Yes
Observations	95543	95543	95543	95543	95543
$R^2$	0.222	0.434	0.005	0.252	0.710
F stat.	240.3	248.7	19.4	861.9	3329.8

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

## 6 Instrumental strategy

Since mutual fund’s portfolio choice is likely endogenous to its voting behavior, I instrument group portfolio similarity measure to establish causality. I use reconstitution of Russell 1000/2000 indices as a source of portfolio variation that is plausibly exogenous to shareholders’ voting practices. The instrumental approach confirms the findings of the previous section.

There are multiple reasons why the OLS results may not be conclusive evidence that mutual funds’ portfolio structure affects election outcomes. One possibility is that the highly diversified mutual funds might be better represented at “boring” firms where shareholders do not often engage in director elections. This way low shareholder turnout might be correlated with pools of highly diversified, but essentially holding very similar portfolios, mutual funds.

Another possibility is that mutual funds endogenously determine their portfolios. Funds’ ownership of a stock might be related to factors that directly affect shareholder turnout. This way a correlation between portfolio similarity and election participation might not represent a causal relation.

To address the possible endogeneity, I exploit reconstitution of Russell 1000 and Russell 2000 indices, widely adopted market benchmarks, as a quasi-natural experiment in changing the stock ownership by mutual funds. A substantial difference in the index-weight of a stock at the top of Russell 2000 and the bottom of Russell 1000, as well as probability of switching an index, drives the changes in portfolios of investors, which rely on Russell indices in their portfolio building.

### 6.1 Russell 1000/2000 indices reconstitution

Russell 1000 and Russell 2000 indices, provided by FTSE Russell, are stock market indices that track the highest-ranking 1000 stocks and stocks ranking 1001 - 3000 respectively. Many investment managers use Russell 2000 to benchmark their performance in “small-cap” to “mid-cap” categories and build portfolios. Every year in May - June, FTSE Russell reconstructs the indices, revealing the result on the last Friday in June.

Historically, there have been two different procedures for Russell 1000/2000 indices reconstitution. Prior to 2007, index assignment followed a strict threshold rule where stocks ranked within the 1-1000 interval were assigned to Russell 1000, and stocks ranked in 1001-3000 were assigned to



Russell 2000. Beginning in 2007, a new approach, called “banding,” was enacted. The threshold between Russell 1000 and Russell 2000 is now covered with a band of a certain dollar size, such that companies that fall into the band at reconstitution do not switch the index. As I concentrate on a data sample from 2009 to 2016 in this paper, I will skip the discussion of former approach to indices reconstitution and I will focus on the latter.

Reconstitution starts by forming a ranked list of 3000+ companies that are eligible to be included in one or more of the Russell indexes. Few criteria for eligibility among others are having stock price above \$1, being a part of the U.S. equity market, having total market capitalization above \$30 million, and having more than 5% of shares available in the marketplace (float) (FTSE Russell, 2019). Total market capitalization of a firm is obtained by multiplying total outstanding shares by the market price (last price traded) on the primary exchange on the rank day<sup>28</sup> in May. FTSE Russell estimates the total shares outstanding by including common stock, partnership units/membership interests, and non-restricted exchangeable shares, while any other type of shares (preferred stock, installment receipts, etc.) are excluded (see FTSE Russell (2019) for a detailed description). Computed total market capitalization allows Russell to sort companies in a long 3000+ list where position in the list determines the rank of a company. FTSE Russell treats the computed market capitalizations as proprietary information and does not make it available to researchers. This hampers the research trying to exploit reconstitution of Russell indices in a regression discontinuity design setting (Wei & Young, 2017). The more recent papers (Heath et al., 2018) focus on the post 2006 period and provide new methodology, immune to selection bias.

Next, a band with a width of 5% of cumulative market cap of Russell 3000E is computed around the market capitalization of security ranked 1000. Any company which total market capitalization falls within the band does not switch the index. Companies outside the band and with ranks below 1000 become Russell 1000 constituents, while such companies with ranks above 1000 become Russell 2000 constituents. Thus, banding procedure provides an additional signal to investors regarding company’s future affiliation with a certain index.

Once the indices memberships have been determined, FTSE Russell adjusts companies’ shares to only include those that can be freely traded by the public (“free float”). Next, within each

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<sup>28</sup>Schedule of rank days is released by Russell in spring and, typically, rank day is the last trading day in May (Mullins, 2014).

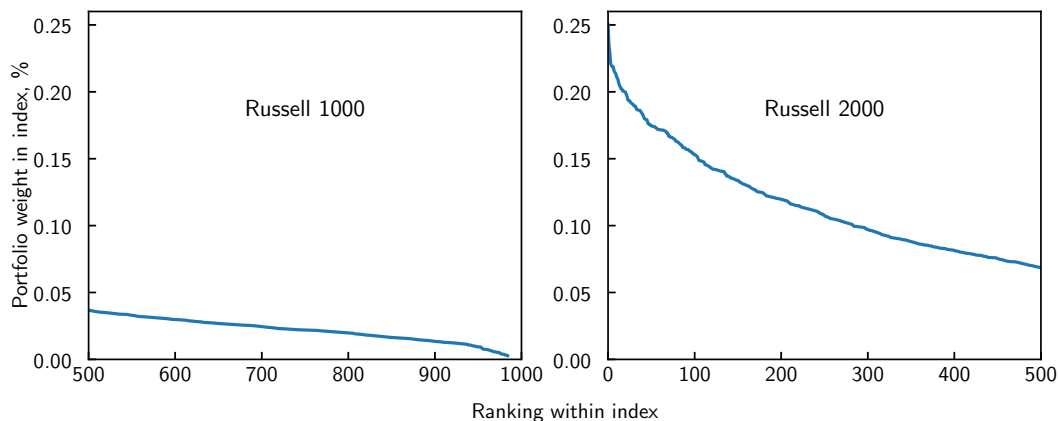


Figure 6: Portfolio weights of stocks in Russell 1000/2000 indices in 2011. Stock’s weight within an index is computed by dividing the stock’s “float market capitalization” by the sum of “float market capitalizations” of all index constituents. “Float market capitalization” is a product of the end-of-June stock’s share price and the number of shares that can be freely traded by the public. Stock’s rank within an index is equal to its position in a list of all index constituents, ordered by their weights within the index starting with the largest value.

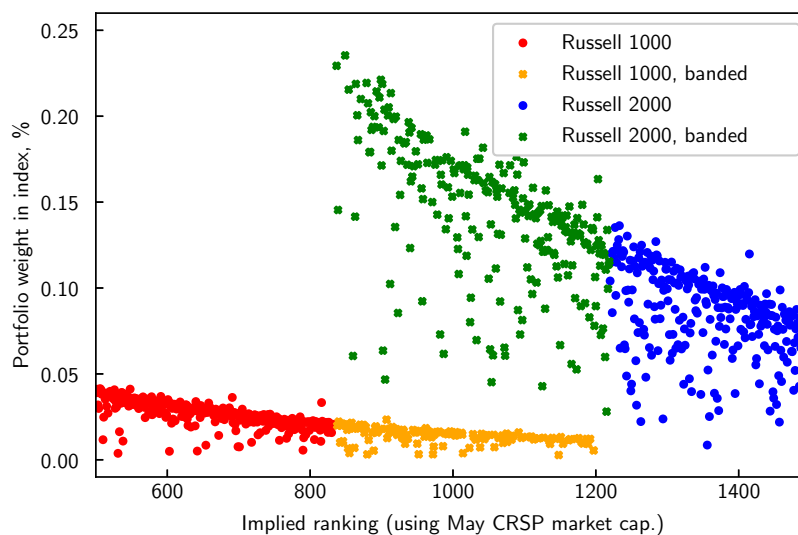


Figure 7: Portfolio weights of stocks in Russell 1000/2000 indices in 2011. FTSE Russell determines securities ranks by using proprietary data on firms’ total market capitalizations on the rank day in May. I compute implied ranks by using May CRSP firms’ market capitalization data.

index separately the float adjusted shares are used to compute constituents’ weights. Given the sorting nature of the indices, companies at the bottom of Russell 1000 index receive substantially lower weights in comparison to the weights of companies at the top of Russell 2000 index. Figure 6 illustrates the difference between the weights in an index for the bottom 500 companies from Russell

1000 and the top 500 companies of Russell 2000 in 2011. The average weights of securities at the bottom and top 500 companies of respective indices are 0.023% and 0.118% respectively.

## 6.2 Exclusion restriction

An important criterion for instrument variable estimation approach is exclusion restriction. I construct four instrumental variables that are based on the features of indices reconstitution. In this section I explore the possible critiques of these instruments.

The first pair is a dummy that a certain security belongs to the Russell 2000 index and its lagged version. Since index reconstitution happens mid-year, for every election before index reconstitution date I use values from previous two years, while after reconstitution date I use the current and the past year's values.

The second pair is the banded status of a firm and an interaction term between the banded status and the inclusion in Russell 2000 index. The banded status is effectively a proxy for a possible index switch in a future. [Wei & Young \(2017\)](#) hypothesize that institutional investors may trade in anticipation of index assignment changes.

In an instrumental regression, I rely on an implicit assumption that these instrumental variables affect the dependent variables (votes cast at elections) only through its influence on the variables of interest. Literature suggests that passive and active funds have a different impact on firm's governance and corporate election outcomes ([Appel et al., 2016, 2018](#); [Schmidt & Fahlenbrach, 2017](#); [Brav et al., 2019](#); [Heath et al., 2018](#)). Russell indices reconstitution has also been associated with a significant changes in index fund ownership at firms that switch the index ([Appel et al., 2016](#); [Heath et al., 2018](#); [Gloßner, 2018](#)). Thus, I control for levels of institutional ownership by including both passive and active ownership shares in my regression. Then, I go the extra mile by exploiting the different nature of the available instruments in order to instrument for both the portfolio similarity and the level of passive ownership. This allows me to disentangle the effect coming from portfolio similarity from the effects found in the literature studying passive ownership influence ([Appel et al., 2018](#); [Heath et al., 2018](#); [Baig et al., 2018](#)). Following [Appel et al. \(2018\)](#) I also control for market capitalization and free float of a firm.

One possible critique is that index switching may generate news coverage or in some other way attract (or reduce) shareholder attention to a company. Thus, some companies may enjoy less or

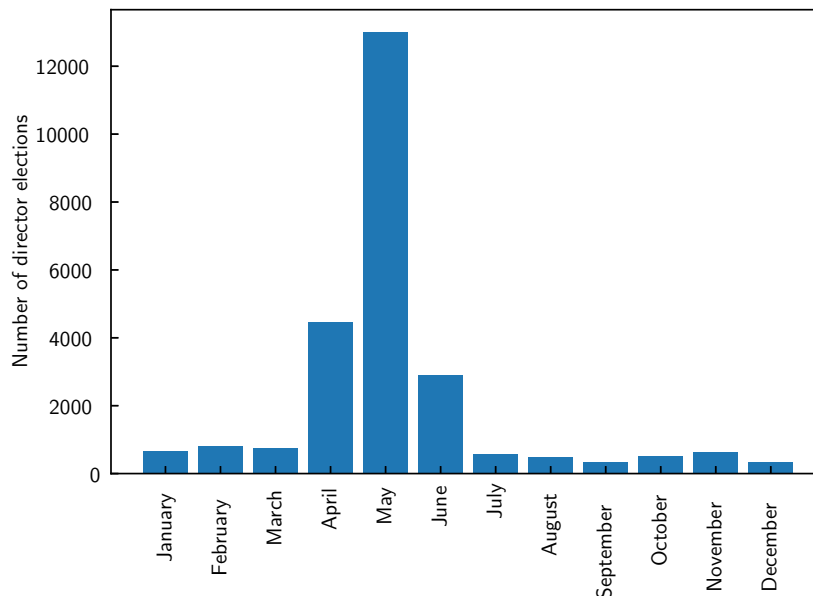


Figure 8: Number of director elections per month in the IV sub-sample.

more shareholder election participation just due to the switch itself. I do not find this concern substantial as the bulk of director elections happens many months after the index reconstitution and any news effect should be worn away by then. Figure 8 provides an illustration that most director elections are over by the end of June when the new lists of constituents become public.

Another possibility for a violation of exclusion restriction arises if firms are able to manipulate their index assignment. Then their actions might affect not only the index assignment but also the shareholders' attitude for election participation. As FTSE Russell does not reveal the true May rankings, firms have small chances to successfully predict their rank and then to manipulate the index they belong to or their banded status by a marginal change in capitalization. The articles that explore Russell reconstitution in regression discontinuity design setting do not find evidence of firms manipulating their index assignment (Boone & White, 2015; Chang et al., 2015).

Finally, since the number of instruments used makes the model overidentified, I perform a Sargan–Hansen test for regressions with statistically significant influence of portfolio similarity (Hayashi, 2000). In all cases the resulting statistic is sufficiently smaller than the one needed in order to reject the hypothesis of the over-identifying restrictions being valid. This strengthens my belief that the exclusion restriction is satisfied.

### 6.3 Weak instruments test

An ambitious goal to instrument two endogenous variables requires a careful attention to the strength of the instruments being used. A simple  $F$ -test will not be sufficient in such case as it does not capture the interplay between the endogenous variables. I rely on a test proposed by [Sanderson & Windmeijer \(2016\)](#) to rule out weak instruments case.

Table 5 summaries the results of the first stage. Both regressions demonstrate an  $F$ -statistic above 10. Thus, the instrument are strong enough at least in the case when just one variable is instrumented.

Table 5: The first stage of the 2SLS regression. Standard errors are robust to cluster correlation (clustered by meetings).

	Similarity measure (1)	% owned by index funds (2)
$Russell2000_t$	0.020** (0.008)	1.466*** (0.330)
$Russell2000_{t-1}$	0.010* (0.006)	-0.273 (0.223)
Banded state	-0.001 (0.005)	-0.303 (0.202)
Banded state $\times$ $Russell2000_t$	-0.029*** (0.007)	0.353 (0.314)
Firm controls	Yes	Yes
Year controls	Yes	Yes
Float and mk.cap. controls	Yes	Yes
Observations	29167	29167
$R^2$	0.238	0.467
Partial F stat.	55.0	177.4

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

[Sanderson & Windmeijer \(2016\)](#) argues that in a case of multiple endogenous variables being instrumented, a simple  $F$ -test is necessary but not sufficient. They provide a conditional  $F$ -test statistic which I compute for my first stage. The values are 79.8 and 94.8 for similarity measure and share of index fund ownership respectively. [Stock, J.H. \(2005\)](#) provide the 5% significance level's critical values for a weak instruments test. The null hypothesis is that instruments are weak

and lead to an asymptotic bias of at least 5%. The critical value for four instruments and two endogenous variables is 11.04. Since both values are substantially higher than the critical value, the null hypothesis of weak instrument is rejected at the 5% level.

## 6.4 Results

Table 6 summarizes the results of IV approach. The main result on the influence of portfolio similarity remains in place. The substantial drop in the share of votes “For” combined with a hike in the number of broker “Non-Votes” suggest the similar pattern of shareholder fatigue and reduced participation in director elections. A notable sign change has happened for the effect coming from share owned by index funds; IV results suggest that an increase in this share raises retail shareholder participation and increases the level of support directors receive at elections.

Among other variables, the changes came from the logarithm of total assets and book to market ratio. The former variable lost its significance in the regression while the latter obtained much more pronounced effects likely due to inclusion of float and market capitalization control variables. The effect of favorable ISS recommendation largely remains the same.

In tables 7 and 8, I modify the group similarity measure by only including shares within the same 1 or 2 digit SIC category. This allows me to see the effect of horizontal shareholding on voting outcomes. Both regressions’ results are in coherence with results in table 6.

## 7 Conclusion

According to my study of mutual funds’ portfolios and voting patterns, portfolio structure has an effect on both individual voting behavior and aggregate outcome of director elections. Funds with more similar portfolios tend to cast identical votes more often. I find that greater within-group portfolio similarity of mutual funds, invested in a firm, causes lower shareholder participation in director elections at this firm.

The observed relation between portfolio structure and individual fund’s voting behavior provides evidence that mutual funds exercise their own judgment to some extent and do not blindly follow ISS or firm’s management recommendations. Moreover, this observation also suggests that firms likely have some market power since the Fisher separation theorem does not seem to hold.

I discover that other shareholders react to the mutual funds' portfolio structure. When a firm is held by mutual funds with closely overlapping portfolios, other shareholders reduce the number of votes they cast. Rational apathy of investors is a plausible explanation here. This result also demonstrates that horizontal shareholding has a tangible effect on corporate governance process.

Table 6: Relationship between mutual funds portfolio similarity and election outcome at director elections (IV approach). Dependent variables normalized by the shares outstanding. Standard errors are robust to cluster correlation (clustered by meetings).

	% For	% Against	% Abstain	% Broker Non-Vote	% Other Non-Vote
	(1)	(2)	(3)	(4)	(5)
Similarity measure	-40.857** (16.723)	6.845 (6.261)	-0.407 (1.093)	22.015** (10.659)	12.404 (10.136)
% owned by index funds	0.675** (0.320)	-0.200* (0.112)	0.012 (0.019)	-0.442** (0.207)	-0.045 (0.200)
% owned by non-index funds	0.285*** (0.053)	0.052*** (0.020)	-0.002 (0.003)	-0.148*** (0.033)	-0.187*** (0.034)
ISS "For" recommendation	15.855*** (0.745)	-17.422*** (0.556)	-0.049 (0.043)	0.831*** (0.320)	0.785** (0.346)
log(Total assets)	-0.376 (0.342)	0.023 (0.119)	0.002 (0.032)	0.252 (0.222)	0.099 (0.221)
Return on assets, %	0.076*** (0.029)	0.022** (0.011)	0.001 (0.002)	-0.019 (0.020)	-0.080*** (0.020)
Book to market ratio	-2.593*** (0.530)	0.286* (0.167)	0.159*** (0.061)	0.963*** (0.338)	1.185*** (0.387)
Leverage	-0.591*** (0.184)	-0.123** (0.060)	0.022 (0.015)	0.748*** (0.133)	-0.056 (0.083)
Year controls	Yes	Yes	Yes	Yes	Yes
Float and mk.cap. controls	Yes	Yes	Yes	Yes	Yes
Observations	29167	29167	29167	29167	29167
$R^2$	0.231	0.462	0.011	0.189	0.136
F stat.	1250.2	1245.1	55.7	1545.3	573.4

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$



Table 7: Relationship between mutual funds portfolio similarity (using only assets within the same 1-digit SIC category) and election outcome at director elections (IV approach). Dependent variables normalized by the shares outstanding. Standard errors are robust to cluster correlation (clustered by meetings).

	% For	% Against	% Abstain	% Broker Non-Vote	% Other Non-Vote
	(1)	(2)	(3)	(4)	(5)
Similarity measure (1 digit SIC)	-56.051** (23.353)	8.930 (8.301)	-0.528 (1.446)	29.071** (14.681)	18.578 (13.463)
% owned by index funds	0.901** (0.371)	-0.259** (0.126)	0.014 (0.021)	-0.535** (0.231)	-0.121 (0.223)
% owned by non-index funds	0.319*** (0.045)	0.049*** (0.016)	-0.002 (0.003)	-0.170*** (0.027)	-0.196*** (0.028)
ISS "For" recommendation	15.140*** (0.818)	-17.190*** (0.558)	-0.054 (0.046)	1.131*** (0.362)	0.973*** (0.369)
log(Total assets)	-0.356 (0.357)	0.023 (0.117)	0.002 (0.031)	0.217 (0.229)	0.114 (0.216)
Return on assets, %	0.102*** (0.027)	0.015 (0.009)	0.001 (0.001)	-0.031* (0.017)	-0.087*** (0.018)
Book to market ratio	-2.529*** (0.549)	0.272 (0.171)	0.159*** (0.061)	0.933*** (0.350)	1.166*** (0.384)
Leverage	-0.610*** (0.195)	-0.119** (0.061)	0.022 (0.015)	0.759*** (0.137)	-0.052 (0.084)
Year controls	Yes	Yes	Yes	Yes	Yes
Float and mk.cap. controls	Yes	Yes	Yes	Yes	Yes
Observations	29233	29233	29233	29233	29233
$R^2$	0.125	0.446	0.008	0.099	0.113
F stat.	1080.8	1196.9	56.7	1396.8	581.5

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

Table 8: Relationship between mutual funds portfolio similarity (using only assets within the same 2-digit SIC category) and election outcome at director elections (IV approach). Dependent variables normalized by the shares outstanding. Standard errors are robust to cluster correlation (clustered by meetings).

	% For	% Against	% Abstain	% Broker Non-Vote	% Other Non-Vote
	(1)	(2)	(3)	(4)	(5)
Similarity measure (2 digits SIC)	-65.216* (35.926)	7.391 (10.006)	-0.792 (1.680)	36.597* (21.819)	22.020 (17.475)
% owned by index funds	1.210** (0.561)	-0.276* (0.157)	0.019 (0.026)	-0.725** (0.338)	-0.228 (0.289)
% owned by non-index funds	0.358*** (0.041)	0.041*** (0.012)	-0.002 (0.002)	-0.189*** (0.025)	-0.209*** (0.022)
ISS "For" recommendation	15.313*** (0.936)	-17.230*** (0.562)	-0.054 (0.045)	1.055** (0.417)	0.916** (0.397)
log(Total assets)	-0.516 (0.494)	0.018 (0.137)	-0.001 (0.034)	0.328 (0.305)	0.171 (0.257)
Return on assets, %	0.149*** (0.034)	0.008 (0.009)	0.002 (0.001)	-0.057*** (0.021)	-0.102*** (0.018)
Book to market ratio	-3.186*** (0.705)	0.351* (0.192)	0.151** (0.063)	1.298*** (0.415)	1.386*** (0.437)
Leverage	-0.553** (0.236)	-0.120* (0.067)	0.023 (0.015)	0.723*** (0.154)	-0.072 (0.096)
Year controls	Yes	Yes	Yes	Yes	Yes
Float and mk.cap. controls	Yes	Yes	Yes	Yes	Yes
Observations	29231	29231	29231	29231	29231
$R^2$	-0.380	0.434	-0.009	-0.416	-0.046
F stat.	805.7	1185.7	55.4	837.5	494.6

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

## Variables dictionary

Table 9: Detailed definitions of variables used.

Variable	Definition	Data source
“Abstain” votes, %	The share of votes “Abstain” out of total shares outstanding. Measured in %.	ISS Voting Analytics
“Against”/“Withhold” votes, %	The share of votes “Against”/“Withhold” (aggregated by ISS) out of total shares outstanding. Measured in %.	ISS Voting Analytics
“For” votes, %	The share of votes “For” out of total shares outstanding. Measured in %.	ISS Voting Analytics
$\ln(\text{Total assets})$	Natural logarithm of firm’s total assets.	Compustat
1 index fund	A dummy variable equal to 1 if one (and only one) mutual fund in a pair is an index fund (has flag “D” in the <code>findex_fund_flag</code> field).	CRSP Mutual Funds Database
2 index funds	A dummy variable equal to 1 if both mutual funds in a pair are index funds (have flag “D” in the <code>findex_fund_flag</code> field).	CRSP Mutual Funds Database
Banded state $\times Russell2000_t$	The interaction term between banded state and $Russell2000_t$	Bloomberg
Banded state	A dummy variable equal to 1, if a firm was in the banded region during the current year’s reconstitution process (if the election date is past the the index constituents announcement date; or previous year if the election date is before that date).	Bloomberg
Book to market ratio	Book to market ratio of the firm. A computation resulting in a negative book to market ratio is treated as a missing value.	Compustat
Broker “Non-Votes”, %	The portion of shares non-voted (no vote cast) by a broker out of total shares outstanding. Measured in %.	ISS Voting Analytics
CIK	Central Index Key used by the SEC	Edgar

Variable	Definition	Data source
Expense ratio	An absolute or geometric average of mutual funds' expense ratios. Data is as of the most recently completed fiscal year. When geometric average is computed, both ratios are censored at zero if negative, multiplied, and then a square root is taken. For absolute difference no censoring is applied. Final result is converted to %.	CRSP Mutual Funds Database
Family size	A natural logarithm of a geometric average or an absolute difference of mutual funds' families sizes. Family size is computed by adding all total net assets of funds belonging to a family. ISS Voting Analytics provides family structure. CRSP Mutual Fund Database provides funds' total net assets.	ISS Voting Analytics and CRSP Mutual Fund Database
Firm Leverage	Firm Leverage computed from the Compustat data.	Compustat
Fund turnover ratio	An absolute or geometric average of mutual funds' turnover ratios. When geometric average is computed, both ratios are censored at zero if negative, multiplied, and then a square root is taken.	CRSP Mutual Funds Database
ISS Against another item	A dummy variable equal to 1 if ISS issues a recommendation to vote against another director nominee at the meeting.	ISS Voting Analytics
ISS Recommendation "For"	A dummy variable equal to 1 if ISS recommends to vote "For" on the proposal, and 0 otherwise.	ISS Voting Analytics
Leverage	Firm's leverage. Computation results are truncated within an interval $[-0.01, 10]$ .	Compustat
Management fee	An absolute or geometric average of mutual funds' management fees. The ratio of management fee and average net assets. When geometric average is computed, both values are censored at zero if negative, multiplied, and then a square root is taken. For absolute difference the individual values below $-3$ are censored at $-3$ .	CRSP Mutual Funds Database

Variable	Definition	Data source
NPXFileID	Name of the N-PX Form file from the SEC that contains data on the mutual funds votes. Used to match the ISS fund ids with additional data available in the N-PX form.	ISS Voting Analytics
Other “Non-Votes”, %	The portion of shares non-voted (no vote cast) not by a broker out of total shares outstanding. Measured in %.	ISS Voting Analytics
$Russell2000_t$	An indicator that a company belongs to Russell 2000 index this year if the election date is past the index constituents announcement date; or previous year (if the election date is before that date).	Bloomberg
$Russell2000_{t-1}$	An indicator that a company belonged to Russell 2000 index last year if the election date is past the current year’s index constituents announcement date; or two years ago (if the election date is before that date).	Bloomberg
Ratio of expense ratios	Ratio of mutual funds’ expense ratios. Evaluated as the larger value divided by the smaller value (as order in a pair of mutual funds should not matter). Data is as of the most recently completed fiscal year. If smaller expense ratio is negative, the value is treated as missing.	CRSP Mutual Funds Database
Return on assets	Return on assets (firm)	Compustat
S&P 500	A dummy variable equal to 1 if firm is a constituent of S&P 500 index at the date of the election.	ISS Voting Analytics and Compustat
Same MSA	A dummy variable equal to 1 if both funds in a pair have their management company addresses within the same Metropolitan Statistical Area.	CRSP Mutual Funds Database
Same family	A dummy variable equal to 1 if both mutual funds belong to the same family.	ISS Voting Analytics

Variable	Definition	Data source		
Total net assets	A natural logarithm of a geometric average or an absolute difference of mutual funds' total net assets. The raw values of funds' total net assets are censored at \$0.1 if they are smaller than this threshold.	CRSP Database	Mutual	Funds
% of Total Equity	An absolute or geometric average of mutual funds' investments in the firm as percentages of total firm's equity.	CRSP Database and Compustat	Mutual	Funds
% of Total net assets	An absolute or geometric average of mutual funds' percentages of their portfolios invested in the firm. When geometric average is computed, both values are censored at zero if negative, multiplied, and then a square root is taken.	CRSP Database	Mutual	Funds
% owned by index funds	The portion of shares owned by index funds (have flag "D" in the <code>findex_fund_flag</code> field) out of total shares outstanding. Measured by aggregating all shares that index funds own at the company.	CRSP Database	Mutual	Funds
% owned by non-index funds	The portion of shares owned by non-index funds (do not have flag "D" in the <code>findex_fund_flag</code> field) out of total shares outstanding. Measured by aggregating all shares that non-index funds own at the company.	CRSP Database	Mutual	Funds

## References

- Allen, C. H. (2007) Study of Majority Voting in Director Elections. *SSRN Electronic Journal*.
- Appel, I. R., T. A. Gormley, & D. B. Keim (2016) Passive investors, not passive owners. *Journal of Financial Economics* **121**, 111–141.
- Appel, I. R., T. A. Gormley, & D. B. Keim (2018) Standing on the shoulders of giants: The effect of passive investors on activism. *The Review of Financial Studies* **32**, 2720–2774.
- Azar, J. (2017) Portfolio Diversification, Market Power, and the Theory of the Firm. *SSRN Electronic Journal*.
- Backus, M., C. Conlon, & M. Sinkinson (2019) The Common Ownership Hypothesis: Theory and Evidence. *Brookings working paper*.
- Backus, M., C. Conlon, & M. Sinkinson (2019) Common Ownership in America: 1980-2017. *NBER Working Paper No. 25454*, 56.
- Baig, A., J. DeLisle, & G. R. Zaynutdinova (2018) Passive Ownership and Earnings Manipulation. *SSRN Electronic Journal*.
- Bebchuk, L. A. & S. Hirst (2019) The Specter of the Giant Three. *SSRN Electronic Journal*.
- Bohlin, L. & M. Rosvall (2014) Stock Portfolio Structure of Individual Investors Infers Future Trading Behavior. *PLoS ONE* **9**, e103006.
- Boone, A. L. & J. T. White (2015) The effect of institutional ownership on firm transparency and information production. *Journal of Financial Economics* **117**, 508–533.
- Brav, A., W. Jiang, T. Li, & J. Pinnington (2019) Picking Friends Before Picking (Proxy) Fights: How Mutual Fund Voting Shapes Proxy Contests. *SSRN Electronic Journal*.
- Brito, D., E. Elhauge, R. Ribeiro, & H. Vasconcelos (2019) Modeling Horizontal Shareholding with Ownership Dispersion. *Economics Working Papers, Católica Porto Business School, Universidade Católica Portuguesa* **01**, 17.
- Brito, D., A. Osório, R. Ribeiro, & H. Vasconcelos (2018) Unilateral effects screens for partial horizontal acquisitions: The generalized HHI and GUPPI. *International Journal of Industrial Organization* **59**, 127–189.
- Cai, J., J. L. Garner, & R. A. Walkling (2009) Electing Directors. *The Journal of Finance* **64**, 2389–2421.
- Cai, J., J. L. Garner, & R. A. Walkling (2013) A paper tiger? An empirical analysis of majority voting. *Journal of Corporate Finance* **21**, 119–135.

- Cha, S.-H. (2007) Comprehensive Survey on Distance/Similarity Measures between Probability Density Functions. *International Journal Of Mathematical Models And Methods In Applied Sciences* **1**, 8.
- Chang, Y.-C., H. Hong, & I. Liskovich (2015) Regression Discontinuity and the Price Effects of Stock Market Indexing. *Review of Financial Studies* **28**, 212–246.
- Choi, S., J. E. Fisch, & M. Kahan (2010) The Power of Proxy Advisors: Myth or Reality?. *Emory Law Journal* **59**, 869–918.
- Choi, S. J., J. E. Fisch, & M. Kahan (2009) Director elections and the role of proxy advisors. *Southern California Law Review* **82**, 649–702.
- Coates, J. C. (2018) The Future of Corporate Governance Part I: The Problem of Twelve. *SSRN Electronic Journal*.
- Cvijanovic, D., M. Groen-Xu, & K. E. Zachariadis (2019) Free-Riders and Underdogs: Participation in Corporate Voting. *SSRN Electronic Journal*.
- DeAngelo, H. (1981) Competition and Unanimity. *The American Economic Review* **71**, 18–27.
- Elhauge, E. R. (2019) The Causal Mechanisms of Horizontal Shareholding. *SSRN Electronic Journal*.
- Elhauge, E. R. (2019). The Greatest Anticompetitive Threat of Our Time: Fixing the Horizontal Shareholding Problem. .
- Elhauge, E. R. (2019) How Horizontal Shareholding Harms Our Economy - And Why Antitrust Law Can Fix It. *SSRN Electronic Journal*.
- Enriques, L. & A. Romano (2018) Institutional Investor Voting Behavior: A Network Theory Perspective. *SSRN Electronic Journal*.
- Feddersen, T. J. & W. Pesendorfer (1996) The Swing Voter’s Curse. *The American Economic Review* **86**, 408–424.
- Fichtner, J., E. M. Heemskerck, & J. Garcia-Bernardo (2017) Hidden power of the Big Three? Passive index funds, re-concentration of corporate ownership, and new financial risk. *Business and Politics* **19**, 298–326.
- Fisher, I. (1930) *The Theory of Interest: As Determined by Impatience to Spend Income and Opportunity to Invest It*.
- FTSE Russell (2019). Construction and Methodology of Russell U.S. Equity Indexes. .
- Getmansky, M., G. Girardi, K. Hanley, S. Nikolova, & L. Pelizzon (2018) Portfolio Similarity and Asset Liquidation in the Insurance Industry. *SSRN Electronic Journal*, 25.



- Gloßner, S. (2018) The Effects of Institutional Investors on Firm Outcomes: Empirical Pitfalls of Quasi-Experiments Using Russell 1000/2000 Index Reconstitutions. *SSRN Electronic Journal*.
- GMI Ratings (2013). Vote Calculation Methodologies. . Technical report, GMI Ratings.
- Gordon, R. H. (2003) Do Publicly Traded Corporations Act in the Public Interest?. *The B.E. Journal of Economic Analysis & Policy* **3**.
- Hanley, K. W. & G. Hoberg (2010) The Information Content of IPO Prospectuses. *Review of Financial Studies* **23**, 2821–2864.
- Hanley, K. W. & G. Hoberg (2012) Litigation risk, strategic disclosure and the underpricing of initial public offerings. *Journal of Financial Economics* **103**, 235–254.
- Hansen, R. G. & J. R. Lott (1996) Externalities and Corporate Objectives in a World with Diversified Shareholder/Consumers. *The Journal of Financial and Quantitative Analysis* **31**, 43–68.
- Hart, O. D. (1979) On Shareholder Unanimity in Large Stock Market Economies. *Econometrica* **47**, 1057–1083.
- Hayashi, F. (2000) *Econometrics* Princeton University Press.
- He, J., J. Huang, & S. Zhao (2019) Internalizing Governance Externalities: The Role of Institutional Cross-Ownership. *Journal of Financial Economics*.
- Heath, D., D. Macciocchi, R. Michaely, & M. C. Ringgenberg (2018) Passive Investors are Passive Monitors. *Working paper*, 49.
- Iliev, P., K. V. Lins, D. P. Miller, & L. Roth (2015) Shareholder Voting and Corporate Governance Around the World. *The Review of Financial Studies* **28**, 2167–2202.
- Iliev, P. & M. Lowry (2015) Are Mutual Funds Active Voters?. *Review of Financial Studies* **28**, 446–485.
- Jill E. Fisch (2017) Standing Voting Instructions: Empowering the Excluded Retail Investor. *Minnesota Law Review* **82**, 11–60.
- Kwon, O.-W. & J.-H. Lee (2003) Text categorization based on k-nearest neighbor approach for Web site classification. *Information Processing & Management* **39**, 25–44.
- Lafarre, A. (2017) Small Shareholder Participation in European AGMs. *SSRN Electronic Journal*.
- Malenko, A. & N. Malenko (2019) Proxy Advisory Firms: The Economics of Selling Information to Voters. *Journal of Finance* **74**, 2441–2490.
- Malenko, N. & Y. Shen (2016) The Role of Proxy Advisory Firms: Evidence from a Regression-Discontinuity Design. *Review of Financial Studies* **29**, 45.

- Matt Egan (2014). Just 27% of investors bother to vote - The Buzz - Investment and Stock Market News. . <http://buzz.money.cnn.com/2014/06/12/shareholders-dont-vote/>.
- Matvos, G. & M. Ostrovsky (2008) Cross-ownership, returns, and voting in mergers. *Journal of Financial Economics* **89**, 391–403.
- Milne, F. (1974) Corporate investment and finance theory in competitive equilibrium. *Economic Record* **50**, 511–533.
- Morton, F. M. S. & H. J. Hovenkamp (2018) Horizontal Shareholding and Antitrust Policy. *The Yale Law Journal* **127**, 2026–2047.
- Mullins, W. (2014) The Governance Impact of Index Funds: Evidence from Regression Discontinuity. *Working paper*, 60.
- Nili, Y. & K. Kastiel (2016) In Search of “Absent” Shareholders: A New Solution To Retail Investors’ Apathy. *Delaware Journal of Corporate Law* **41**, 55–104.
- Salop, S. & D. O’Brien (2000) Competitive Effects of Partial Ownership: Financial Interest and Corporate Control. *Antitrust L.J.* **67**, 559–614.
- Sanderson, E. & F. Windmeijer (2016) A weak instrument F-test in linear IV models with multiple endogenous variables. *Journal of Econometrics* **190**, 212–221.
- Schmalz, M. C. (2018) Common-Ownership Concentration and Corporate Conduct. *Annual Review of Financial Economics* **10**, 413–448.
- Schmidt, C. & R. Fahlenbrach (2017) Do exogenous changes in passive institutional ownership affect corporate governance and firm value?. *Journal of Financial Economics* **124**, 285–306.
- Schnell, D. K. & A. Chen (2019) Counting Shareholder Votes. *Insights: The Corporate & Securities Law Advisor* **33**, 3–7.
- Schwartz-Ziv, M. & R. Wermers (2019) Do Institutional Investors Monitor Their Large vs. Small Investments Differently? Evidence from the Say-on-Pay Vote. *SSRN Electronic Journal*.
- Sebastiani, F. (2002) Machine Learning in Automated Text Categorization. *ACM Computing Surveys* **34**, 1–47.
- SEC (2003). Final Rule: Disclosure of Proxy Voting Policies and Proxy Voting Records by Registered Management Investment Companies, 17 CFR Parts 239, 249, 270, and 274. .
- Sias, R., H. J. Turtle, & B. Zykaj (2013) Hedge Fund Crowds and Mispricing. *Management Science* **62**, 764–784.

- Stock, J.H. (2005) Testing for weak instruments in linear IV regression. In *Identification and Inference for Econometric Models, Essays in Honor of Thomas Rothenberg.*, pp. 557–586. Cambridge University Press.
- Stokdyk, P. S. B. & J. H. Trotter (2016) Proxy Disclosure Recommendations. *Harvard Law School Forum on Corporate Governance and Financial Regulation*, 4.
- The Office of Investor Education and Advocacy (2012). Spotlight on Proxy Matters - The Mechanics of Voting. . [http://www.sec.gov/spotlight/proxymatters/voting\\_mechanics.shtml](http://www.sec.gov/spotlight/proxymatters/voting_mechanics.shtml).
- Wei, W. & A. Young (2017) Selection Bias or Treatment Effect? A Re-Examination of Russell 1000/2000 Index Reconstitution. *SSRN Electronic Journal*.
- Yermack, D. (2010) Shareholder Voting and Corporate Governance. *Annual Review of Financial Economics* **2**, 103–125.

# Appendix

## Data matching procedure

The ISS Voting Analytics dataset lacks a mutual fund identification variable that would be common with other popular datasets on mutual funds, like CRSP Mutual Funds database and Thomson Reuters 13f. This is a known issue in the literature, and [Schwartz-Ziv & Wermers \(2019\)](#); [Matvos & Ostrovsky \(2008\)](#) and [Iliev & Lowry \(2015\)](#) provide their solutions to the problem. In this paper, I improve on the combined approach by semi-manually verifying the funds' names match between the ISS's and SEC EDGAR's data.

First, I use the `NPXFileID` field to retrieve the corresponding file from EDGAR database for each record in Voting Analytics database. This allows me to associate a `CIK` field from EDGAR with voting records. Then, I focus on a subset of mutual funds with a same `NPXFileID` value and establish a match by funds' names between Voting Analytics and EDGAR file (I use `Series_Name` field from the N-PX filing). This step appends Voting Analytics data with `Series_ID` and `Ticker` fields that identify individual fund in an N-PX filing.

I perform name matching between funds within an N-PX filing (identified by `Series_Name`) and funds in ISS Voting Analytics dataset with a corresponding link to the N-PX file. I do so in a two step procedure. First, for a fund from ISS dataset I rank all funds from an N-PX filing by their Levenshtein distance in their names to the fund in question. For best matches with Levenshtein distance of 3 or smaller (where 0 corresponds to a perfect match) I assume that I assume that funds in both datasets represent the same fund. Second, for all unmatched funds (with minimum distance of 4 and larger) I conduct a manual name match (assisted by sorting N-PX filing's funds by their similarity to a fund in question). If no match seems reasonable, I assign a no-match label.

Second, I use ticker data from N-PX filings to match individual funds to CRSP Mutual Funds database. Since a ticker might be shared by different funds over time, I only accept matches that happen no more than 1 calendar year apart.

An alternative approach would be to use `crsp_cik_map` provided by WRDS. This linking dataset contains association between `Series_ID` and `CIK` fields from N-PX filings and corresponding `crsp_fundno`.

Finally, I use `MFLinks` dataset to connect CRSP Mutual Fund data to information in Thomson Reuters Mutual Fund Ownership dataset.