Catch the conscience of the king: evidence of activists influencing investors *

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Abstract

This paper studies whether hedge fund activists cater to mutual funds in a proxy fights, and its impact on shareholder's attention and voting. Using fund families historical shareholder proposal votes, I construct a machine learning model to measure the fund family's preference in terms of phrases. I find that activists are more likely to use phrases that corresponds to preferences of major shareholders in the target firm. The persuasion is associated with favourable funds attention, and voting outcomes for the proxy attack.

JEL Classification: G23, G32, G34

Keywords: Investor Activism, Shareholder Proposal, Mutual Fund Preference, Text-based analysis, Machine learning

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"As well as these hedge funds are looking for returns, the push for governance is coming from a larger and larger number of public pension funds and investment managers, more of whom are active in this area every year."

- Howard Sherman, CEO Institutional Shareholder Services

On July 1st, 2019, EQT's largest shareholder, T. Rowe Price issued a press release stating support for dissident Rice Group nominees. A week later, at EQT's annual meeting, shareholders elected all seven Rice nominated directors. This event is one of the many examples, on how the support of a major institutional shareholder change the course of a proxy attack. Activist hedge funds (activists) often hold limited shares and need support from other shareholders to implement any strategic change. Increasingly, the shareholder base is getting concentrated in the hands of few mutual fund families (fund families)[1]. The concentrated ownership structure of the target firm (target) makes it imperative for the activists to take into account the preferences of fund families that hold significant voting power[2]. However, the activists face an uphill battle as fund families often support target's management, and tend to be less involved with activism. In this paper, I examine whether activists, while designing proxy fights, appeal to large shareholder's preferences; and how the shareholder specific appeal affects fund family's attention and voting outcome.

The median activist stake in a target before a proxy fight during 1994–2011 in Brav et al. (2015) sample is 6.4%, this is not enough to play a determinative role in voting outcomes. As such, the result of the proxy fight lies mostly in the hands of other shareholders. Furthermore, retail investors, who own around 30% shares, are apathetic and less supportive of shareholder proposals[3]. Therefore, getting the support from institutional shareholders is critical for a successful proxy contest. Fortunately for the activists, institutional investors are increasingly working behind the scenes to catalyze changes to the corporate gover-

[1] As of December 2018, one of BlackRock, Vanguard or State Street was the largest shareholder in 438 of the S&P 500 companies. Russell Reynolds finds that the three big fund families collectively own 18.7% of all the shares in the S&P 500.

[2] Tom Ball, CEO Vanderbilt Consulting notes in an interview with TheStreet "With the increasing concentration of ownership it is the top ten holders who will win it or lose it for you ... You fight over middle ground. Support on one side or the other of largest two or three out of the top five will make the difference."

[3] ProxyPulse 2019 reports retail shareholder (institutional) ownership at 30% (70%), participation in voting at 28% (90%), support for directors who failed to attain majority at 77%(30%).

nance, ward off management entrenchment, and improve firm's strategy. These investors are not merely supporting activists once a campaign has begun. They are discussing a variety of companies, and in some cases, the institutional investors are even giving ideas to the activists[4]. An example of how the relationship between activists and fund families are changing comes from Larry Fink's, CEO of BlackRock, annual letter to CEOs. In 2015, Fink argued that activist investors put pressure on and create incentives for corporate leaders to generate short-term gains at the expense of long-term value creation. In 2018, Fink admitted that the interaction between management and so-called activists is often very productive for investors like his funds[5]. On the other side, making sure that the large investors share activists view is a first-order priority before the hedge fund take a big stake and press for change.

My goal is to quantify each fund's preference and show that activists cater to preferences of funds that hold more shares. I start with the assumption that the way funds vote is representative of their preferences. Matvos and Ostrovsky (2010), Morgan et al. (2011) find systematic differences in mutual fund voting, indicating a divergent preferences[6]. I use the variations in voting, with respect to shareholder proposal text to estimate a text-features based fund preference. The text-based preference comprises of weights associated with word phrases that impact fund families voting decisions. For example, during 2017–2018, DWS voted "for" in 97% of climate-related proposals, as opposed to Vanguard, which voted "for" in only 12% of proposals[7]. So a machine learning model trained on these proposals will give a much higher weights for phrase such as "climate_change", "environmental_concerns" for DWS, compared to Vanguard. The text-based preference has two useful features: (i)

[4]"Periodically, we are approached by large institutions who are disappointed with the performance of companies they are invested in to see if we would be interested in playing an active role in effectuating change" says William A. Ackman, founder of Pershing Square Capital in New York Times Dealbook

[5]In a letter sent to chief executives of the 500 largest publicly traded U.S. companies, Fink stressed that short-term thinking is getting in the way of long-term business growth. "...It is critical, however, to understand that corporate leaders' duty of care and loyalty is not to every investor or trader who owns their companies' shares at any moment in time, but to the company and its long-term owners...": Letter to corporates, March 31, 2015. At the Reuters Global Investment 2018 Outlook Summit, Fink said "The role of activists is getting larger, not smaller, in many cases their role is a good one."

[6]If the shareholders have the same incentives: to promote the behavior of directors that serves the best interests of the company. We will still see differences in fund voting behavior, simply due to random noise. However, we would not see systematic differences.

[7]Ceres annual report on climate-related proxy voting shed light on which mutual fund companies take climate risks seriously

It allows fund preference to be time variant, dependent on the way funds voted in two years period before the measurement date. (ii) its variation is interpretable and provides insight into the origins of fund incentives. These feature enables us to understand the relation between proposal content and expected fund-voting, its fluctuation over time, and the aspects that were important to investors.

Using the weights associated with phrases in shareholder proposals, I estimate the voting outcome for each attack based on the frequency with which these phrases occur in proxy text. As an example, a proxy fight in 2019 that includes "climate_change", "environmental_concerns" phrases will likely have a higher activist support from DWS, compared to Vanguard, since DWS favored climate related proposals much more than vanguard during 2017–2018. I standardize the shareholder and proxy voting, in terms of probability of fund family voting against the management (AMGT). I estimate the relationship between AMGT and the frequency of words in shareholder proposal text using support vector regression (SVR). The key advantage of this method over ordinary least squares (OLS) is its ability to deal with a large feature space. I find that SVR predicts AMGT well out-of-sample. The SVR predicted funds voting against management, $\widehat{AMGT}$, on attack texts describes 35.6% of the variation in actual voting data.

The theoretical activism paradigm lies in the relationship that shareholders (principals) need to monitor and provide incentives to managers (agents) so that the managers maximize shareholder value. Ross (1973), Jensen and Meckling (1976) finds that there are agency problems, and it affect the fair market value of the firm's stock. However, the theoretical models predict a difference in methods, time horizons, and perspectives on managerial decision-making prerogatives between mutual fund institutions and hedge fund activists when it comes to solving these agency problems. Mutual funds seeks to reduce agency problems via optimal contract structure (Goetzmann et al. (2003), Lambert and Larcker (2004)), investment strategy (Goetzmann et al. (2007)), and governance structures (Guercio and Hawkins (1999), Gillan and Starks (2007)). Hedge fund activists, on the other hand, are more likely to seek direct influence on managerial actions (Gantchev (2012), Edmans et al. (2013)) with an immediate impact on share price (Brav et al. (2015)). However, both the parties often find themselves in a symbiotic relationship - while the hedge fund needs fund families for fund families' voting strength, fund families need hedge funds for hedge fund's slacker regulations and fiduciary standards (Brav et al. (2008)).

Motivated by these works, I study whether activists do the fund family's bidding during a proxy fight. I begin by measuring the likelihood of fund family voting against the management on an attack ($\widehat{AMGT}$) based on the weights associated with phrases in proxy text. I find that a one standard deviation (one percent) increase in fund family holding of target share is associated with 0.6% (1.03%) increase in $\widehat{AMGT}$. The result holds even if I restrict variations within attack and fund family. In essence, I find that given a particular attack, the proxy text of attack is more geared towards fund families that hold a higher equity share in target. Even within a fund family, the proxy text is more geared towards the fund when the fund holds a higher equity share. The strong result indicates that the hedge fund activists take into account preferences of fund families, while designing the proxy text, and fights on topics and content that matters to the major shareholders.

A major concern, as with most machine learning models, is the validation of textual analysis prediction. I employ two methods to validate my findings. First, I measure fund families attention to each attack in terms of the number of times the fund's IP address accessed attack filings on SEC.gov website. I find that a one standard deviation increase in $\widehat{AMGT}$ is associated with 0.3 more attack document views. The estimation again is robust subject to fixing attack and fund family level variations. While SEC.gov filing view is just one of the many channels firm gather information on attack, it provides a good representative for overall attention on corporate governance (Bauguess et al. (2013), Iliev et al. (2018), Gormley et al. (2020)). The estimation is robust to the inclusion of fund family equity holding in the target firm.

Second, I verify my predicted against management voting with actual proxy voting. I find that a one standard deviation increase in $\widehat{AMGT}$ is associated with 0.06 standard deviation increase in actual against management voting, after fixing attack and fund family level variations. The predicted voting explains 35% of variation in actual voting, after fixing attack level variation. Thus the SVR estimated against management voting by fund families predicts funds attention, and actual voting on the proxy attack.

1 Contribution

This paper makes two primary contributions to the broad literature that examines hedge fund activism. First, I provide and document an interpretable method to measure mutual fund preferences. The method contributes to the research that requires investigating determinants of fund behavior, and preferences. Second, I show that hedge fund activists pander to fund family preferences in line with fund family equity share. The confluence in fund family and hedge fund goals provides a way to reconcile the ongoing dilemma of divergent optimization between mutual fund families (joint portfolio maximization) and hedge funds (target value maximization).

Prior literature has focused on the likelihood of an attack based on the characteristics of three players in the activism game (i) target: smaller market value of equity (Bradley et al. (2010)), under performed their industry over the previous 24 months (Greenwood and Schor (2009)) (ii) activist: longer lock-ups and withdrawal notification periods (Clifford (2008)), performance-based compensation contracts (Mietzner and Schweizer (2011)) (iii) investors: institutional investors (Brav et al. (2008)), active funds, pro-activist voting (Brav et al. (2018)), less common mutual fund blockholder peers (Gu and Zhang (2020)). To the best of my knowledge, the extant literature on investor characteristics in hedge fund activism has been done on the extensive margin i.e. whether the hedge fund activist attack or skip a target firm based on who holds the voting shares. I look into the intensive margin instead, after an activist attacks a target, how it designs the proxy content in order to garner support from the major shareholders.

Broadly, my paper contributes to a growing body of work that applies text-based analysis to fundamental economic questions. Recent work uses a more human-centric approach, classifying the proposals into types and subsequently assessing fund family voting. He et al. (2018) document that less myopic funds are more likely to vote for environmental and social issues. Li et al. (2019) finds that holding based corporate social responsibility score for funds is positively associated with voting favorably on social responsibility proposals. Brav et al. (2018) uses variation in the votes cast by funds to create a "persuadablity" measure. This paper is the first to extract information about mutual fund preferences from shareholder proposal text content. The SVR method is able to differentiate proposals within a type, in terms of the phrases used, and is therefore better suited to extract fund level variations in voting.

The paper proceeds as follows. Section 2 and Section 3 describes the data and methodology used to construct the likelihood of fund voting against the management for an attack. Section 4 tests the hypothesis that activists write proxy text in a way to garner support from larger shareholder. Section **??** validates SVR estimates, and measures its impact on fund attention and voting. Section 7 concludes.

2 Data

Dataset used in the paper includes mutual fund voting data, shareholder proposal text, attack proxy filings text, results of proxy attacks, and log files of fund family accessing proxy filings.

2.1 Shareholder proposal text and voting data

McCahery et al. (2016) show that institutional investors frequently employ voice in their shareholder engagements. 53% of the institutional investors report voting against management as a shareholder engagement channel; second only to discussions with top management (63%). I exploit the voting channel to measure investor preference, over engagement behind the scenes, because of the public availability and standard nature of data points. The shareholder proposal data include shareholder proposal text, management recommendation, and mutual fund vote.

I start with Voting Analytics data, compiled by Institutional Shareholder Services (ISS) available through Wharton Research Data Services, (WRDS). The database includes mutual fund proxy voting records (N-PX filings) for all institutions filing with Securities and

Exchange Commission (SEC). SEC has required mutual funds to disclose how they vote proxies concerning portfolio stocks since July 2003. As such, proxy voting data in the paper covers the period from July 2003 to October 2018.

The voting dataset contains 452 thousand unique proposals, including 10,642 proposals sponsored by shareholders. I exclude management sponsored proposals altogether, as the origin of these proposals and therefore voting is endogenous and may not reveal much about fund family preference. Focusing on the shareholder proposals, also helps with imbalanced dataset problem[8]. The problem occurs if the dataset contains many more samples from one class than from the rest of the classes. For an average proposal (including management sponsored proposals), mutual fund families are very unlikely to vote against the management. During 2003–2018, mutual funds voted against the management for 9% of management sponsored proposals. However, this is not a concern for shareholder proposals, where against management voting is 42% during the period. I match shareholder proposal voting information, with shareholder proposal text available via SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. I use Central Index Key (CIK) to Committee on Uniform Securities Identification Procedures (Cusip) link table, provided by WRDS, to match the two datasets. I supplement this link table with CIK-Cusip database, made from parsing 13D/13G filings[9].

Every firm is required to file Definitive Proxy Statement Form (DEF 14A) with the SEC when a shareholder vote is required. I use text-similarity of proposal's heading in DEF14A with description in ISS database, along with proposal sequencing number to match proposal in ISS data with that from SEC. Apart from director elections, the proposals are sequentially put. I take the relevant proposal section from DEF14A, and assign it to the ISS voting information. However, in the case of director elections, which often involves more than one director, the DEF14A contains information of all the directors contesting in a single proposal. In this case, I assign all the paragraphs from the DEF14A director election proposal section, as part of a particular director election proposal if her/his name appears in the paragraph.

[8] Kubat et al. (1997) show that adding examples of majority class could have detrimental effect on the learner's behavior.

[9] Code to extract CIK-Cusip table is available on GitHub from Ekaterina Volkova

I am able to assign 6,176 proposal text from SEC out of 10,642 shareholder proposal from ISS. The difference in numbers is because (i) the ISS data includes shareholder proposal for companies across the globe, while SEC filings are done by US based companies (ii) some of the proposals are written in a non standard format, which makes parsing them precisely difficult. I explain the process of extracting shareholder proposals, and matching proposals with voting records in Appendix A.

To standardize the different ways fund families vote against the management for a proposal, I define a dummy – against management (AMGT). For a particular mutual fund portfolio, AMGT is one if the portfolio does not precisely follow management recommendation for the proposal. Therefore AMGT is one if the management recommendation is "for", and the mutual fund portfolio votes "abstain", "do not vote", "withhold", or "against". To get fund family level AMGT, I average portfolio level AMGT across fund family for the proposal.

I use the name of the mutual fund portfolios to match a portfolio with a fund family. The list combines mutual fund subsidiaries into one fund family. As an example, Allianz Global Investors purchased Nicholas-Applegate Capital Management, and Pacific Investment Management Company in 2000. In 2008, the company invested $2.5 billion in Hartford Financial Services Group. So, in my dataset, all the mutual fund portfolios with names containing the word Allianz, Nicholas-Applegate, PIMCO, and Hartford are part of the Allianz fund family. I have 190 unique fund family that have voted on at least hundred shareholder proposals in two years prior to a confrontational proxy fight during 2004–2019.

Table 1 reports the number of shareholder proposals with matched text for each year from 2003 to 2018. Given the goal of this study to analyze the text, I limit the shareholder proposals sample to proposals, where I was able to match text information with reasonable confidence. The second number in each cell indicates the percent of proposals where ISS or management went against the management. The ISS recommended against the management for 63% of shareholder proposals. As expected larger fund families are well diversified, and therefore have voted in most of the shareholder proposal in any particular year. PNC has voted on 91% of shareholder proposals between 2003 and 2018, followed by Prudential Financial at 89% and AIG Sunamerica at 88%. Overall, my sample contains 359 unique

Table 1:
Stockholder proposal by year and mutual fund family vote.
This table provides descriptive statistics on stockholders proposals by year and by mutual fund family vote. I match shareholder proposal voting information (including fund family voting, management recommendation, and ISS recommendation) from WRDS with shareholder proposal text filed with SEC. To match the two data sets, I use meeting date, filing date, text similarity, and proposal sequence number. The columns (2), (3), (4), (5), and (6) show voting history of the five biggest US mutual fund families by asset under management as of 2017, based on balance sheet data, released by Banks around the world. Each shareholder proposal gets a vote from all the mutual fund families that own shares in the target company. The number inside round brackets indicates percent of proposals with an against management vote during the year. For column (1), the number in bracket is for percent of proposals for which ISS recommended against the management. I define a vote as against management if the fund family does not exactly follow management recommendation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Year	Shareholder Proposals	PNC, incl. BlackRock	Vanguard	Charles Schwab	State Street	Fidelity	All Mutual Fund Family
2003	42 (40)	24 (27)	-	15 (20)	-	-	841 (29)
2004	499 (45)	439 (27)	17 (34)	343 (16)	7 (14)	15 (42)	15,692 (31)
2005	480 (50)	452 (35)	425 (40)	380 (16)	337 (10)	400 (26)	24,777 (31)
2006	488 (62)	440 (39)	483 (19)	483 (57)	83 (16)	479 (24)	37,437 (42)
2007	398 (60)	364 (47)	380 (18)	384 (62)	46 (11)	344 (27)	27,674 (41)
2008	374 (62)	261 (52)	313 (26)	330 (65)	324 (21)	334 (37)	21,228 (45)
2009	529 (72)	406 (56)	459 (16)	510 (68)	494 (30)	523 (40)	39,973 (52)
2010	360 (77)	344 (33)	327 (20)	301 (49)	317 (22)	327 (36)	24,980 (51)
2011	257 (78)	249 (45)	226 (34)	193 (63)	221 (36)	226 (46)	14,598 (59)
2012	358 (65)	328 (41)	292 (31)	242 (49)	304 (42)	329 (39)	21,577 (51)
2013	497 (65)	492 (27)	478 (18)	412 (37)	464 (35)	494 (23)	34,142 (44)
2014	534 (62)	530 (20)	521 (17)	418 (30)	516 (39)	521 (22)	38,383 (41)
2015	573 (71)	538 (31)	533 (15)	476 (17)	533 (38)	540 (22)	51,438 (44)
2016	413 (66)	391 (24)	393 (17)	360 (19)	380 (37)	389 (19)	34,507 (41)
2017	371 (60)	353 (27)	355 (20)	296 (25)	331 (30)	346 (28)	30,497 (40)
2018	3 (100)	2 (0)	3 (0)	-	2 (0)	2 (0)	104 (41)
Full Sample	6,176 (63)	5,613 (35)	5,205 (21)	5,143 (40)	4,359 (31)	5,269 (29)	417,848 (44)

mutual fund family, with an average (median) of 1,163 (479) voting observation or 19% (8%) of all the shareholder proposal during 2003–2018.

The fund families, compared to ISS, are less likely to go against the management. The friendliness is in line with the existing literature, which show that fund families support management when they have business ties Davis and Kim (2007), cross-ownership in a merger Matvos and Ostrovsky (2008), other peers supporting management Matvos and Ostrovsky (2010), or pension ties Ashraf et al. (2012). In fact, fund families have voted in support for management, even when it seemed to go against shareholders interest. For example, in 2015 Vanguard, Blackrock, and State Street voted against Trian's candidates for Dupont's board of directors. After the failed activism event, Dupont's stock price declined abruptly, the company missed earnings, and the CEO "retired voluntarily". DuPont shortly thereafter announced a merger with Dow Chemical to handle problems that Trian had identified.

Among the top five biggest US mutual fund families by asset under management, Vanguard is the least likely to vote against management, followed by Fidelity and State Street. For the overall dataset, the AMGT is much higher than the big five fund families, possibly because smaller fund families tend to be active mutual funds and more willing to show their dissent to management. Smaller firm voting more against the management works against the machine learning methods for testing the paper's hypothesis that the proxy text predicts a higher probability of fund families voting against management, when funds own more shares. So my result has to overcome this general drift of bigger fund families voting more in favour of management.

2.2 Proxy fight text

I gather information related to proxy fight from the filings that occur during contested solicitation of votes. During a proxy fight, activists and management put forth their viewpoint and send proxy cards to shareholders. The shareholders sign and return proxy cards to the party they support. Once returned, these signed proxy cards are essentially votes. Both the parties accumulate votes via the returned proxy card and use them at the shareholders meeting, often the annual shareholder meeting. For the vote solicitation process, the activists file PREC14A (Preliminary Proxy Statement in Connection with Contested Solicitations) and DEFC14A (Definitive Proxy Statement in Connection with Contested Solicitations). In addition, DFAN14A (Additional Definitive Proxy Solicitation Materials Filed by Non-Management) is also filed by activists if the proxy solicitations are not supported by the registrant. I use these forms to identify, and gather text, for activists contested interventions. Norli et al. (2014), Alexander et al. (2010), Fos and Tsoutsoura (2014), and Brav et al. (2018) use a similar approach.

The forms are available to the public via SEC's EDGAR system. I construct my proxy text dataset from 2004 to 2019, as the mutual fund voting record is available from July 2003. This leaves some mutual fund voting record for the machine learning model to construct fund family preference in 2004. I parse each DFAN, DEFC, and PREC filing (or attack filing) to extract the filer and subject company. I restrict the sample by cross-referencing the filer with a list of investment managers that have filed a Schedule 13F holdings report at some point in their history. Institutions holding more than $100 million in US stocks file 13F reports. Greenwood and Schor (2009) employ a similar process to exclude corporate cross-holding with activism from portfolio investors. I exclude duplicate filings in EDGAR system, usually each document is filed twice, with target and attacker central index key separately.

Proxy fights typically span few months involving many filings. I bunch together all the filings for a filer-subject pair, if the difference between consecutive filing dates for these documents is less than 180 days. I also manually remove filings related to merger and acquisition, litigation, banter etc. I get a total of 533 confrontational proxy attacks, during the period 2004–2019, with a mean (median) 7.85 (5) filing per attack. In Appendix B, I explain the format of DFAN, DEFC or PREC filings and textual features that I employ to extract activist's communication with the shareholders.

The solicitations includes proposals related to director nomination, board declassification, executive compensation, board independence, capital structure, business strategy, etc. The solicitations are rich in text content, and avoid boilerplate filing that we often see in other company documents. The documents are often written in a letter format, where the activists address shareholder discussing how the management has failed, and the areas where the focus should be, and finally their plans to improve shareholder value.

Several investor attack starts with a 13D filing, discussions in media, and eventual retraction or agreement without any attack filings. For example, on August 06th, 2015, Icahn Capital filed 13D to engage in discussions with Cheniere Energy. Three weeks later, the two firms entered into an agreement. There were no DFAN, DEFC or PREC filings; as such, this attack is not part of my analysis. 13D filings are beneficial ownership filings, required for investors when they own more than 5% in any class of a company's securities and intends to influence the management. I, however, do not use 13D filings to identify attack because 13D filings often do not contain information related to activists' contentions with the manager. I also did not use media reports to determine the contention, as the sources and linguistic differences add noise to the information.

Table 2:
Prominent activist investors and their target firm during 2004–2019.
The table shows the major confrontational proxy fights in terms of the market capitalization of the target firms, for hedge fund activists that have at least three confrontational attacks. The proxy fight is identified based on PREC14A, DEFC14A, or DFAN14A filings for an activst and a target pair. For an activist-target pair, if the difference between filing date is more than 180 days I assign it to a separate fight. Target and attacker names are parsed from the SEC filings.

Activists	Attack (#)	Major Targets
Breeden Capital Management	2	Applebees, PIMCO
Icahn Enterprises	39	Time Warner, Yahoo, Dell, eBay, AIG, Clorox, Family Dollar, Motorola, Tyson, Xerox, Cigna, Biogen
Land & Buildings Investment Management	8	Macerich, MGM Resorts, Taubman Centers
Marcato Capital Management	3	Lear Corp, Deckers Outdoor Corp, Buffalo Wild Wings
P Schoenfeld Asset Management	3	T-Mobile
Pershing Square Capital Management	2	Allergan Inc, Automatic Data Processing
Starboard Value	22	Bristol Myers, Office Depot, Dollar Tree, Yahoo, AOL
Steel Partners	11	Rowan Companies, GenCorp
Third Point	9	Dow Chemicals, Campbell, Yahoo
Trian Funds	3	P&G, DuPont, Heinz

In Table 2, I show major activists along with their attack during my sample period. In terms of frequency of attack by activists, some of the well know activists such as Icahn Capitals (39), Starboard Value (22) lead the list. However, the activism share is fragmented, and only nine activists have double digit confrontational proxy attacks during 2004–2019. The 533 proxy fights is shared among 177 unique shareholder activists, with the median number of attacks by activists as one. Often a group of attackers together attack a firm as a wolfpack Coffee Jr et al. (2016), Wong (2019) or coordinate by co-filing Schedule 13Ds (about 22% of Brav et al. (2008) sample). However, the SEC filing is done by the lead attacker and thus contain one filer name. Therefore, the share of each attacker is higher than reflected in Table 2. Also, of note, is that the number of confrontational proxy fight is significantly lower than activist attacks referred in literature. Hedge fund activists only use proxy contests as a threat since it is costly for both parties. Gantchev (2012) estimates campaign ending in a proxy fight costs $10.71 million on an average. Thus, only 10-12% activist campaign threaten a proxy contest and 7% eventually go for proxy voting.

As an example of what these proxy filings discuss, lets see the attack on Proctor & Gamble (P&G), the biggest firm in terms of market capitalization in my sample. Trian Fund Management, started its activist campaign against P&G for the election of its nominee, Nelson Peltz, to the Board of Directors at the 2017 annual meeting of shareholders. P&G responded that its Board and management team is actively executing its strategy to achieve balanced, sustainable long-term growth and value creation. Trian Fund mailed a letter to shareholders detailing why it views that adding an independent director can lead to the breakthrough ideas P&G needs, and why it is necessary to cut through P&G's rhetoric so shareholders can make an informed decision. Trian created a website www.RevitalizePG.com, where it shared material in connection with the election. In total, Trian filed a total of 60 DFAN14A to communicate with the shareholders. While Nelson Peltz was not elected to the Board, the results was close. The Board decided to expand and accommodate Nelson Peltz.

2.3 Fund family holding data

Since 2003, mutual fund portfolios are required by SEC to file their holdings quarterly, which is available via Center for Research in Security Prices (CRSP) in WRDS. However, some portfolios report more frequently than a quarter in CRSP holding database. To not count portfolios twice, I begin with a complete list of available mutual fund portfolio from CRSP mutual funds summary. I then populate holding information for each portfolio from CRSP mutual funds holdings. CRSP mutual funds holdings provide data in terms of market value of both bond and equity. Since shareholder proposals are voted on by equity owners, I exclude bond securities. I combine the portfolio holdings across fund family for each target firm in a particular month.

I start with matching target firm with the fund family holdings data for the attack month. If the holding for the attack month is unavailable, I check in the previous two months. Fund families holding data do not change drastically month to month, because funds often replicate index or other set goals. Next, I get company's market capitalization from CRSP's monthly stock data. I use the product of shares outstanding with the share price to calculate market capitalization. For private firms, such as Dell Technologies in 2013, for which share price is not available, I use book value of common equity from S&P Capital IQ as market capitalization.

Table 3 shows the top ten fund families with the biggest stake, or voting power in my sample ranked based on average percent of market capitalization they hold in target firms. I filtered the table for fund families that have a stake in at least hundred confrontational attacks during the period 2004–2019. Among the filtered fund families, Vanguard holds the largest portfolio of the target firms, averaging at 3.89% of targets share. PNC and Fidelity follow suit at 2.43% and 2.04%, respectively. Out of the 436 confrontational activism event during 2004–2019 for which I have holdings data, 130 have a fund family that owns more than 10% of target stocks. Sometimes, the largest investor is a smaller fund family. In fact, the top three firms based on average holding in targets (in the table I filter based on holdings in at least hundred attacks) are Wintergreen Advisers (18.13%), Fairholme Capital Management (12.49%) and Longleaf Partners (5.50%).

Figure 1:
Share of stocks held by mutual fund families at the beginning of a confrontational attack.
The colored stack show fund families that have a stake in at least hundred confrontational attack, and on average hold more than 1% of target stocks. The holding data is extracted from CRSP, while the confrontational attacks are identified based on PREC14A, DEFC14A, and DFAN14A filings. The top attack, in terms of target market capitalization, is annotated for each year.

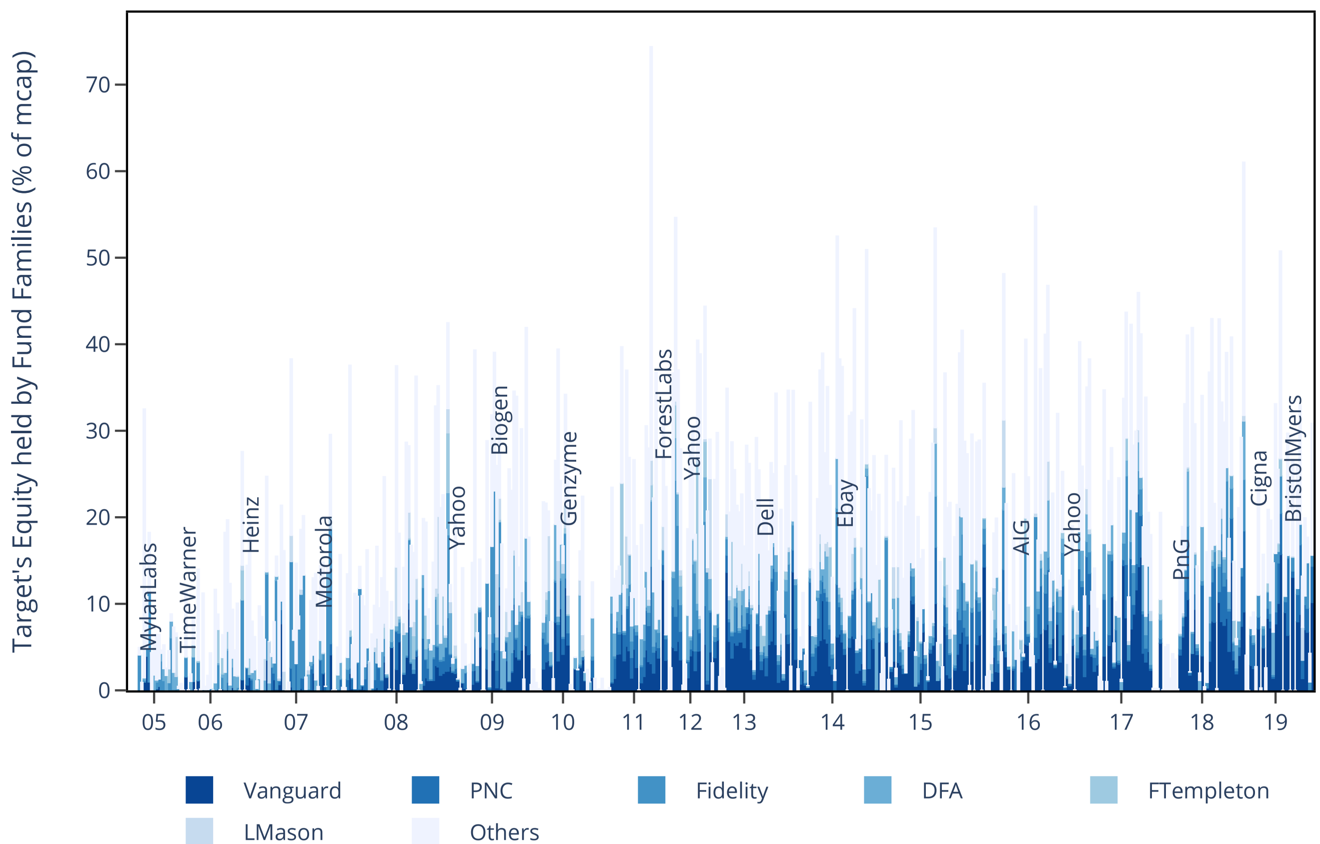


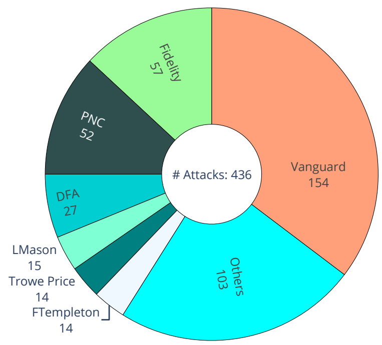
Table 3:
Top 10 mutual fund family in terms of average fraction of target's shares they hold before a proxy attack, during 2004–2019.
The list is filtered for mutual fund families that have a stake in at least hundred confrontational attacks during the period

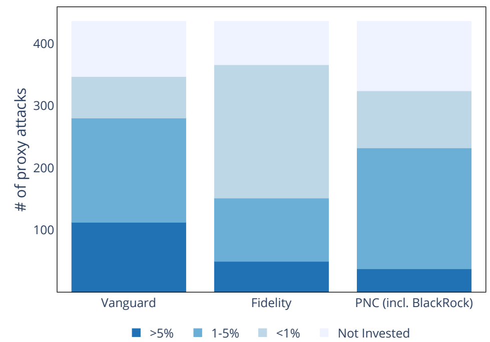
Mutual Fund Family	Inv. in Target (#)	Avg. Holding (% mcap)
Vanguard	352	3.89
PNC (incl. BlackRock, Barclays, Merril Lynch, Ntnl City Bank)	323	2.43
Fidelity	375	2.04
Dimensional Fund Advisors	312	1.73
Franklin Templeton	101	1.6
Legg Mason (Incl. Permal, Pvt Capital Mgmt, Royce & Associates)	179	1.14
T Rowe Price	269	0.87
Gabelli	115	0.76
Ameriprise (Incl. Columbia)	232	0.66
State Street	276	0.5

Figure 1 shows the fraction of shares of the target firm held by the largest mutual fund families at the beginning of each attack. Mutual funds hold 16.8% of activism target's stock on an average, with the median being 14.8%. The holdings have increased through the years, in line with mutual funds holding a larger chunk of US equity. We also see a decreased number of confrontational activist attacks around the year 2009, in line with Burkart and Dasgupta (2014) framework, which show that activism slow in economic downturns when overall cash flows from activism are lower. For each year, I annotate the attack that has largest market capitalization for the target. Yahoo Inc, is one of the major firm that has been targeted more than once - by Third Point, Starboard Value and Icahn Enterprises in 2012, 2016 and 2018 respectively. The figure reiterates the fact that fund families are a major player when it comes to whether a particular activism event will succeed or fizzle out.

While it seems like the usual suspects such as Vanguard, BlackRock are the major shareholders in all the attacks, and hedge funds essentially have to pander to the same fund families irrespective of the attack. Figure 2 show otherwise, the top three fund families Vanguard, Fidelity, and PNC are the largest shareholders in 60% of the attacks. However,

Figure 2:
Largest shareholders in targeted firm before the attack; and variations in targeted firm holdings, by fund family
The list is based on 436 confrontational attack, with holding information during the period 2004–2019



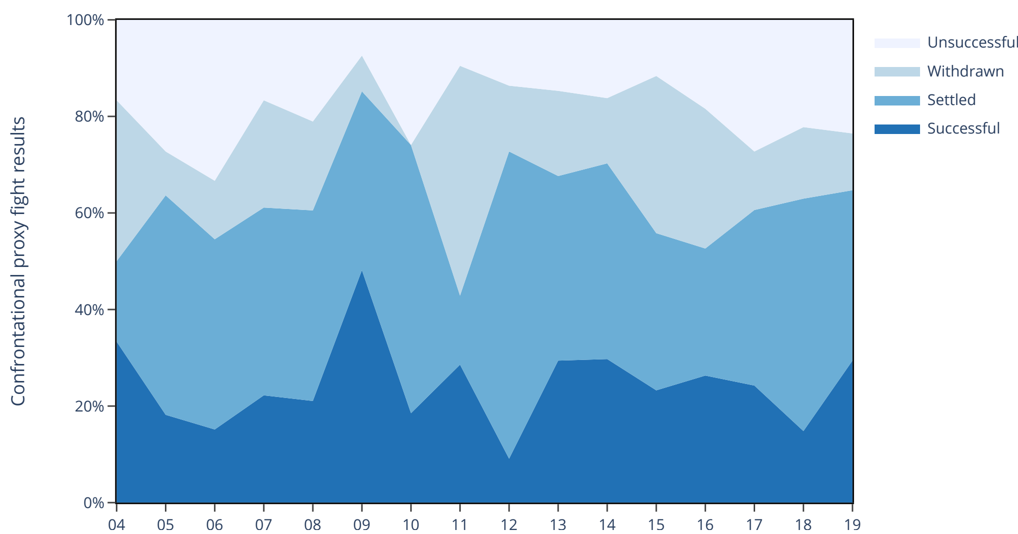


the list of largest shareholders contain fifty unique mutual fund families. The distribution of holdings for top three fund families show that Vanguard owns less than one percent of target shares 36% of attacks, while PNC and Fidelity own less than 1% of target share in 47% and 65% respectively. The distribution underlines that the institutes which hold voting power varies across target firms, and the hedge funds have to tailor their approach instead of just catering to the same few fund families.

2.4 Outcome of Attacks

I use CapitalIQ platform, available from S&P, to gather information on how the attacks panned out. Out of the 530 attack in my sample, I was able to get results for 461 of them. Few of them have missing information, and few are ongoing. The CapitalIQ platform classifies attack results into four categories. An attack is deemed "Successful" if the activist's suggestions (often board of director nominations) win the shareholder election. If the management and attacker feel they could discuss and compromise, without going into a formal election the attack is considered "Settled". Settlement often happens when the management feel that the attacker's case is strong, and the attacker is likely to win the election. In these situation, the management settles typically to avoid embarrassment of losing the election. Opposite happens in the case of "Withdrawn", here the activist get the signal that it will likely not be able to garner enough support for its demands and thus tries to cut losses, and withdraws the case. Lastly, if the activist participate in the election and is unable to secure required votes, the attack is deemed "Unsuccessful".

Figure 3:
Stacked area chart for attack outcomes
The graph plots the outcome of attacks during the period 2004–2009. Each attack is assigned to the year when the attack began i.e. the earliest date of PREC14A, DEFC14A, or DFAN14A filing by the activist pertaining to target. The values are normalized to hundred percent each year. The information on proxy fight results are available via S&P CapitalIQ.



In hedge fund activism literature, as discussed in Brav et al. (2015), "Settlement" is often taken equivalent to "Successful", and "Withdrawn" equivalent to "Unsuccessful". Figure 3 show the distribution of attack outcome. 63% of the confrontational proxy fights are successful during 2004–2019. The success ratio peaks at 85% for attacks that originated in 2009. The number is above 60% throughout, except for attacks that began in 2011 where the success ratio drops to 43%.

Out of the 530 attacks, 199 resulted in an actual confrontation involving shareholder voting. I use ISS voting data, discussed in Section 2.1, to get voting records of the fund families. To identify the proposals associated with an attack, I start with all the shareholder meetings for the target firm. I filter out the meetings which have no shareholder sponsored proposals, occurred more than 30 days before the attack's end date, or occurred 365 days after the attack's end date. I use a 30-day window, because activists often communicate with shareholders after the voting to inform meeting results and offer gratitude. After the filtering, I choose the first meeting after the attack's beginning date. For the selected meeting dates, I choose all the shareholder proposals that do not contain the string "Management Nominee". I aggregate against management voting, by averaging at the proxy fight level i.e. if the fund family supported one out of three activist proposals, the AMGT will be 0.33. I get a total of 1,901 fund voting records, involving 77 shareholder proposals.

2.5 Fund's access of attack filings on SEC Server

SEC's Division of Economic and Risk Analysis (DERA) assembles information on internet search traffic for EDGAR filings through SEC.gov, covering the period February 14, 2003, through June 30, 2017. The EDGAR log file is publicly available. The log file contains masked IP address providing the first three octets of the IP address with the fourth octet obfuscated with a three-character string, so as not to reveal the full identity of the IP. To assign these masked IPs to funds, I use the linking table from Digital Elements. The linking table contains names of the organizations, for which the IP address is registered as of December 31st, 2016.

I follow Iliev et al. (2018) to identify EDGAR activity that relates to governance research. First, I remove all the masked IP addresses which accessed EDGARs website more than a thousand times, as these addresses are often bots. I also require the fund family to view filings for at least 1% of their holdings every quarter. Going back from 2016 Q4, if a fund family viewed less than 1% of their holdings in two consecutive quarters, I remove the fund family from my sample prior to the first under 1% quarter. I combine views occurring within five minutes for an IP-document pair.

For each attack, I use the accession number provided in DEFC, DFAN and PREC filing to make a list of attack documents. I sum the number of times a fund family viewed one of the attack documents from the date the attack begin, by attacker filing the first document, to 30 days after the attack ended, the last document filed in the attack. I describe the method used in this paper to extract information from EDGAR log files in Appendix C.

In total, I gather fund views of filings for 427 attacks, involving 115 unique parents. My data set contains 244 thousand attack-fund pair, with an average of 1.04 views by a fund family for an attack. Counting only the positive views, I have 40 thousand attack-fund pair, involving 73 unique fund families, on 278 attacks. The average positive number of views by fund family is 6.39 views per attack.

3 Methodology

I begin by describing how I use the fund family voting on shareholders proposal data to construct text-feature based measure of mutual fund family preferences. I assume throughout that the voting choice by the fund family provides a good and stable reflection of its concerns. The assumption is in line with SEC directive[10], which suggests fund managers to implement a reasonably formulated voting policy.

3.1 Proposal text implied fund family preference

Quantifying previous voting decisions on various proposals is the most natural and measurable way to measure the preferences of a mutual fund family. I use a window of two-year to assign relevant proposals for a fund family, this keeps the preference time-variant. Therefore to measure the fund family's preference on a particular day, I include shareholder proposal which occurred within two years of that day. I do this exercise, only for fund families who have voted in more than hundred shareholder proposals during the period, to have adequate training sample for the machine learning method.

To standardize the shareholder proposal text data, I remove HTML tags, punctuation,

[10]"should consider reasonable measures to determine that it is casting votes on behalf of its clients consistently with its voting policies and procedures.": 2019 SEC Proxy Voting Guidance

and digits. The text data, inherently, is plagued with differences in cases, inflectional endings, filler words, which makes the feature size unmanageable. To reduce the number of distinct features, I lowercase the text and then lemmatize[11] each word and keep words that are English words but not stop words[12] . I use an n-gram size of five[13] to extract features from the text. I omit n-grams that appear less than 1% or more 70% of the proposals in order to remove misspelled, and frequently used legal terms, etc. I get a total of 9,832 ngrams, comprising of 2,465 unigram, 4,991 bigram, 1,593 trigram, 567 4-gram, 216 5-gram. Each shareholder proposal text is therefore represented by xt, a K = 9,832 vector of n-gram frequencies, i.e.,

$$x_{t,i} = count\ of\ ngram\ n\ in\ proposal\ t \tag{1}$$

I combine the shareholder proposal text data with how the fund family voted on them with respect to management recommendation, $AMGT_t$, with a linear regression model:

$$AMGT_t = w_0 + \mathbf{w}.\mathbf{x}_t + \nu_t \tag{2}$$

where **w** is a K vector of regression coefficients. Thus, predicting how likely the fund family is to vote against management from the text data is a regression problem like any other. However, the high dimensionality of text makes ordinary least squares and other standard techniques infeasible. Thus, using machine learning based textual analysis is vital. I employ Support Vector Regression (SVR)[14] by Drucker et al. (1997). SVR estimation procedure is shown to perform well for short samples with an extremely large feature space K. The method is used in finance literature by Kogan et al. (2009) to predict risk from financial reports, and Manela and Moreira (2017) to measure news implied volatility. The

[11]Lemmatization removes inflectional endings and returns the base or dictionary form of a word. So, “stockholders will be asked to approve a proposal” becomes “stockholder will be ask to approve a proposal”. Separately, I experiment with stemming and find similar results.

[12]I use python’s natural language toolkit English corpora to identify English and stopwords. Removing stopwords from “stockholder will be ask to approve a proposal” leaves us with “stockholder ask approve proposal”.

[13]I use countvectorizer available via scikit-learn. So the sentence “stockholder ask approve proposal” results is four uni-grams – “stockholder”, “ask”, “approve”, “proposal”; three bi-grams and so on. I also consider different degree n-grams and find practically identical results.

[14]I discuss alternative approaches in the robustness section.

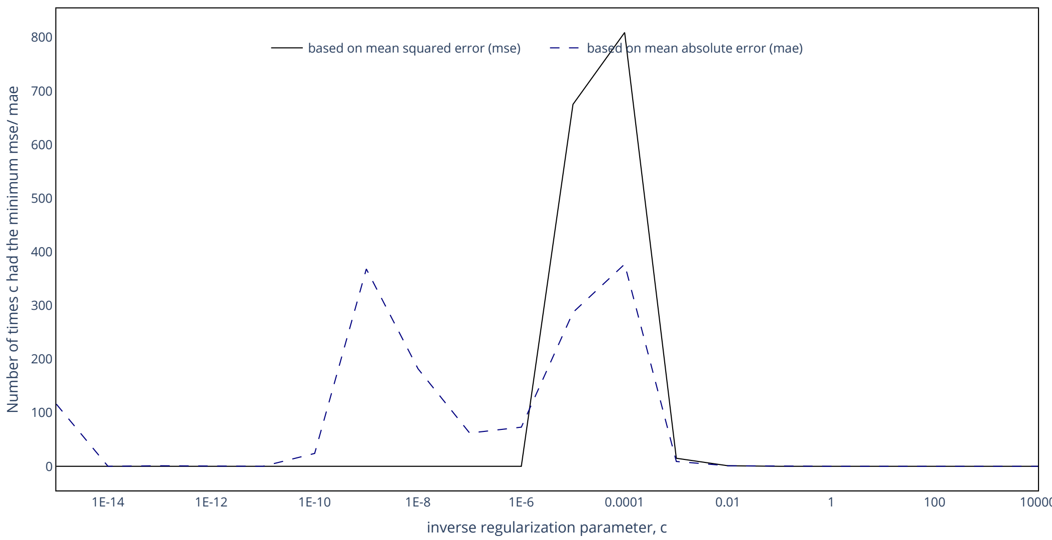
full treatment of SVR is beyond the scope of this paper. I document an intuitive glimpse into this method and the structure that it implicitly imposes on the data. SVR is an L2 penalized model with a margin of tolerance (ϵ), which minimizes the following objective:

$$H(\mathbf{w}, w_0) = \sum_{t \, \in \, train} g_\epsilon(v_t - w_0 - \mathbf{w}.\mathbf{x}_t) + \frac{\mathbf{w}.\mathbf{w}}{2c} \tag{3}$$

where $g_\epsilon = \max(0, |e| - \epsilon)$ is an ϵ-insensitive error measure, which ignores errors of size less than ϵ i.e. it only penalizes samples whose prediction is at least ϵ away from their true target. The loss function is similar to Gaussian linear regression, except SVR adds a penalty for each dimension of coefficient, **w**, that deviates from zero via a inverse regularization parameter c. The minimizing coefficients vector **w** can be completely described as a linear combination of the training observations. Only some of the train observations' weights are nonzero; and the associated data values are called the support vectors, thus the name support vector regression. SVR shines in high dimensional text regression owing to excellent generalization capability, high prediction accuracy, and dimension independent computational complexity. The cost of SVR is that the kernel cannot adapt itself to concentrate on sub-spaces of **x** (Hastie et al. (2009)). For example, if the fund families vote is dependent on topics such as "climate_change", which often occurs with "paris" (from Paris Agreement on Climate Change), the SVR will assign similar weights to both the n-grams.

Ultimately, how well a machine learning method works is dependent on how well it predicts out of sample (OOS) observations. SVR estimation requires user to choose two hyper-parameters that control the trade-off between in-sample and out-of-sample fit (the ϵ insensitive zone and inverse regularization parameter c). I use insensitive zone, ϵ value of 1 percent. So, the SVR method does not penalize the cost function if the difference between actual and predicted AMGT is less than one percent. I use a three-fold grid search algorithm for the proposal voting data, to pick inverse regularization parameter, c, from 10^j, where j ranges from -15 to +4. I focus more towards c below 1 as the strength of the regularization is inversely proportional to c. Figure 4 indicates the best performing regularization parameter for mean squared and mean absolute error. Regularization parameter, c = 0.0001 has the

Figure 4:
Best performing inverse regularization parameter for SVR
Based on SVR results of 25 randomly selected fund families at the end of each quarter during the period 2004–2019. For each SVR run, GridSearch package, available via scikit-learn, finds the inverse regularization parameter with the lowest mean squared and mean absolute error.



lowest mean absolute error and mean squared error for 25% and 54% of my run sample. The run sample includes 25 randomly selected fund family each quarter totaling to 1500, during 2004–2019.

3.2 Validating text-features coefficients

The machine learning method described in section 3.1, essentially assigns a coefficient to each of the K = 9,832 text-features. In this section, I check the validity of SVR coefficients from two perspectives: (i) are coefficients aligned with fund family voting history (ii) do coefficients follow fund family policy documents. The exercise substantiate the machine learning prediction with observable variables.

3.2.1 Text-features coefficients line with historical voting

The coefficient associated with a text feature indicates the marginal increase in likelihood by fund family for voting against the management if the shareholder proposal text contains the text features. For example, the coefficient on ”declassify board of director” for Morgan Stanley in December 2010 is 0.0047, this shows that Morgan Stanley is 0.47% more likely to vote against the management for every instance of ”declassify board of director” in a shareholder proposal text. I employ the following equation to test whether the SVR coefficients are in line with fund family historical voting:

$$w_{n,f,t} = \beta AMGT\_frac_{n,f,t} + \delta_{f \times t} + \epsilon_{n,f,t} \tag{4}$$

where w represents the SVR coefficient associated with an n-gram, n, for a fund family, f, at time t. $AMGT\_fract$ show the fraction of times the fund family voted against the management when the text-feature w occurred in a shareholder proposal. $\delta_{f \times t}$ show fund family cross time level fixed effect and the error, $\epsilon_{n,f,t}$, is clustered at the fund family level. I choose the time period, t, to be 31st December for each year from 2004 to 2018. I calculate the w and $AMGT\_frac$ for each fund family which have voted more than a hundred times in past two years from the timestamp.

The results, reported in Table 8, confirm that the SVR is putting weights in line with how the fund family have voted during the two year period. For every on standard deviation increase (xx%) in fund family voting against the management for shareholder proposals containing the n-gram the SVR assigns xx more weight to the n-gram. Within a fun family cross year, the SVR assigns higher coefficients to n-grams which are part of shareholder proposals where the fund family voted against the management.

3.2.2 Text-features coefficients line with fund family policy guidelines

Mutual funds share prospectus of their funds to shareholders yearly, describing among other things - risks, investment strategies and fund’s proxy voting guidelines. The prospectus is filed with SEC as post-effective amendment form or 485BPOS. Proxy guidelines across mutual funds within a fund family remain consistent for a given year. Therefore, to gather voting policy text for a fund family, I look for the prospectus of the biggest mutual fund that is part of the fund family. Subsequently, I look for cues such as ”Proxy Voting Guidelines”,

Table 4:
Does SVR assign weights in line with fund family voting history?
This table reports estimates of a regression of SVR n-gram coefficients on fraction of shareholder proposals that contained the n-gram, on which the fund family voted against the management. Specifically, I estimate:

$$w_{n,f,t} = \beta AMGT\_frac_{n,f,t} + \delta_{f\times t} + \epsilon_{n,f,t}$$

where w represents the SVR coefficient associated with an n-gram, n, for a fund family, f, at time t. $AMGT\_fract$ show the fraction of times the fund family voted against the management when the text-feature w occurred in a shareholder proposal. $\delta_{f\times t}$ show fund family cross time level fixed effect. The time period, t, is chosen to be 31st December for each year from 2004 to 2018. I calculate the w and $AMGT\_frac$ for each fund family which have voted more than a hundred times in past two years from the timestamp. $AMGT\_fract$ is scaled by the standard deviation of the underlying variable, meaning coefficients can be interpreted as the effects of a one standard deviation change in the determinant. Standard errors, $\epsilon_{n,f,t}$, are clustered at the fund family level, and *t*-statistics are reported in brackets below the coefficient estimates. The symbol *, **, and *** indicate significance at 10%, 5%, and 1% respectively.

	SVR Coefficients $\times$ 10,000		
	(1)	(2)	(3)
$AMGT\_frac$	0.785***	1.34***	1.86***
	[617.44]	[30.54]	[32.83]
Fund Family FE	-	Yes	-
Fund Family $\times$ Year FE	-	-	Yes
Observation	17,733,101	17,733,101	17,733,101
R^2	0.021	0.037	0.053

”Proxy Voting Policies and Procedures” to extract the proxy voting guidelines. I am able to gather xx proxy guidelines, across xx fund families during 2004–2018.

Proxy guidelines describe fund policies on different corporate governance issues such as director elections, auditor approvals, compensation issues, corporate structure, shareholder rights, social policy etc. Going through proxy guidelines could not only reveal differences across different fund family's preferences, but also differences within a fund family guidelines across years. For example, many fund families have become more inclined to vote against the management on social issues.[15]

While the SVR assigns both positive and negative coefficients to each of the n-grams. It is unclear how the coefficients should be affected by presence of those n-grams in the proxy guidelines document. While occurrence of n-grams such as ”right to call shareholder meeting” indicate that the fund family wants improve this right and thereby would vote against the management if shareholder proposals contain this n-gram. This would give these n-grams a more positive coefficient. Some of the fund families also write about things that they feel are part of management decision prerogative and thus would vote with the management on those proposals. To circumvent this ambiguity, I look for absolute value of the coefficients. The assumption here is that when a fund family mentions a particular n-grams in their proxy guidelines, the n-gram is important to their voting decisions. An important n-gram would have a higher absolute value of coefficients, more positive if the n-gram is about supporting shareholders and more negative if the n-gram is about supporting management. In this section, I look for whether the SVR coefficients follow fund family policy guidelines. I employ the following equation:

$$abs(w)_{n,f,t+1} = \beta count_{n,f,t} + \delta_{f\times t} + \epsilon_{n,f,t} \tag{5}$$

where $abs(w)$ represents the absolute SVR coefficient associated with an n-gram, n, for a fund family, f, at time t + 1. $count$ is the number of times an n-gram appeared in the

[15]Vanguard on social issues (i) in 2010: ”regardless of our philosophical perspective on the issue these decisions should be the province of company management unless they have a significant tangible impact on the value” (ii) in 2019: ”The funds will evaluate each proposal on its merits and support those where we believe there is a logically demonstrable linkage between the specific proposal and long-term shareholder value of the company.”

fund family's proxy guidelines text filed in year t. Since, I use a training period of two years for SVR, I relate n-gram counts, from the proxy guideline document, to the SVR coefficients of n-gram calculated at the end of next year. $\delta_{f\times t}$ show fund family cross time level fixed effect and the error, $\epsilon_{n,f,t}$, is clustered at the fund family level.

Table 5:
SVR coefficients with respect to proxy voting guidelines
This table reports estimates of a regression of absolute n-gram coefficients on the number of times the n-gram appeared in the fund family's proxy guidelines text. Specifically, I estimate:

$$abs(w)_{n,f,t+1} = \beta count_{n,f,t} + \delta_{f\times t} + \epsilon_{n,f,t}$$

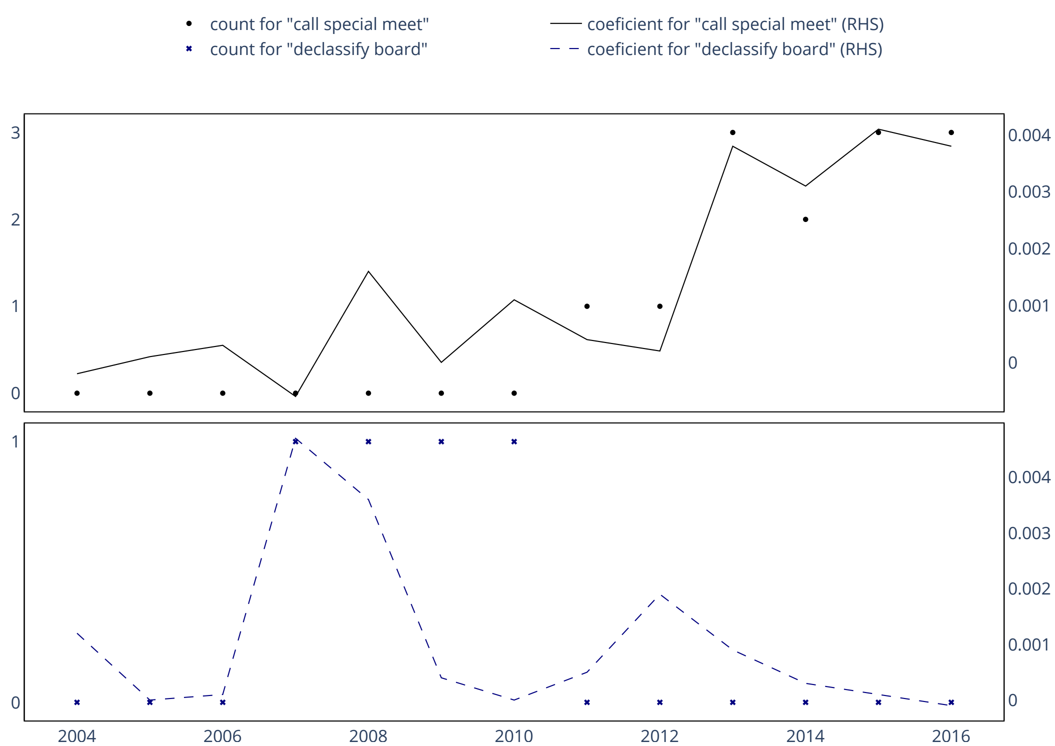
where $abs(w)$ represents the absolute SVR coefficient associated with an n-gram, n, for a fund family, f, at the end of year t + 1. $count$ is the number of times an n-gram appeared in the fund family's proxy guidelines text filed in year t. $\delta_{f\times t}$ show fund family cross time level fixed effect. (1), (2), and (3) show result for all the 9,832 n-grams. For (4), (5), and (6), I filter out n-grams for a fund family if the n-gram is not present in any of the fund family's proxy guidelines. $count$ is scaled by the standard deviation of the underlying variable, meaning coefficients can be interpreted as the effects of a one standard deviation change in the determinant. Standard errors, $\epsilon_{n,f,t}$, are clustered at the fund family level, and *t*-statistics are reported in brackets below the coefficient estimates. The symbol *, **, and *** indicate significance at 10%, 5%, and 1% respectively.

	absolute SVR coefficient $\times$ 10,000					
	(1)	(2)	(3)	(4)	(5)	(6)
Count	0.736***	0.734***	0.744***	0.477***	0.476***	0.500***
	[217.46]	[7.64]	[7.77]	[82.87]	[7.44]	[7.82]
Fund Family FE	-	Yes	-	-	Yes	-
Fund Family $\times$ Year FE	-	-	Yes	-	-	Yes
Exclude policy absent n-grams	-	-	-	Yes	Yes	Yes
Observation	2,192,536	2,192,536	2,192,536	358,206	358,206	358,206
R^2	0.021	0.04	0.064	0.019	0.045	0.075

The results, reported in Table 5, confirm that the SVR is putting weights in line with what fund family mention in their voting proxy guidelines. Within a fund family for a particular year, we see that coefficients are higher in absolute terms for n-grams which are mentioned more in the proxy guidelines. Some of the n-grams which appears in shareholder proposal may not appear in proxy guidelines of a fund family at all. It could be argued that the n-grams that do not appear could indeed be less significant for voting decisions, and that's why we have a positive coefficients associated with counts. To allay these concerns, in column (4)–(6), I include only those n-grams which appeared at least once in the proxy guidelines text for the fund family. The results remain robust for the smaller subsample of n-grams, which appeared at least once in the proxy guidelines documents for a fund family.

As an example, figure 5 show variation in SVR coefficients of ”call special meet” and ”declassify board” for Morgan Stanley across time. We see as Morgan Stanley mentions more about shareholder’s right to have special meeting, the SVR coefficient also increases. Similarly, a decreased mention of board declassification in proxy guidelines is associated with a lower SVR coefficients.

Figure 5:
Line and scatter chart for count and coefficients of ”call special meet” and ”declassify board” for Morgan Stanley
The graph plots the number of times the n-gram is used in proxy guidelines, and subsequent SVR coefficients, for Morgan Stanley during the period 2004–2016. Proxy guidelines text is extracted from form 465BPOS via EDGAR. The SVR coefficient is measured at the end of next year after the proxy guideline text filing.



3.3 Likelihood of Fund Family Supporting a Proxy Fight

To determine fund preferences for a particular proxy fight, I take into account all the shareholder proposals voted on from the first proxy filing date (attack date) to two years before the attack date. I look into each fund family separately and consider only those families who have voted in at least hundred shareholder proposals during the period. For each fund family, I solve SVR regression Equation 2. I begin with 533 confrontational fights during 2004–2019. I get a total of 526 attacks for analysis after filtering on having fund families with hundred voting information in two years prior to attack date.

Illustrating with an example, let's look into P&G 2017 attack by Trian Funds. The first proxy (between DEFC, DFAN, and PREC) filed by Trian was a DFAN14A on July 17th, 2017. So I begin with all the shareholder proposals during the period July 17th, 2015–July 17th, 2017. I get a total of 189 fund families, which have voted in at least hundred of these shareholder proposals. Subsequently, I run a separate SVR for each of the fund families, using the whole shareholder proposal data available for the fund family during the two years.

For the 189 fund families, the average mean absolute error with text is 0.24, while the average mean absolute error without the text is 0.38[16]. The model is accomplishing a reduced error by iterating through weights to each of the n-grams in the proposal. If most of the text document where the fund family voted against (with) management contains the phrase "restrict_stock_award" ("initiate_appropriate_process") then the SVR will assign a positive (negative) weight to the phrase. At the end of the process, we have a model that has weights associated with each of the n-grams. Here a positive (negative) weight to a phrase implies that the fund family is more likely to vote against (with) the management whenever the phrase occurs in the shareholder proposal text.

Once I have the weights in the SVR model, I measure how likely the fund family is going to vote against the management based on the proxy attack text. I limit the probabilities at one (zero), if the predicted number is above (below) the cutoff. I get a predicted AMGT for

[16]this is expected since machine learning models are known to work well in-sample, owing to large feature set available to fit the data

each fund family. The number represents the likelihood of fund family to vote against the management (equivalently - in favor of the activists) in a confrontational proxy fight.

3.4 Sample and descriptive statistics

For my primary analysis, I use predicted AMGT value for each fund family which have voted in at least 100 shareholder proposals in the two years prior to the attack date. Separately, I also show my results only for fund families that have a stake in the target firm. My sample includes 522 confrontational proxy attack (437 with holding information), involving 287 unique fund families, during 2004–2019. In total, I predict a total of 66,836 (12,582 non-zero holding) probability of fund family voting against the management,

Table 6:
Summary statistics
This table reports summary statistics of key variables. Column (1), and (2) show statistics for all the mutual fund families that have voting information available for at least hundred shareholder proposal in two year period prior to the attack. Column (3), and (4) report the numbers for a smaller sample of mutual fund families that hold shares in the target firm. Fund holding is measured in terms of fraction of equity owned by a mutual fund family. $\widehat{AMGT}$, or the predicted probability of fund family voting against management for an attack, is measured using SVR method on the proxy attack text.

	All fund families		Fund families with target stocks	
	Holding (in %)	$\widehat{AMGT}$	Holding (in %)	$\widehat{AMGT}$
Observations	66,836	66,836	12,582	12,582
Mean	0.09	0.48	0.49	0.48
Std. Deviation	0.63	0.40	1.37	0.40
Minimum	0	0	0	0
25th Percentile	0	0.05	0.01	0.05
Median	0	0.44	0.06	0.43
75th Percentile	0	0.94	0.26	0.97
Maximum	18.58	1	18.58	1

Table 6 summarizes the sample set. The average holding by fund family when the proxy fight begins is 0.49% of market capitalization of the target firm. The standard deviation being 1.37%. The median holding is 0.06%, and the 75th percentile is at 0.26%, indicating, as expected, that the data set is left-skewed bounded by zero. Out of the 12,582 fund family holding information, 11,113, or 88%, are less than 1%. The maximum holding we have in our sample is 18.58% by Putnam Investments in Altisource Residential Corporation in January 2016, when Altisource was attacked by Oliver Press Partners. For the overall sample, the holding statistics are smaller owing to 54,790 observation with zero holdings.

The two sample are however comparable in terms of predicted AMGT, or the probability of fund family to vote against management in a proxy attack. The average value for predicted AMGT, is 48%. The SVR model predicts that, on average, fund families are equally likely to support the management or the activists. The median number is similar at %44. The 25th percentile is 7%, and 75th percentile is 94%. Predicted AMGT bunching at zero and one, is in line with how most portfolios in a fund family vote as a block in shareholder proposals. The portfolios either support the management, or vote against, in unison.

Figure 6 shows a scatter plot of the average estimated AMGT, probability of fund family voting against the management, for each holding percent. Bulk of the dataset is in the left corner, with only 279, or 2.19%, of observations have fund family owning more than 5% of target firm. For most of the holding percent, the average $\widehat{AMGT}$ is above 40%. The numbers show an increasing trend, indicating a positive association between fund family owning shares in target and proxy text predicting a higher chance of fund family voting against the management. For the three big fund families, we see an increasing trend in $\widehat{AMGT}$ with respect to holdings as well. The SVR method predicts, on average, Fidelity and BlackRock, compared to Vanguard, are more likely to vote against the management. The AMGT prediction is in line with how these fund families voted in shareholder proposals, illustrated in Table 1.

4 Results

Coming back to the paper's hypothesis - activists, during a proxy fight, use language in a way to persuade the major institutional investors in the target fund. If that were true, we would see a positive association between the number of shares of the target a fund family owns and the likelihood of the fund family voting in favor of activists based solely on proxy

Figure 6:
Scatter plot of fund family holding and average expected probability of voting against the management.
The figure plots the two key variables: percent of market cap mutual fund family holds in a target on the x-axis, and average estimated AMGT, probability of fund family voting against the management in the proxy fight. The holding data is left skewed, with 89% of data points under 1%. I present the x-axis in log format to zoom in the values closer to zero. I round the holding data to the nearest holding tick mark, and average out the $\widehat{AMGT}$ for the particular tick mark. The radius of data points corresponds to the number of observations around the tick. I also include the three largest fund families, in terms of number of voting information in the sample.

text. I employ the following equation, to test the hypothesis:

$$\widehat{AMGT}_{f,a} = \beta Holding_{f,a} + \delta_a + \epsilon_{f,a} \tag{6}$$

where $\widehat{AMGT}_{f,a}$ is the predicted probability that a fund family, f, will vote against management based on proxy attack, a, text. $Holding$ refers to the percent of market capitalization the fund family owns of the target company, before the attack begins. I include attack level fixed effect, δ_a, to ensure that the estimates are identified using within-attack variation in ownership. I also report my estimates without fixed effect and fund family level fixed effect as well. Finally, I cluster the standard errors, $\epsilon_{f,a}$, at the attack level.

Table 7:
Do activists design proxy text to garner support of major investors
This table reports estimates of a regression of probability of voting against management on fund family holding of target shares. Specifically, I estimate:

$$\widehat{AMGT}_{f,a} = \beta Holding_{f,a} + \delta_a + \epsilon_{f,a}$$

where $\widehat{AMGT}_{f,a}$ is the predicted probability that a fund family, f, will vote against management based on proxy text. Holding is the percent of equity the fund family owns of the target company before the attack, and is standardized. δ_a is the attack level fixed effect, I also report results without fixed effect, and fund family level fixed effect. In this table, I focus on two ways of looking into our sample set, combined with three combinations of fixed effects. (1), (2), and (3) take into account all the fund families for which there were at least hundred voting observation, available in two year period prior to attack. (4), (5), and (6) show result for a sub-sample containing fund families that have a stake in the proxy fight i.e. the fund family owns a non-zero share in target firm. Standard errors, $\epsilon_{f,a}$, are clustered at the attack level, and *t*-statistics are reported in brackets below the coefficient estimates. The symbol *, **, and *** indicate significance at 10%, 5%, and 1% respectively.

	Probability of fund family voting against management					
	(1)	(2)	(3)	(4)	(5)	(6)
Holding	0.00535***	0.00369*	0.00724***	0.0142***	0.0111***	0.0122**
	[3.47]	[1.95]	[3.12]	[3.99]	[2.87]	[2.48]
Attack level FE	-	Yes	-	-	Yes	-
Fund family level FE	-	-	Yes	-	-	Yes
Exclude families with no holdings	-	-	-	Yes	Yes	Yes
Observation	66,836	66,836	66,836	12,582	12,552	12,561
R^2	0	0.133	0.098	0.001	0.204	0.066

Table 7 reports estimates for the association of predicted activist support on fund family holdings using variants of Equation 6. For the entire sample, containing all the fund families which have more than hundred voting records in two years prior to the attack, I have a total 66,836 proxy text predicted probability of fund family voting against the management. I assign equity share of zero to the fund families that are not invested in the target firm. I employ three combination of fixed effects level: (1) no fixed effect (2) attack level fixed, and (3) fund family level fixed effect. The percentage of shares held by fund families in the target firm is significantly (at 1% level) associated with how likely the fund family is to vote against the management of the target firm. The economic magnitude of the relationship is sizable. A one percent increase in fund family holding (1%/0.63% = 1.59 standard deviation) of target fund shares is associated with around 0.8% (1.59×0.535%) increase in the fund family voting in support of activist proposal. The relationship is robust to various levels of fixed effects (i) attack level fixed effects - fixes differences related to ISS recommendation (which is unique for each proxy attack), target firm performance and strategy, etc. (ii) fund family level - fixes differences associated with fund family voting patterns.

Column (4), (5), (6) of Table 7 reports estimates for a sub-sample of data set, which includes only fund families that are invested in the target firm at the beginning of an attack. For the sub sample, I have a total of 12,582 proxy text predicted probability of fund family voting against the management. We see a similar result, robust to changes in fixed effects. Within a proxy attack, the proxy text solicit 0.8% (0.73×1.11%) more support for every one percent (1%/1.37% = 0.73 standard deviation) increase in holdings. In essence,the activists are gearing the proxy fight text more towards the preferences of major institutional shareholders in the target firm.

An alternative mechanism by which we will have a positive association between fund family holding and voting with activists for proposal text is if the larger fund families such as Vanguard, PNC, Fidelity, etc are just in general more likely to agree with the activists. We see in Section 2.1 that this is not the case. The fund families with higher holdings, which happen to be passive index investors often, are less likely to vote against the management in shareholder proposals. Since our training data is not skewed we are unlikely to see the pattern in our predicted, or test sample. In Table 7, the regression results with fund family fixed effect (3), and (6) further support the hypothesis. For a particular fund family, the probability that the fund will support activists based on proxy text increase by 1.1% (1.59×0.724%) for every percent increase (1%/0.63% = 1.59 standard deviation) in fund's holding in the target firm. Thus, the text is geared towards the major institutional holder of the target firm, as opposed to just the major institutional investors in general.

Figure 7:
Box plot of coefficient for five largest fund families
The graph plots the coefficient of regression of $\widehat{AMGT}$ on fund family holding in target firm (Equation 6), run separately for each fund family. The box and whiskers indicate one standard deviation and two standard deviation distance from coeficient respectively.

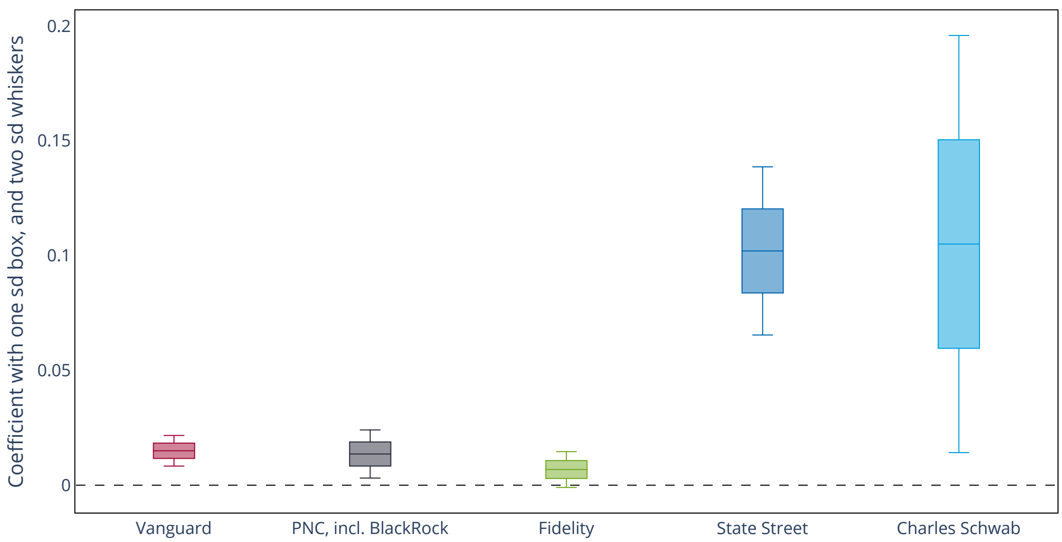


Figure 7 shows coefficient of Equation 6 for each of the five biggest fund families. The coefficient is above zero and is significant at 5% for Vanguard, BlackRock, State Street and Charles Schwab. For Fidelity, the coefficient is significant at 10%. For each of the fund family, we see that proxy text predicts a higher support for the activists, when the fund family owns a higher stake in the target firm. This substantiate the hypothesis that the activists write the proxy text in a way to solicit support from investors with higher voting power. The activists cater to the influential fund families by talking about topics, and phrases which matters to the fund family in their proxy fights.

4.1 Limitations of the text-based voting measure

Many factors, including the content of an attack's proxy text, firm-specific performance, general economy, relationships between fund family and target firm, reputation of attacker, etc. play a role in how a fund family votes. As such, the text-based measure is likely to predict a fraction of the whole variation in voting. However, the result of regression in Section 4 is unbiased given it includes attack and parent level fixed effect.

A second critique of the text-based method is associated with how I create the prediction. Instead of predicting one voting outcome for an attack, I furcate it into fund family level measures. Thus, the predicted against management vote is correlated across an attack text. The correlation could reduce the standard error of β and boost significance. Clustering at the attack level mitigates this risk.

Lastly, my training sample, which contains proposals at the annual meeting, is not the same as my prediction sample, the confrontational attack text. The discrepancy occurs because of the dearth of confrontational attacks, which reached a voting stage. In Section 2.4, we see that only 199 confrontational attacks went for voting during the period 2004–2019. This sample is not enough to run a machine learning algorithm. To mitigate the differences, I filter out all the management proposal and train the sample on shareholder proposals only. Shareholder proposals are often more in line with activists proposals in proxy attack text. Moreover, during 2003–2018, the voting on shareholder proposals (44% against the management) is in line with fund family voting against the management for attack proposals, which was 48%.

5 Impact of activists pandering to funds

In this section, I look into the effect of activists catering to institutional investors. I answer three questions here: (i) do fund family pay more attention to attacks that cater to fund preferences. (ii) do attacks that are geared towards large institutional shareholders perform better for the activists. (iii) Lastly, do specific fund families to which the attack is more geared towards vote more favourably with the activists.

5.1 Fund's pay attention when activist speak to their preference

A natural question to ask is, do fund family pay more attention to attacks which pertain to their preferences. If that were true, we would see fund families with higher predicted against management voting, $\widehat{AMGT}_{f,a}$, care more about the attacks. To test this hypothesis, I estimate:

$$View_{f,a} = \beta \widehat{AMGT}_{f,a} + \delta_a + \epsilon_{f,a} \tag{7}$$

where View represents the number of times attack documents were accessed by fund family for an attack, from the date attack began to 30 days after the attack ended. δ_a show attack level fixed effect and the error, $\xi_{f,a}$, is clustered at the attack level. The model is estimated over the January 2004 - June 2017 period.

The results, reported in Table 8, confirm that mutual fund families put more attention on the attack that caters to their preferences. The estimated coefficient is positive and statistically significant (at the 1% level) using either attack level variation or fund family level variation. For an average firm, a one standard deviation (or 40%) increase in predicted probability of fund voting against the management is associated with 0.11 more views of filing documents on SEC website by the fund. The average number of views by a fund family for an attack is 0.48. Bauguess et al. (2013) points out that the fund families views, as measured from EDGAR log files, likely under represents the actual views. The numbers are higher, if we look at the sample of fund families which own target stocks. The result of the analysis on the smaller sub-sample is provided in Appendix D.

Iliev et al. (2018), Gormley et al. (2020) show that the fund families pay more attention when they have a higher stake in a firm. Also, in Section 4, we see that the text-based measure of fund voting against the management is dependent on the equity share the fund owns. Therefore, to mitigate the omitted variable problem, I include the fund's equity share

Table 8:
Do funds conduct more research on attacks that speaks to their preferences?
This table reports estimates of a regression of fund family access of attack text filings on the probability of voting against management. Specifically, I estimate:

$$View_{f,a} = \beta \widehat{AMGT}_{f,a} + \delta_a + \delta_f + \epsilon_{f,a}$$

where $View_{f,a}$ is the number of times a fund accessed attack filings between the date when the attack was initiated to 30 days after the attack got over. The attack beginning (end) date is based on the first (last) date of filing DEF, DFAN or PREC by activists. $\widehat{AMGT}_{f,a}$ is the predicted probability that a fund family, f, will vote against management based on proxy text. δ_a, and δ_f are attack level and fund family level fixed effects. (1), (2), and (3) shows result for three fixed effects. (4), (5), and (6) controls for fund family equity holdings. All independent variables are scaled by the standard deviation of the underlying variable, meaning coefficients can be interpreted as the effects of a one standard deviation change in the determinant. Standard errors, $\epsilon_{f,a}$, are clustered at the attack level, and *t*-statistics are reported in brackets below the coefficient estimates. The symbol *, **, and *** indicate significance at 10%, 5%, and 1% respectively.

	Number of times fund family viewed attack filing on SEC.gov website					
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{AMGT}$	0.0854***	0.0849***	0.115***	0.0774***	0.0771***	0.112***
	[4.24]	[3.59]	[4.69]	[3.86]	[3.36]	[4.57]
Holding				0.379***	0.363***	0.248***
				[18.9]	[7.03]	[5.24]
Attack FE	-	Yes	Yes	-	Yes	Yes
Fund family FE	-	-	Yes	-	-	Yes
Observation	34,179	34,179	34,178	34,179	34,179	34,178
R^2	0.001	0.106	0.163	0.011	0.115	0.167

in the target firm as a control in part (4), (5), and (6) of Table 8. The results indicating higher attention from mutual fund family, when the text is geared towards their preferences, still holds.

5.2 Attacks which are geared to investors succeed

Getting the support of major institutional investors, is key for a successful attack. In Section 4, we see that activists use textual features in a way to attract support from prominent shareholders. In this section, we look into whether such tactics by activists lead to a better outcome. I begin with the equation:

$$Win_a = \beta \sum_f Holding_{f,a} * \widehat{AMGT}_{f,a} + \delta_{year} + \epsilon_a \tag{8}$$

where Win_a is a dummy variable equal to one if the outcome of the attack is in activist's favour ("Successful" or "Settled" defined in Section 2.4). The dependent variable is the probability of fund voting against the management, weighted by the fund's holding in target firm. The weighting results in one dependent variable for each attack, thus our sample size is 460. The dependent variable is essentially the predicted against management vote an attack would garner. δ_{year} is year level fixed effects. The error, ϵ_a, is robust and computed with the sandwich estimator of variance.

In Table 9, we see that attacks which have a higher weighted score of investors voting against the management are indeed more likely to succeed. The results are significant at 10%. A one standard deviation increase (8%) in weighted $\widehat{AMGT}$ for an attack is associated with 56% increase in the likelihood of activist winning the proxy attack. Thus the attacks which were pertaining more to funds preferences, and thus have higher weighted probability of fund voting against management, are more likely to end up in favor of activist.

5.3 Fund families support attacks geared towards them

In this section, I investigate whether the mutual fund families vote per the text-based predicted voting outcome. In Figure 3, we see that 199 (43%) confrontational attacks, out of

Table 9:
Pandering to investors, positively affects attack outcome
This table reports estimates of regression of attack outcome on holding weighted text-based measure of voting against management. Specifically, I estimate:

$$Win_a = \beta \sum_f Holding_{f,a} * \widehat{AMGT}_{f,a} + \delta_{year} + \epsilon_a$$

where Win_a represents a dummy which is one if the attack result is in attackers interest ("Successful" and "Settled"). The dependent variable is the text-based predicted probability of investors voting against the management, $\widehat{AMGT}$, weighted by their holding, $Holding_{f,a}$. The holding weighted $\widehat{AMGT}$ is standardized. The attack outcome is gathered from CapitalIQ database, and holding data is from CRSP. δ_{year} is year level fixed effects. The error, ϵ_a, is robust and the *t*-statistics are reported in brackets below the coefficient estimates. The symbol *, **, and *** indicate significance at 10%, 5%, and 1% respectively.

	Indicator for activist win in a confrontational proxy attack		
	(1)	(2)	(3)
Holding weighted $\widehat{AMGT}$	0.0415*	0.0415*	0.0444*
	[1.84]	[1.81]	[1.8]
Robust Standard Error	-	Yes	Yes
Year Fixed Effect	-	-	Yes
Observation	460	460	460
R^2	0.007	0.007	0.043

461, went to actual voting. The rest of them were either settled, withdrawn, or currently ongoing. I use the voting data on these attacks, and compare text-based voting prediction.

As discussed in Section 4.1, there are factors, other than the content of the proxy text, which dictates fund family voting. To test my the hypothesis, fund family voting more favourably on attacks which speak to their preferences, I need for a fixed attack the text-based fund voting, $\widehat{AMGT}_{f,a}$, be predictive of the actual fund vote, $AMGT_{f,a}$. Specifically, I estimate:

$$AMGT_{f,a} = \beta \widehat{AMGT}_{f,a} + \delta_a + \delta_f + \epsilon_{f,a} \tag{9}$$

where $AMGT_{f,a}$ is the fraction of mutual funds, for a fund family, that voted against management recommendation for the shareholder proposals during the attack's annual meeting. $\widehat{AMGT}_{f,a}$ is the text-based predicted against management voting. δ_a, δ_f show attack level and dund family level fixed effect. The error, $\epsilon_{f,a}$, is clustered at the attack level. The model is estimated over 2004–2019 period for all the confrontational activists attack that went to the voting stage.

In Table 10, I find that text-based predicted voting is positively associated with the actual voting outcome. The estimated coefficients are positive and statistically significant (at the 1% level) for attack level and fund family level fixed effect. For every one standard deviation (44%) increase in text-based predicted against management voting, I find 3% increase in fund family voting against the management. Thus, the text-based measure of voting outcome is in line with the actual voting outcome, robust to within attack or fund level variations.

6 Robustness

In this section, I discuss the limitations and robustness of voting estimates. In particular, I demonstrate whether the text-based voting prediction, predicts the actual voting outcome, and is sensitive to changing parameters.

Table 10:
Actual votes follow text-predicted votes
This table reports estimates of regression of fund family against management voting on attack proposals on the text-based measure of voting against management. Specifically, I estimate:

$$AMGT_{f,a} = \beta \widehat{AMGT}_{f,a} + \delta_a + \delta_f + \epsilon_{f,a}$$

where $AMGT_{f,a}$ is the percent of mutual funds, under a fund family, which voted against the management on attack proposals. Attack proposals is the shareholder proposals in the target's shareholder meeting relevant to the attack. I identify relevant meeting as the first meeting after the attack begins, that also falls within 30 days before to 365 days after the attacks end date. Attack's beginning (end) date is based on the first (last) date of filing DEF, DFAN or PREC by activists pertaining to the target. $\widehat{AMGT}_{f,a}$ is the predicted probability that a fund family, f, will vote against management based on proxy text. $\widehat{AMGT}_{f,a}$ data is standardized to have a normal distribution. δ_a, and δ_f are the attack level and fund family level fixed effect. Standard errors, $\epsilon_{f,a}$, are clustered at the attack level, and *t*-statistics are reported in brackets below the coefficient estimates. The symbol *, **, and *** indicate significance at 10%, 5%, and 1% respectively.

	Against management voting for confrontational attacks		
	(1)	(2)	(3)
$\widehat{AMGT}$	0.0186*	0.0468***	0.0315***
	[1.88]	[4.44]	[3.27]
Attack Fixed Effect	-	Yes	Yes
Fund Family Fixed Effect	-	-	Yes
Observation	1,458	1,454	1,420
R^2	0.002	0.557	0.61

6.1 Changing Parameters

To be done.

6.2 Inclusion of ISS Recommendation

To be done.

7 Conclusion

Institutions that manage mutual funds are an important component of financial markets. However, they are increasingly restricted both legal and incentive wise, to engage with managers in a way that illicit fast change. Hedge funds, on the other hand, have slacker regulation and more appetite for dealing with a hostile management. However, hedge funds often lack the voting strength required to push through their proposals. In this paper, I document evidence of hedge funds pandering to institutional investors' preferences.

I use fund family voting history on shareholder proposals to measure fund families preference; and subsequently funds' likelihood of voting against the management on confrontational proxy fights. The text-based probability of fund voting against the management is positively associated with funds' holding in target shares. The results are robust even if I look within proxy fight and fund family level variations. The machine learning predicted voting is in line with actual voting by the fund family, and also predicts the level of attention a fund family pays to a proxy attack. The finding suggest that the shareholder base's implicit preferences play a crucial role in activist proxy solicitation. Moreover, the activists provide a channel via which fund preferences affect corporate governance.

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Appendices

A Assigning proposal text to ISS voting data

Voting records of the fund family, at the mutual fund level, is available from Institutional Shareholder Services (ISS). I aggregate mutual fund voting information into fund family voting data, based on the names of the mutual funds, mergers and acquisition, and investment relationships among fund families. During the period 2003–2018, I have 359 fund families, which have voted in at least hundred proposals. These fund families voted on a total of 10,679 unique shareholder proposals. The number of times a fund family occur in the sample is dependent on whether the fund holds voting shares in the proposal's firm. Therefore, a more diversified firm such as PNC, which also includes BlackRock, has voted on 9,582 proposals, while a less diversified fund family such as Phocas Financial Corp have voted in hundred shareholder proposals. In total, I have 691 thousand voting records of fund families on shareholder proposal between 2003 and 2018.

For the 10,679 unique shareholder proposals in the 691 thousand fund family voting record, I match the proposals to the text available in definitive proxy statement (DEF14A) filings. To make a suitable match, I start by slicing the shareholder proposal for a particular Central Index Key (CIK) and subsequently for a particular meeting date. The mean (median) number of proposals for a firm on a meeting date is 2.17 (1); the maximum is 57. Usually proposals pertaining to director elections are grouped as one in DEF14A filings. Therefore, for searching in DEF14A, I combine all the director election proposal into one proposal. The ISS voting data also provide a small description of the proposal, record date, meeting date, and proposal item number.

DEF14A filings are available at Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system, made available via Securities and Exchange Commission (SEC). The SEC provides indexes to all public filings, which includes CIK, type of form, filing date, and weblink for each filing. For all the proposals from ISS data on a specific meeting date, I slice SEC index file for the particular CIK, DEF14A filing, and filing date in between the record and meeting date. The slicing gives me the suitable DEF14A that would likely contain the proposals.

I parse the DEF14A HTML file using Beautiful Soup python package. I remove all the tables, whitespace, accented characters, and non-UTF encoding. I also filter out the first 75, which has filer information, and the last 75 lines, which are often errors from PDF to HTML conversion, from the filings. Once I have the clean DEF14A text, I look for sections of the filing that correspond to the specific proposal. To get the starting line for a proposal, I assign a score to each line of the DEF14A based on how likely it matches ISS proposal description and item number. Subsequently, I choose the line with the maximum score. I assign higher scores if the line (i) is uppercase, (ii) contains words such as proposal, number, no., item, etc. (iii) contains same words as it appears in ISS description (iv) less than 80 characters (v) contains the same number as ISS item number. Sometimes the proposals are written in two lines - the first line containing item number and the second containing the description. To take this into account, I repeat the same process by combining two consecutive lines and checking the score improvement.

To find the starting line for the next proposal, I begin five lines after the previous proposal's start line. Proposals in DEF14A are typically sequentially put; thus I choose the ending for a proposal as two lines before the starting of the next one. To get the last proposal's ending, I begin five lines after start and look for the phrase 'The Board of Directors recommends'. In case of no match, I take the ending line as fifty lines after the starting line. I assign the text between the starting line and the ending line in DEF14A to each proposal. For director election proposals, which generally have one proposal for all the nominated directors, I choose paragraphs between the starting line and the ending line that contains the name of the director listed in ISS proposal. In the end, I remove proposal text that contain less than 30 words. Out of the 10,679 shareholder proposals, I am able to assign text to 6,176 proposals.

B Extracting text associated with each attack

Proxy text associated with confrontational proxy attacks are characterized by two fields - "FILED BY", which contains hedge fund information, and "SUBJECT COMPANY", which contains information on target firm. To get information on these attack text, I begin with the filer particulars. Every institutional investment managers with at least $100 million in equity assets under management are required to file 13F form with SEC. Thus, I look for CIKs that have filed 13F-HR, 13F-NT, or 13F-E form to make a list of all the investment firms. Next, I look for form DEFC14A, DFAN14A, and PREC14A filed by the investment firm and parse filer and subject company CIKs. Usually, the subject company files the same document with SEC, using its CIK for an easier access to shareholders. I remove the duplicate filings, and keep only the filings under activists name. I remove filings that doesnt contain text and refer to an external exhibit document. I also filter out filings related to merger and acquisition, litigation, tweet. I get a total of 4,159 proxy filings related to confrontational attacks, which includes 290 DEFC14A, 3,484 DFAN14A, and 385 PREC14A filings. I combine these proxy filings if they are less than 180 days apart, with matching activist and target firm. However, in two cases, I combine filings that are more than 180 days apart - 2006 attack on Sunset Financial and 2018 attack on Alpine dividend fund. After combining the filings, I get a total of 530 confrontational proxy attacks, during the period 2004–2019, with a mean (median) 7.85 (5) filing per attack.

The proxy filings contain information related to activist identification, activist's message to shareholders, voting procedure, activist's holding in the target firm, other legal disclosure. Sometimes the activist also discusses their portfolio, past activism success etc. For this project, I parse out an activist's message to shareholders from each filing and combine the messages across filing to get confrontational attack text. To parse out the message part, I look for cues that begin and end messages. I use around a hundred cues to get the beginning and the end of the message to shareholders; Table 11 lists the ten most common cues.

Table 11:
Cues to parse message to shareholders
This table reports a subset of cues to get the message to shareholders, from a proxy document. [ACTIVIST] ([TARGET]) is placeholder for the name of activist (target) from identification section in the proxy document.

Message Begin Cue	Message End Cue
Reasons for the solicitation	Sincerely yours
Ladies and Gentlemen	Warm regards
Dear Fellow Shareholder	Sincerely
Dear Board of Directors	Best
[ACTIVIST] is seeking your support for	Please sign date and return the gold proxy card today
The following is the text of a press release issued by [ACTIVIST]	Security holders are advised to read the proxy statement and other documents related to the solicitation of proxies
confirms intention to nominate [ACTIVIST]	Urge you to vote your shares on the green proxy card
find proxy materials for the important annual meeting of [TARGET]	Please address any correspondence to [ACTIVIST]
being furnished to you the stockholders of [TARGET]	For further information including full biographies of our management team
soliciting proxies from holders of shares of [TARGET]	Any other relevant documents are available at no charge on the secs website

C Processing fund's information acquisition via EDGAR

The search traffic data for SEC.gov covers the period February 2003 through June 2017. EDGAR log file data set includes information on visitor's Internet Protocol (IP) address, date, timestamp, CIK, and filing document's accession number. The IP address in the dataset is in version 4 (IPv4) format, which defines an IP address as a 32-bit number separated in four 8-bit numbers. A dot separates each 8-bit number, and the number between the dots could be between 0 and 255 $(2^8 - 1)$. So a typical IP address, let's say BlackRock's (PNC in my sample), looks like 199.253.64.128. However, the last octet of IP address in log files are replaced with alphabets. The replacement is done in a way to preserve the uniqueness of IP address without revealing the full identity of the visitor. Thus, if Blackrock accesses the SEC.gov website from the IP address, the log file show an entry 199.253.64.mns. In essence, the EDGAR log file dataset has a 24-bit (IP3) address for each EDGAR server activity. Fortunately, most of the fund family register large blocks of IP address; for example, BlackRock owns the IP addresses ranging from 199.242.6.0 to 199.242.6.255. As such, IP3 address is a sufficiently precise representative for IPv4 address.

Loughran and McDonald (2017) suggests to separate EDGAR requests generated by robots from server requests by regular investors. I classify an IP address as a robot, if it requests more than a thousand filings in a day. I remove IP addresses classified as robots for that particular day. To include only valid EDGAR activities, I follow Drake et al. (2015) and exclude activities that are not related to governance research. I remove index pages (index.htm),icons (.ico), XML filings (.xml), and filings that are under 500 bytes in size. I also combine views by an IP address, if they are less than five minutes apart and for the same filing.

The second part of my dataset is a lookup table from Digital Element, a geolocation data and services firm, that contains timestamp of IP addresses (IPv4) and registered organization name as of December 2016. I use regular expression, such as (.*blackrock.*) for BlackRock Financial Management, to get IPv4 associated with fund families. To assign IP3 blocks to fund families, I use a similar procedure as Iliev et al. (2018). In case if a fund family owns all or a subset of the IP3 address and no other fund family owns an address from the IP3 block, I attribute it to the fund family. If two or more fund families own a subset of IP3 block, I assign it to the family that contains the most IP address for the IP3 block. If two fund families own an equal number of IP addresses in an IP3 block, I drop those IP3 blocks. The chances of overestimating views from assigning an entire IP3 block to a fund family if they own a fraction of addresses is low, as it is unlikely for non-financial firms to access filings from SEC.gov.

Next, I look for the validity of IP3 blocks assigned to the fund family. The IP address to the organization name lookup table is a snapshot from December 2016. However, fund families sometimes change their underlying technology infrastructure and, in that process, register for different IP3 blocks. To make sure that I have credible IP3 blocks, I go back quarterly from December 2016 and see what fraction of holdings do fund family access through the EDGAR server. I use CRSP mutual fund data to get fund family holdings. If a fund family does not access more than 1% of its holding in two consecutive quarters, I stop including the fund family before the quarter. For example, Cambiar Investors accessed 1.9%, 3.3%, 0.0%, and 0.1% of its holdings in 2015Q4, 2015Q3, 2015Q2, and 2015Q1 respectively. Therefore, I exclude Cambiar Investors from my sample before June 2015.

Subsequently, I match valid IP3 blocks from the organization lookup table with IP3 from EDGAR log files. I identify attack documents based on the accession number of the filing in log files, and SEC's index files. To measure the number of times a fund family accessed proxy attack related filings, I aggregate views for attack's accession number during the attack period. I define attack period as beginning from the first attack (DEFC, DFAN, or PREC) filing and ending 30-day after the last attack filing. The fund families views, as measured from EDGAR log files, likely under-represents the actual views. As mentioned in Bauguess et al. (2013), the EDGAR log files do not contain any requests for SEC filings from EDGAR's FTP site. Moreover, internet service providers cache frequently requested documents for future ease of reference. So requests for the same content that have been cached may not be captured by the log file.

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