JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 58, No. 7, Nov. 2023, pp. 2820–2851

doi:10.1017/S0022109022001156

https://doi.org/10.1017/S0022109022001156 Published online by Cambridge University Press

# Shining a Light in a Dark Corner: Does EDGAR Search Activity Reveal the Strategically Leaked Plans of Activist Investors?

Ryan Flugum
*University of Northern Iowa College of Business*
ryan.flugum@uni.edu

Choonsik Lee
*University of Rhode Island College of Business*
choonsiklee@uri.edu

Matthew E. Souther
*University of South Carolina Moore School of Business*
matthew.souther@moore.sc.edu (corresponding author)

## Abstract

We provide evidence of a network of information flow between activists and other investors prior to 13D filings. We match EDGAR search activity to investor IP addresses, identifying specific investors who persistently download information on an individual activist's campaign targets in the days prior to that activist's 13D disclosures. This outside investor's knowledge of pending activist campaign plans seems to benefit both parties: the informed investor, unnamed in the 13D, increases its holdings in the targeted stock prior to the price surge upon 13D disclosure, while the activist earns voting support that increases their likelihood of pursuing and winning a proxy fight.

## I. Introduction

On Oct. 12, 2015, activist hedge fund John Doe Management[1] filed a Form 13D, disclosing 6.9% ownership and an intent to pursue an activist campaign in target firm Industrial Corp (IC). The next day, IC's stock rose by 10.9%. On Oct. 9,

The authors thank an anonymous referee, Adam Aiken, Nicole Boyson, Douglas Cumming, Richard Evans, Nickolay Gantchev, Reza Houston, Hyeongjun Kim, Nhan Le, Andrea Paltrinieri, Xinyu Wang, Yaxuan Wen, Steven Zheng, and session participants at the University of Rhode Island, the University of South Carolina, Ball State University, the 2020 Boca Corporate Finance and Governance Conference, the 2020 Annual Conference on Asia-Pacific Financial Markets, the 2021 Financial Markets and Corporate Governance Conference, the 2021 Joint Conference with the Allied Korea Finance Associations, the 2021 Financial Intermediation Research Society (FIRS) Conference, the 2021 Financial Management Association (FMA) Annual Conference, and the 2021 Southern Finance Association (SFA) Annual Conference for their valuable comments and suggestions. The authors also appreciate the American Registry for Internet Numbers (ARIN) for providing the historical WhoIs data (WhoWas) for our research. This article represents the opinions of the authors and is the product of academic research. Any errors are the fault of the authors.

[1]This example is based on an actual event in our study. To anonymize the involved parties, we have assigned pseudonyms, shifted the dates by less than 6 months, and altered the market reactions by less than 0.5%.

just days before that disclosure, an IP address owned by a different financial institution, AAA Group, became suddenly interested in IC, logging onto the SEC's EDGAR database and downloading IC's financial statements. This IP address had not accessed any information pertaining to IC in the preceding months.

Perhaps this was merely a coincidence. However, less than 1 year later, on Sept. 15, 2016, the same IP address belonging to AAA Group went to EDGAR and displayed a similar sudden interest in the financial statements of Medical Devices Inc. (MD). Just days later, on Sept. 18, John Doe Management again filed a 13D disclosing an activist stake in MD, and MD's stock rose by 10.8%. One might suggest that AAA Group is highly skilled at predicting activist campaigns, but the only campaigns they seem to predict are those of John Doe Management. Though we have anonymized the names, dates, and targeted firms, the above illustration is common to many activist campaigns, where a particular outside investor's IP address consistently predicts the targets of a given activist.

Although we cannot pinpoint exactly how AAA Group became aware of the campaigns, one possibility is that our anonymized activist hedge fund shared details of its pending campaigns with an outside investor group. What reason would they have for doing this? In each of the above cases, John Doe Management subsequently launched a proxy fight in the target firm, thus needing to build a coalition of shareholder voting support to get their slate of directors elected by shareholders. By allowing certain informed shareholders to build positions in the targeted stock ahead of the disclosure-related price surge, activists can add a friendly base of voting support to their campaign, increasing their likelihood of winning any fight with managers (Dimson, Karakas, and Li (2015), Crane, Koch, and Michenaud (2019), He and Li (2022), and Brav, Jiang, Li, and Pennington (2021)). Consistent with this conjecture, John Doe Management went on to win the proxy fight in each of these campaigns.

In this study, we identify institutional investors appearing to have nonpublic information about pending activist 13D filings. Because these filings are typically met with a positive stock price reaction at the target firm, prior knowledge of these events is immensely valuable. The records of SEC EDGAR downloads allow us to investigate this type of information sharing and potential informed trading. Rarely can we document whether individual traders actually have valuable information or what that information might be, but the EDGAR log files present a unique opportunity to identify the link between an activist and the exact investment firm that persistently appears to have nonpublic information pertaining to that activist.

We investigate search activity on the SEC's EDGAR website during the "event window:" the time between when an activist exceeds 5% ownership and when that activist discloses the ownership in the 13D filing (once passing the 5% ownership threshold, activists have 10 days to disclose the ownership via the 13D). The search activity is reported by IP address, which we then match to specific institutional investors. We look for investors who download information about the activist's target during the event window but who have not accessed information on the same firm during the preceding 50 days. Therefore, our attention is focused on investors that display a sudden interest in a specific firm immediately before a 13D filing.

We find that certain institutional investors are especially adept at predicting a specific activist's targets, downloading information about multiple campaign targets from that activist during the corresponding event windows. This pattern of informed EDGAR access is consistent with these investors having information about the activist's targets. We note that these informed investors are unaffiliated with the activist and are not named on the 13D filing. After establishing the presence of these investors, we analyze their effects on the market and the activist's strategy.

We first define our measure of interest. We consider an IP address to be a SUSPECT_IP if i) it downloads information about a campaign target during the event window for at least 2 campaigns belonging to a single activist, ii) it has not accessed information on that same target firm for the 50 days preceding the event window, and iii) it belongs to an investment firm. Our variable of interest in our main tests, run at the activist campaign level, takes a value of 1 if a SUSPECT_IP is present at the campaign.

Our empirical analysis begins by examining the market trading activity in the event window. We note that prior research documents heightened turnover and returns in the pre-13D window. However, if outside investors have been informed of the pending campaign, we would expect to see trading activity elevated to an even higher level. We indeed find this to be the case: the presence of a SUSPECT_IP is associated with increased trading volume in the underlying stock; average turnover increases by approximately 0.5% of total shares outstanding beyond the level normally associated with a 13D filing. We acknowledge that this finding could suffer from endogeneity concerns; if the activist's block acquisition increases trading volume, this elevated volume could attract attention to firm filings on EDGAR. Such an explanation appears unlikely for two reasons. First, SUSPECT_IPs do not appear to be widespread predictors of all activist activity but instead seem to have information pertaining solely to one specific activist. A financial institution classified as a SUSPECT_IP only has a 0.10% chance of downloading information about any *other* activist's targets during the event window. Second, we also find elevated trading volume for SUSPECT_IP campaigns within the sample of 13G to 13D switchers, which would not suffer from the endogeneity concern: an activist that already filed a 13G is not acquiring a 5% block again.

Who has tipped these apparently informed investors? If the activist is the source of the information, they would likely wait to share their plans until after they have acquired most of their position so that higher prices do not increase their costs. We next investigate the timing of the SUSPECT_IP access in relation to the activist's acquisition activity. We find that the activist's acquires shares at a substantially slower rate in the days following the IP access. Further, less than 6% of the activist's total position would be affected by potentially higher prices following the information spread.

We next examine the post-13D returns associated with SUSPECT_IP campaigns. If the pending campaign information has any value for the receiving party, we would expect to see evidence of that here. Similar to other activist campaigns, we find that 13D filings associated with a SUSPECT_IP earn significantly positive abnormal returns on the magnitude of 4–7%. To be clear, we do not argue that this result is causal. Rather, this result merely documents the financial benefits to the informed investor. An investor who consistently receives these profits from the activist is more likely to support the activist in a proxy fight.

https://doi.org/10.1017/S0022109022001156 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109022001156 Published online by Cambridge University Press

Institutional investors have a variety of tools to profit from private information, many of which are reported infrequently or do not require reporting at all. We use the limited view of portfolio holdings provided by quarterly 13F filings to determine whether the SUSPECT_IP owner trades on this information. We find that informed investors are more likely than other institutional investors to increase their holdings in the target firm between the quarters ending before and after the 13D filing, consistent with the informed investor trading on their information. Further, we find that 13F filers are significantly more likely to acquire shares in activist campaigns for which they are classified as SUSPECT_IP than in campaigns in which they are not.

While quarterly 13F reports provide evidence consistent with the SUSPECT_IPs actively trading the target firm before the 13D filing, the exact timing of those trades within the quarter is unclear. We next examine a small but unique subset of campaigns for which the 13F reporting date is within the event window. We find that SUSPECT_IPs report increased holdings in the target firm during this window, indicating that their trading activity indeed occurs before the activist's 13D filing.

We then shift our analysis to how the activist benefits from this shared information. If the activist is indeed the source of the information, we would expect to see some benefit accrue to them, likely in the form of an easier campaign. The activist's subsequent share purchases in the targeted stock could provide some evidence of this. If the activists are facing difficulty earning shareholder support over the course of the campaign, they may be forced to purchase additional shares in the target firm to augment their voting power. However, sharing plans may bring on investors friendly to their cause, reducing the likelihood of additional purchases. We find this trend to be true; the probability that activists increase their stake beyond the level reported in the initial 13D filing decreases by approximately 10% when a SUSPECT_IP is present.

Finally, we examine the possible benefits of the informed SUSPECT_IPs for the activist's subsequent campaign strategy. If an activist has additional voting support from investors who entered the stock before the 13D disclosure, they should have a higher degree of confidence in spending the formidable resources toward a proxy fight (Gantchev (2013)). We indeed find that this is the case; campaigns with a SUSPECT_IP are more likely to enter into a proxy fight in the year following the 13D filing. Further, we find evidence that conditional on entering a campaign, the activist is more likely to win a board seat or otherwise accomplish their stated goals when a SUSPECT_IP is present. These results support the activist's incentives for sharing the plans; they allow other firms to share in the profits in exchange for additional voting support.[2]

Millions of IP access points appear in EDGAR download records. Given the large numbers of investors accessing EDGAR data each day, we next perform several robustness tests designed to address the possibility that our results could be driven by spurious download activity unrelated to the pending activist campaign.

[2]Prior work uses N-PX voting records, filed only by mutual fund companies, to examine outsider voting support for activists (see, e.g., Kedia, Starks, and Wang (2021)). Within the subset of campaigns that proceed all the way to a proxy fight, only four campaigns had a SUSPECT_IP that subsequently filed Form N-PX. All four SUSPECT_IP N-PX filers voted in favor of the activist.

We first verify our main findings by reidentifying suspects and rerunning our main tests in two placebo situations to serve as counterfactuals for our main findings. The first test reidentifies suspects in the target firm using a placebo date 1 year prior to the 13D filing. Similarly, a second placebo test matches each activist target to a nonactivist target on the same date with a similar propensity for being an activist target; we then reidentify suspects based on these matched firms. In both placebo tests, we find a substantially smaller number of Suspects, and we find no evidence that the newly identified placebo suspects are acquiring shares in the target firm.

We then rule out similar concerns of spurious downloads by examining the entirety of EDGAR access points from SUSPECT_IPs. We find that their download activity is informative: sudden interest in a firm by a SUSPECT_IP is significantly more likely to predict a pending 13D compared to a control group of seemingly uninformed downloads. Further, when separating the sample into activists that are associated with SUSPECT_IPs and those that are not, we find that the predictive power of SUSPECT_IP downloads is limited to the 13D filings from SUSPECT-associated activists; SUSPECT_IP downloads have no measurable impact on the likelihood of subsequent 13D filings from an activist that has never been associated with a SUSPECT_IP. Taken together with the placebo results, we conclude that our identification approach is not spurious but is likely the result of an outside investor with nonpublic information about a pending campaign.

Is this type of shared information and subsequent trading illegal? The laws on this are murky. The SEC does not regulate this type of information; consequently, there is currently no obligation to keep this information internal, as there would be with, for example, a pending earnings report. However, the SEC requires disclosure of alliances between investors to be included in the 13D filing.[3] If the activist and the SUSPECT_IP have not disclosed any arrangements or agreements, they could face action from the SEC. The SEC recently opened investigations into several hedge funds for allegedly failing to disclose these arrangements (https://www.wsj.com/articles/sec-probes-activist-funds-over-whether-they-secretly-acted-in-concert-1433451205).

We note that, while our results generally point to the activist sharing information, it is impossible to know with certainty the exact mechanism by which the SUSPECT_IP becomes informed. It is possible that the SUSPECT_IP is an activism surveillance professional receiving informative but noisy signals of imminent activism, rather than being tipped by the activist filing the 13D. Such an explanation would be consistent with most of our findings. Regardless of the exact mechanism of information spread, it seems that both the activist and the SUSPECT_IP benefit.

If the activist is sharing information, they do face tradeoffs if campaign information is shared before the 13D. Our study documents the benefits in the form of a stronger voting base in a proxy fight and a greater likelihood of success, which, by sharing campaign information, can be had with an overall lower level of long-term portfolio concentration in the target firm. These benefits come at a cost, however: additional traders may limit the activist's ability to acquire shares at lower prices in the days immediately before the 13D filing. Regardless of their

[3]Securities Exchange Act of 1934, § 240.13d–1. Also, see the SEC's guidance and interpretation available at https://www.sec.gov/divisions/corpfin/guidance/reg13d-interp.htm.

https://doi.org/10.1017/S0022109022001156 Published online by Cambridge University Press

motivations, our evidence suggests that at least some activists are willing to accept this tradeoff.

This study relates to recently proposed Congressional legislation. The Brokaw Act, initially proposed by Senator Tammy Baldwin in 2016 and reintroduced as bipartisan legislation in 2017, makes several changes to 13D requirements, including giving the Securities and Exchange Commission (SEC) more authority in determining whether investors collaborated as a group. The Act has thus far remained unpassed and has struggled to gain traction, partially due to the absence of empirical evidence of collaborative efforts between investors (Brav, Heaton, and Zandberg (2018)). Our study is the first to present evidence suggesting that activists may benefit from the presence of other investors who are informed of their actions. Additionally, the SEC recently proposed revisions to 13D legislation that would regulate informed trading during the pre-13D period more explicitly (https://www.sec.gov/rules/proposed/2022/33-11030.pdf). The proposal borrows from the rules laid out in the Brokaw Act.

## II. Related Literature

Several recent published and working papers make use of EDGAR log data, which allows researchers to identify the exact timing in which investors access various filings and make inferences about aggregate investor attention (see, e.g., Loughran and McDonald (2017), Iliev, Kalodimos, and Lowry (2021)). Crane, Crotty, and Umar (2022) and Chen, Cohen, Gurun, Lou, and Malloy (2020) look specifically at information-gathering by institutional investors, showing investors who access certain EDGAR documents outperform those who do not. Our study differs from this concurrent work by identifying a specific piece of information held by certain traders, and establishing a novel channel through which the information is obtained.

Our study also complements a strain of literature studying trading activity around the 13D. Seminal work by Brav, Jiang, Partnoy, and Thomas (2008) shows that 13D-announcement returns for activist hedge funds average 7%. Since then, others have shown announcement returns to be a function of factors such as the target's inherent characteristics, the activist's reputation, the composition of the 13D, and early engagement between the target and the activist (Greenwood and Schor (2009), Klein and Zur (2009), Krishnan, Partnoy, and Thomas (2016), Aiken and Lee (2020), and Schoenfeld (2020)). More recent research examines the trading activity of corporate insiders ahead of a 13D; these insiders acquire more shares when they detect share acquisition by activists, which gives the insiders more voting power to combat the activist (Chabakauri, Fos, and Jiang (2022)).

Regarding coordination between the activist and other investors, Brav, Dasgupta, and Mathews (2022) provide a model showing "wolf pack" formation to be a consequence of blockholders' competition for investment capital; forming the pack increases their chance of a successful campaign, giving the perception of skill. Several studies, including Becht, Franks, Grant, and Wagner (2017), Crane, Koch, and Michenaud (2019), Wong (2020), Kedia, Starks, and Wang (2021), and He and Li (2022), provide empirical evidence that a greater chance of campaign success indeed occurs when there is a common association between the activist and a target's shareholders. These studies use a range of proxies for such coalitions that include social connections, prior voting behavior, abnormal trading before the 13D, and institutional trades associated with the activist. In contrast to these studies, we focus on a specific channel of the wolf pack formation – the research activities of other investors and their relationship with the activist. Our study adds to this literature by providing evidence of how activists can benefit from outside parties with informative signals about a pending campaign.

## III. Data and Methodologies

### A. Sample Construction

Our initial sample starts with activist campaigns in FactSet's SharkRepellent data. While SharkRepellent includes various types of shareholder activism cases, we restrict our sample to those campaigns with a Schedule 13D filed with the SEC. The SEC requires that an investor file a Schedule 13D or a Schedule 13G form when their ownership passes the 5% threshold, and investors with the intention of exerting control over the target firm must file a Schedule 13D over a Schedule 13G. Thus, our sample consists of activist campaigns with nontrivial costs for the initial block acquisition. To minimize potential data error, when there are multiple reported campaigns associated with the same Schedule 13D, we keep the first campaign to our sample and drop the later ones. In addition, since our methods require at least 2 campaigns by the same activist, we exclude those campaigns with only one activist-target pair in our sample.

We then examine EDGAR search activity for these target firms during the period before the 13D disclosure. The EDGAR Log File data set contains information on internet search traffic for EDGAR filings from Feb. 14, 2003, through June 30, 2017. We investigate search activities on the target firm's major financial and proxy statements.

We note that search activities on the target firms could be associated with other corporate events rather than the activist campaign. For example, search activities may be triggered by a proxy contest or a proposed merger filed on the same target. In these situations, an activist may file a Schedule 13D later due to its possible participation in the contest or the merger deal, making it difficult to determine whether the search activities are related to the activism announcement or the underlying event. To mitigate this concern, we use a filtering process to construct a clean sample. First, we exclude activist campaigns with preceding 13D or proxy statements filed by a dissident, including the activist itself, during the 60-day window before the announcement of the activist campaign. Similarly, we exclude campaigns with a merger announcement in the SDC Platinum or a merger agreement in the target's Form 8-K[4] filing in the 60-day window before the activism announcement. We also exclude campaigns with the explicit intent of merger arbitrage in the SharkRepellent database because this indicates that the filing activist

[4]The merger agreement restriction requires Item 1.01 in Form 8-K which was made available after a major overhaul of the Form 8-K structure by the SEC on Aug. 23, 2004. There may be possible omissions of required items during the early period immediately after the overhaul, and thus we restrict our sample to campaigns starting from Jan. 1, 2005.

targeted the firm due to an ongoing merger deal. We also verify that the 13D filings are not distress-related by parsing the 13D filing for mentions of "distress" or "Chapter 11" under the Purpose of Transaction section (Item 4); however, this restriction does not eliminate any additional campaigns from the sample.

Finally, we require stock returns, trading volume, and accounting variables from CRSP and Compustat, and institutional ownership measures from Thomson's 13F data. Our final sample runs from 2005 to June 2017 and includes 1,286 campaigns with a total of 236 unique activists and 1,267 unique target firms. Appendix A explains our data construction process in greater detail.

## B. Methodologies to Identify a Suspicious IP Address in Activist Campaigns

In this section, we explain our methods to identify suspicious IP addresses appearing in our sample of activism campaigns. We first collect all the IP addresses conducting search activities on target firms in our sample during the window beginning the day that the activist surpasses 5% ownership (the "Event Date") and ending the day before the filing [Event Date, $-1$].[5] Following Loughran and McDonald (2017), we exclude search activities ending at an index page without looking at the details of the filing and search activities by web crawlers identified by the SEC and other possible robots with more than 50 filing requests in a given day. We use this procedure to identify search activities by regular, nonrobot investors for relevant research on the target firm. We focus on search activities for the most significant financial, operational, and governance-related forms: 10-K, 10-Q, and proxy statements.

From the pool of the IP addresses, we define a COMMON_IP as one conducting search activity before the 13D for more than one campaign by the same activist. Considering these search activities consistently occur before the announcement, the COMMON_IPs seem to be well-informed. However, we acknowledge the possibility that some sophisticated investors may conduct thorough research to identify potential activist targets before the 13D. Thus, we investigate the same IP's search activities in the preceding days up to Day $-60$ and eliminate any COMMON_IPs that have search activity on the target firm in this window. Our attention is therefore exclusively on investors that display a sudden interest in the target firm immediately before the announcement of campaigns by the same activist. This type of sudden attention is highly unlikely to occur by coincidence.

However, there may be some remaining concerns. For example, a COMMON_IP with no prior access may be an IP associated with a different department or office under the filing activist fund. Also, an activist fund manager may do research at home, in restaurants, or any other place with a different IP address before disclosing the campaign. To rule out these possibilities, we attempt to find the identity behind each IP. We use the American Registry for Internet Numbers' (ARIN) WhoWas database to extract the organization information for each IP. WhoWas provides historical details about the ownership of an IP, and we

[5]Our results are all robust to employing a uniform 10-day Suspect identification window across all campaigns instead of the actual campaign event windows. These results are available upon request.

https://doi.org/10.1017/S0022109022001156 Published online by Cambridge University Press

collect all the historical registration details to identify the organization owning the IP address as of the time of the activist campaign.[6]

While various organizations have registered ownership of IP addresses, others may have IP addresses through Internet Service Providers (ISPs). In this situation, an investment firm could be accessing a firm's documents through a third-party internet provider. To overcome this limitation, we use the most conservative approach by classifying the IP address as a SUSPECT_IP only if it is registered to an investment management firm or an investment bank. When the IP address is identified as a different type of organization such as a university, nonprofit organization, retail bank, or ISP, we exclude it from our sample. We also exclude an IP if it belongs to the filing activist or any other campaign participants. This approach leaves us with a small subset of SUSPECT_IPs. However, we have a high degree of confidence that we have identified investors with the capital and incentive to trade on the information; these investors are therefore the most likely beneficiaries of informative signals about a pending activist campaign.

We note that our estimation measure likely underestimates the true extent of informed outside investors. If, for example, the informed investor downloads the target firm's filings the day prior to the event date, they would not show up in our estimate. We base our measure on the event date because it is the trigger date at which the filing becomes imminent, although a less conservative approach would yield higher numbers of SUSPECT_IPs. We also note that we are only focusing on one narrow channel in which an investor can research the firm. If the investor instead downloads target firm information from other data sources such as Bloomberg or FactSet, or if the investor accesses from their home or public wi-fi, they would also not appear in our data; the nature of our data set requires research through EDGAR. Given these limitations, the fact that we find any evidence at all of informed trading suggests that the true extent may be larger than estimated in our tests.

## C. Descriptive Statistics

In Panel A of Table 1, we show summary statistics for our final sample of activist campaigns by the activist type. The most popular type is hedge fund companies in both the total number of campaigns and the unique number of activists. However, when we measure the frequency of campaigns per activist, investment advisors use activist campaigns most frequently. In Panel B of Table 1, we present yearly statistics for the number of campaigns with at least one SUSPECT_IP.

Table 2 provides details of SUSPECT_IP access activity. As shown in Panel A of Table 2, 69 campaigns have one SUSPECT_IP, 15 campaigns have two SUSPECT_IPs, and relatively few campaigns have more than two. Panel B of Table 2 shows that SUSPECT_IP in our sample are associated with 1.32 different activists, on average. Each suspect is associated with roughly 34.6% of an activist's campaigns that have suspect IP access.

[6]The EDGAR Log File data provides only the first three octets of the IP address. For example, an IP in the EDGAR Log File data may be coded as 123.123.123.abc with the fourth octet obfuscated with a 3-character string. We use Chen et al. (2020) to map the hidden octet with an actual octet.

TABLE 1
Campaign Summary Statistics

Table 1 includes summary stats of our sample of activist campaigns over the years 2005 to 2017 (2017 includes campaigns for the first half of the year only). Panel A displays SharkRepellent holder-type classifications of the campaign activists. In cases where there are multiple names listed in the Dissident Group in SharkRepellent, we use the name on the respective 13D filing that is linked to the filer CIK to classify the observation. Panel B includes summary stats of the campaigns by year. SUSPECT_IP is defined in Appendix B. Displayed in Panel B are the number of campaigns and SUSPECT_IP access by year.

*Panel A. Campaign Activist Types*

| Holder Type | Number of Campaigns With This Holder Type | Unique Activist CIK | Average Number of Campaigns Per Activist CIK |
|---|---|---|---|
| Corporation | 3 | 1 | 3.00 |
| Hedge fund company | 976 | 170 | 5.74 |
| Individual | 27 | 6 | 4.50 |
| Investment adviser | 187 | 20 | 9.35 |
| Mutual fund manager | 16 | 5 | 3.20 |
| Other institutions | 8 | 4 | 2.00 |
| Other stake holders | 69 | 30 | 2.30 |

*Panel B. Campaign IP Summary Statistics by Year*

| Year | No. of Campaigns | No. of Campaigns With Suspect IP (% of Yearly Campaigns) | Average No. of Suspect IP at Suspect Campaigns | Median Target Market Cap ($M) |
|---|---|---|---|---|
| 2005 | 88 | 1 (1.14%) | 1.00 | 202.86 |
| 2006 | 119 | 3 (2.52%) | 1.00 | 249.67 |
| 2007 | 169 | 8 (4.73%) | 1.25 | 282.26 |
| 2008 | 138 | 15 (10.87%) | 1.20 | 249.46 |
| 2009 | 73 | 6 (8.22%) | 1.17 | 70.15 |
| 2010 | 69 | 4 (5.80%) | 1.75 | 201.97 |
| 2011 | 78 | 8 (10.26%) | 1.38 | 273.63 |
| 2012 | 100 | 6 (6.00%) | 1.83 | 236.06 |
| 2013 | 98 | 7 (7.14%) | 1.43 | 185.22 |
| 2014 | 131 | 14 (10.69%) | 1.43 | 342.72 |
| 2015 | 115 | 10 (8.70%) | 1.30 | 398.44 |
| 2016 | 93 | 5 (5.38%) | 1.20 | 226.92 |
| 2017 | 15 | 3 (20.00%) | 1.00 | 865.71 |

In Panel C of Table 2, we report the type of filings that SUSPECT_IPs access. Quarterly reports (10-Q) make up the largest proportion of accessed filings, but this is driven by the fact that corporations file more 10-Qs than 10-Ks or proxy statements.

Some may argue that SUSPECT_IPs could simply follow the stock holdings in the activist's portfolio. Thus, in Panel D of Table 2, we display SUSPECT_IP access activity of the activist's other holdings to demonstrate the uniqueness of the SUSPECT_IP we identify. We obtain each activist's total holdings reported in the Thomson Reuters 13F database at the quarter immediately before the activist announces a campaign. The activists of the 90 campaigns we identify as having a SUSPECT_IP hold an average of 306 firms in their portfolios. During the same event window that we identify an IP as suspect, these same IP access EDGAR documents for fewer than four of the activist's other holdings, on average. This access equates to a mere 3.27% of holdings and clearly shows the uniqueness of the connections we identify.

Another potential concern is that SUSPECT_IPs are merely tracking firms that are likely to be targeted by activists, and some market event during the event window alerts these investors to the increased likelihood of a pending 13D. If this were the case, we would expect these investors to regularly download filings of activist targets during the event window. The final row of Panel D of Table 2 reports the likelihood of the SUSPECT_IP downloading filings for another activist's

https://doi.org/10.1017/S0022109022001156 Published online by Cambridge University Press

TABLE 2

Suspect IP Access Summary Statistics

Table 2 displays the access summary statistics for SUSPECT_IP. Panel A displays the number of campaigns by number of unique SUSPECT_IP accessing the campaign. Panel B displays the average number of activists that each SUSPECT_IP is associated with and the average percentage of the activist's suspect campaigns for which the SUSPECT_IP is identified. Panel C displays the frequency of SUSPECT_IP access within each type of SEC document we use in the identification process. Panel D displays summary statistics regarding SUSPECT_IP access of other holdings of the respective activist for which the SUSPECT_IP is identified, as well as access of campaigns for which the IP has no connection. Specifically, during the event window in which we identify an IP as SUSPECT, we determine the number of the activist's other holdings that are accessed by this same IP and in the same event window. The final row of Panel D displays SUSPECT_IP access of campaigns by activists for which the SUSPECT_IP is not connected.

*Panel A. Suspect IP Frequency Per Campaign*

| No. of Suspects | No. of Campaigns |
|---|---|
| 1 | 69 |
| 2 | 15 |
| 3 | 4 |
| 4 | 1 |
| 5 | 1 |
| Total | 90 |

*Panel B. Suspect IP-Activist Link*

| | Mean | 25th Percentile | 50th Percentile | 75th Percentile |
|---|---|---|---|---|
| ACTIVISTS_FOLLOWED_BY_SUSPECT_IP | 1.32 | 1 | 1 | 1 |
| PERCENT_OF_CAMPAIGNS_ACCESSED_BY_SUSPECT_IP (%, CONDITIONAL) | 34.559 | 9.091 | 20.000 | 50.152 |

*Panel C. Research Activities by Suspect IP in the Campaign Targets*

| Form Type | No. of Accesses by Suspect | No. of Campaigns with Accesses |
|---|---|---|
| 10-K | 88 | 54 |
| 10-Q | 106 | 58 |
| PROXY_STATEMENTS | 26 | 12 |

*Panel D. Other Access Activity by Suspect IP*

| Variable | Mean | Std. Dev. | 25th Percentile | 50th Percentile | 75th Percentile |
|---|---|---|---|---|---|
| TOTAL_ACTIVIST'S_OTHER_HOLDINGS | 305.833 | 544.316 | 12 | 23 | 681.25 |
| SUSPECT_IP_ACCESS_OF_ACTIVIST'S_OTHER_HOLDINGS | 3.878 | 6.702 | 0 | 1 | 3.75 |
| SUSPECT_IP_ACCESS_OF_ACTIVIST'S_OTHER_HOLDINGS (%) | 3.272 | 4.453 | 0 | 0.909 | 5.675 |
| RANDOM_ACCESS_OF_OTHER_ACTIVIST_CAMPAIGNS_PER_SUSPECT_IP (%) | 0.097 | 0.115 | 0.02 | 0.084 | 0.09 |

campaign targets during the same window. SUSPECT_IPs on average (even at the 75th percentile) only access 0.10% (0.09%) of targets of other activists during the event window, suggesting that they are not serial predictors of pending 13D filings.

Table 3 reports descriptive statistics for the target firms in our sample. TOTAL_IP reports that the average campaign has 37.85 unique IPs conducting search activities on a target firm's major filings prior to the activist campaign, unconditional on any filtering process. The average number of IPs doing research on more than one campaign by the same activist during the event window, denoted COMMON_IP, is 0.85, much less than the 37.85 for TOTAL_IP. Once we exclude those IPs showing interest in the target firm well before the date in which the activist reaches 5% ownership, IPs which we denote as COMMON_IP_NO_PRIOR_ACCESS, the average decreases to 0.51, a nearly 40% reduction from the average for COMMON_IP. Finally, we construct our variable of interest, SUSPECT_IP, as an indicator variable equal to 1 if, within the set of COMMON_IP_NO_PRIOR_ACCESS for a campaign, we identify the owner of the IP address as an investment

TABLE 3

Variable Summary Statistics

Table 3 includes the summary statistics of our sample of 1,286 campaigns and the variables we use throughout our multivariate tests. We provide variable descriptions in Appendix B.

| Variable | Mean | Std. Dev. | 25th Percentile | 50th Percentile | 75th Percentile |
|---|---|---|---|---|---|
| TOTAL_IP | 37.852 | 48.937 | 11.000 | 23.000 | 46.000 |
| COMMON_IP | 0.850 | 1.559 | 0.000 | 0.000 | 1.000 |
| COMMON_IP_NO_PRIOR_ACCESS | 0.506 | 1.104 | 0.000 | 0.000 | 1.000 |
| SUSPECT_IP | 0.070 | 0.255 | 0.000 | 0.000 | 0.000 |
| NUMBER_OF_CAMPAIGNS | 19.896 | 27.186 | 4.000 | 10.000 | 20.000 |
| LOG_OF_NUMBER_OF_CAMPAIGNS | 2.388 | 1.031 | 1.386 | 2.303 | 2.996 |
| BHAR [−1, 1] | 0.032 | 0.070 | −0.007 | 0.023 | 0.060 |
| BHAR [−10, −1] | 0.008 | 0.106 | −0.040 | 0.010 | 0.059 |
| BHAR [0, 10] | 0.036 | 0.111 | −0.024 | 0.024 | 0.086 |
| MARKET_CAP ($M) | 1,229.100 | 2,671.110 | 87.232 | 247.192 | 940.496 |
| MARKET_LEVERAGE | 0.171 | 0.222 | 0.000 | 0.064 | 0.303 |
| ROA | −0.034 | 0.224 | −0.048 | 0.008 | 0.053 |
| INSTITUTIONAL_OWNERSHIP | 0.596 | 0.322 | 0.342 | 0.653 | 0.859 |
| LOG_OF_AMIHUD_ILLIQUIDITY | −6.144 | 3.199 | −8.667 | −6.302 | −4.066 |
| PRIOR_12_MONTH_RETURN | −0.057 | 0.454 | −0.352 | −0.110 | 0.151 |
| PRIOR_36_MONTH_RETURN | 0.110 | 0.855 | −0.424 | −0.062 | 0.398 |
| TURNOVER (EVENT DATE, −1] | 0.010 | 0.012 | 0.002 | 0.006 | 0.014 |
| TURNOVER [−120, −61] | 0.008 | 0.008 | 0.002 | 0.006 | 0.011 |
| OWNERSHIP_BY_ACTIVIST (%) | 8.160 | 3.990 | 5.400 | 6.700 | 9.600 |

management firm or an investment bank. The SUSPECT_IP indicator has an average of 0.07, reflective of the stringent identification process we utilize.

Buy-and-hold abnormal returns show positive returns centered around the announcement date, consistent with the consensus in the shareholder activism literature (see, e.g., Brav et al. (2008)). Our sample shows meaningful cross-sectional variations based on Market Cap, Leverage, ROA, and Institutional Ownership. Target firms tend to show negative returns for the performance in the past year. Considering positive returns for the performance in the past 3 years, the decline in the performance for the most recent year could be a cause for the activism campaign.

# IV. Empirical Findings

## A. Do Suspect IPs Trade on the Information?

We first evaluate the market implications of SUSPECT_IP access around the announcement of a campaign. If informed investors are trading on this information, we would expect to see a heightened level of trading activity before the campaign disclosure. Further, if there is an incentive for investors to act on this shared information, we would also expect to find higher returns following the campaign disclosure.

We test for differences in turnover leading up to campaign announcement using the following OLS model specification:

$$\text{(1)}\quad \text{SHARE\_TURNOVER}_i = \beta_0 + \beta_1 \text{SUSPECT\_IP}_i + \sum_{k=2}^{16} \beta_k \text{CONTROL}_i + \varepsilon_i.$$

The dependent variable in regression (1) is firm $i$'s average daily turnover from the day after the activist exceeds 5% ownership to the day before the campaign announcement (i.e., the (Event Date, $-1$] day window). The independent variable

https://doi.org/10.1017/S0022109022001156 Published online by Cambridge University Press

of interest is the SUSPECT_IP indicator variable. If suspicious IP activity is associated with increased trading activity, we expect a positive and statistically significant coefficient, $\beta_1$, throughout these regressions.

The remaining independent variables in regression (1) include controls for activist, campaign, and firm characteristics. We control for investors' general interest in the target firm by including the Total IP access of the firm's financial statements during the window prior to the announcement. We control for the activist's campaign characteristics by using indicator variables that are 1 if the activist's campaign demands include changes to the firm's board (BOARD_DEMANDS), changes to the firm's corporate governance (GOVERNANCE_DEMANDS), or a broad set of values (VALUE_DEMANDS) ranging from acquisitions activities to payout policy. We control for each activist's campaign experience (LOG_OF_CAMPAIGNS) by including the natural log of 1 plus the number of 13D filings made by the activist in our sample. To control for the initial ownership stake of each activist, we include the ownership percentage (OWNERSHIP_BY_ACTIVIST) listed on the campaign 13D filing. We also include the market reaction on the campaign announcement (BHAR [−1, 1]) to control for the market's assessment of the prospects of a successful campaign.

Our set of firm characteristic controls includes the log of each firm's market cap as of the most recent fiscal year-end before the start of the campaign, market leverage as of the most recent fiscal year, and operating performance, which we measure using a firm's return on assets from the most recent fiscal year. Institutional ownership has a profound effect on various aspects of activism.[7] We, therefore, include each firm's total institutional ownership from the Thomson Reuters 13F database as of the quarter before the initial 13D filing.

Finally, we control for the target firm's stock characteristics using the cumulative returns over the 12 and 36 months before the month of the campaign announcement and the liquidity of the firm's shares over the prior calendar year. Liquidity is of particular importance to trading activity in activist campaigns since liquidity directly affects the ability of the activist, and their peers, to assemble a meaningful position in the target (Edmans, Fang, and Zur (2013), Collin-Dufresne and Fos (2015), Norli, Ostergaard, and Schindele (2015), and Gantchev and Jotikasthira (2018)). The proxy of liquidity that we use is the average Amihud illiquidity measure over the prior calendar year (Amihud (2002)). We also include each target's average daily turnover during the [−120, −61] day window so that we may interpret $\beta_1$ on the SUSPECT_IP indicator as a change in turnover during the (Event Date, −1] day window. Last, we include year-fixed effects, industry-fixed effects using the 48 Fama–French industry classification, and activist fixed effects. We provide a detailed description of our variables in Appendix B.

The results of regression (1) are displayed in models 1 through 3 of Table 4. In each of the models, the coefficient estimate of $\beta_1$ on SUSPECT_IP is positive and statistically significant, suggesting that greater SUSPECT_IP access is associated with greater trading activity. For example, the estimates of 0.005 and 0.003 for $\beta_1$ in models 1 through 3 equate to an increase in turnover of 0.50% and 0.30% of

[7]See, for example, Appel, Gormley, and Keim (2016), Gantchev and Jotikasthira (2018), Appel, Gormley, and Keim (2019), Brav et al. (2021), Kedia et al. (2021), and He and Li (2022).

TABLE 4

Suspect IP Access and Abnormal Turnover

Table 4 displays the results of OLS regression that we specify as follows:

$$\text{SHARE\_TURNOVER}_i = \beta_0 + \beta_1 \text{SUSPECT\_IP}_i + \sum_{k=2}^{16} \beta_k \text{CONTROL}_i + \varepsilon_i.$$

We estimate this regression at the campaign – target firm level. The dependent variable is firm $i$'s average daily turnover following the activist's acquisition of a 5% ownership stake to the day before the announcement of the activist's campaign (i.e., the (Event Date, −1] day window with the announcement date as day zero). We measure daily turnover as daily volume divided by shares outstanding. The variable of interest is the SUSPECT_IP indicator variable that is 1 if the respective campaign has at least one SUSPECT_IP, and 0 otherwise. Appendix B contains all variable descriptions. We measure firm characteristics as of the target firm's most recent fiscal year end. We compute a target's institutional ownership as of the most recent quarter before the campaign announcement. We compute a target firm's Amihud (2002) illiquidity as the average of monthly illiquidity over the year prior to the campaign announcement year. Prior 12- and 36-month stock performance is measured in the months preceding the campaign announcement month. We control for each firm's base level of turnover by including firm $i$'s average daily turnover over the [−120, −61] day window from the campaign announcement date. We include year-fixed effects, industry-fixed effects using 48 Fama–French industries, and activist fixed effects. We compute $t$-statistics using heteroscedasticity-robust standard errors (White (1980)). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| | Turnover (Event Date, −1] | | |
|---|---|---|---|
| | 1 | 2 | 3 |
| SUSPECT_IP | 0.005*** | 0.003** | 0.003* |
| | (3.36) | (2.41) | (1.82) |
| TOTAL_IP | | 0.001*** | 0.001* |
| | | (2.89) | (1.85) |
| BOARD_DEMANDS | | 0.002*** | 0.002** |
| | | (3.00) | (2.03) |
| GOVERNANCE_DEMANDS | | −0.001** | −0.002** |
| | | (−2.04) | (−2.09) |
| VALUE_DEMANDS | | −0.001 | −0.000 |
| | | (−1.12) | (−0.54) |
| LOG_OF_CAMPAIGNS | | 0.000 | 0.040** |
| | | (0.08) | (2.30) |
| LOG_OF_MARKET_CAP | | 0.000 | 0.001 |
| | | (1.10) | (1.26) |
| MARKET_LEVERAGE | | 0.002 | 0.002 |
| | | (1.23) | (1.04) |
| RETURN_ON_ASSETS | | −0.001 | −0.002 |
| | | (−0.84) | (−1.44) |
| INSTITUTIONAL_OWNERSHIP | | 0.001 | 0.001 |
| | | (0.73) | (0.76) |
| LOG_OF_AMIHUD_ILLIQUIDITY | | −0.000 | −0.000 |
| | | (−0.66) | (−0.97) |
| PRIOR_12_MONTH_RETURN | | −0.000 | −0.000 |
| | | (−0.31) | (−0.61) |
| PRIOR_MONTH_RETURN | | 0.001** | 0.001** |
| | | (2.03) | (2.21) |
| OWNERSHIP_BY_ACTIVIST | | 0.000*** | 0.001*** |
| | | (4.60) | (4.76) |
| BHAR [−1, 1] | | 0.004 | 0.003 |
| | | (0.82) | (0.64) |
| TURNOVER [−120, −61] | 0.869*** | 0.670*** | 0.688*** |
| | (15.23) | (9.63) | (9.22) |
| Industry-fixed effects | No | Yes | Yes |
| Year-fixed effects | No | Yes | Yes |
| Activist-fixed effects | No | No | Yes |
| No. of obs. | 1,286 | 1,286 | 1,286 |
| Adj. $R^2$ | 0.378 | 0.435 | 0.472 |

total shares outstanding during the (Event Date, −1] day window of the campaign announcement. Put differently, these effects show turnover increases by roughly 59.28% and 35.57% from the turnover of the average target firm in the [−120, −61] day window.

https://doi.org/10.1017/S0022109022001156 Published online by Cambridge University Press

TABLE 5

Activist Trading Activity in the Pre-13D Window

Table 5 considers activist trading activity taking place within the [−10, −1] campaign announcement window for campaigns that have SUSPECT_IP access. For this analysis, we use the 60 days of trading activity disclosed in the Suspect campaign 13D filings. “First IP Access” denotes the first date that the SUSPECT_IP downloads information on the target firm.

| Description | Mean | Diff | *t*-Statistics |
|---|---|---|---|
| DAILY_PERCENT_ACQUISITION_PRIOR_TO_FIRST_IP_ACCESS (as % of outstanding shares) | 0.34% | 0.21% | (3.75) |
| DAILY_PERCENT_ACQUISITION_AFTER_FIRST_IP_ACCESS (as % of outstanding shares) | 0.13% | | |
| TOTAL_PERCENT_ACQUISITION_PRIOR_TO_FIRST_IP_ACCESS (as % of reported 13D ownership) | 14.16% | 8.79% | (3.62) |
| TOTAL_PERCENT_ACQUISITION_AFTER_FIRST_IP_ACCESS (as % of reported 13D ownership) | 5.37% | | |

Throughout the models in Table 4, the coefficient estimates on our set of controls identify market effects consistent with our expectations. For example, greater IP access in the days leading up to the announcement and greater ownership by the activist are positively associated with the change in turnover during the days leading up to a campaign.

We recognize potential endogeneity concerns with the elevated turnover in Table 4 and next perform several robustness tests. We begin by examining the activist’s trading activity. If the activist is sharing information about their upcoming 13D filing, they likely will do so only after they have acquired most of the shares that they intend to purchase. Table 5 examines trading activity of activists in suspect campaigns during the 10 days prior to disclosure of their 13D. We find that the activist acquires more shares per day (both as a percentage of target shares outstanding and as a percentage of the activist’s final reported 13D ownership level) prior to the first suspect IP access than they do after access. Further, only 5.37% of the activist’s total share acquisition would be affected by outsiders trading on the information, so the cost of potentially higher acquisition prices would be minimal.

In Table C1 of the Supplementary Material, we address reverse causality concerns about turnover being driven by the activist’s trades. We examine the subset of filers switching from 13G to 13D. These activists have a previously disclosed 5% stake and are therefore unlikely to be driving higher turnover during the event window. Although the sample is small at only 8 campaigns, we continue to find significantly higher in SUSPECT_IP switchers relative to nonsuspect switchers.

We also acknowledge that the findings of Di Maggio, Franzoni, Kermani, and Sommavilla (2019), who find evidence of leaking by the activist’s brokers, could drive the turnover results: if brokers are leaking the trading activity of activists, it will create more trading volume caused by the informed parties. We note that such leaking would be of no benefit to the activist, which would be inconsistent with our overall findings. However, we address this concern in Table C2 of the Supplementary Material, where we eliminate any activist-SUSPECT_IP pairs that are reported to have the same prime broker in the Lipper TASS database and use same model specification in Table 4. We obtain similar results to those in Table 4 with greater turnover taking place among our suspect campaigns. We conclude that broker leaking is not a primary driver of our findings.

TABLE 6

Abnormal Returns of Suspect Campaigns

Table 6 displays summary statistics of the abnormal returns for activist campaigns with SUSPECT_IP access. We compute abnormal returns over various windows within the [−20, 20] day window centered at the announcement date of the activist campaign. The abnormal return measures we use are i) the buy and hold abnormal returns (BHAR), ii) the market model adjusted cumulative abnormal return (MCAR), iii) the Fama–French 3-factor model cumulative abnormal return (FF3CAR), iv) and the Fama–French 5-factor model cumulative abnormal return (FF5CAR). To compute BHAR we use the CRSP Value-Weighted Index as a benchmark. To compute MCAR, FF3CAR, and FF5CAR, we estimate factor models using each target's daily returns in the [−160, −60] day window relative to the target's activist campaign announcement (i.e., day zero). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| Window | Return | Mean | Std. Dev. | 25th Percentile | 50th Percentile | 75 Percentile |
|---|---|---|---|---|---|---|
| [−1, 1] | BUY_AND_HOLD_ABNORMAL_RETURN | 0.0385*** | 0.0712 | −0.0148 | 0.0245 | 0.0742 |
| | MARKET_MODEL_ADJUSTED_CUMULATIVE_ ABNORMAL_RETURN | 0.0421*** | 0.0704 | −0.0105 | 0.0263 | 0.0809 |
| | FF3_MODEL_ADJUSTED_CUMULATIVE_ABNORMAL_RETURN | 0.0416*** | 0.0655 | −0.0018 | 0.0339 | 0.0784 |
| | FF5_MODEL_ADJUSTED_CUMULATIVE_ABNORMAL_RETURN | 0.0412*** | 0.0672 | −0.0019 | 0.0381 | 0.0813 |
| [−20, 20] | BUY_AND_HOLD_ABNORMAL_RETURN | 0.0438** | 0.1917 | −0.0595 | 0.0491 | 0.1559 |
| | MARKET_MODEL_ADJUSTED_CUMULATIVE_ ABNORMAL_RETURN | 0.0855*** | 0.2245 | 0.0000 | 0.0981 | 0.2048 |
| | FF3_MODEL_ADJUSTED_CUMULATIVE_ABNORMAL_RETURN | 0.0491** | 0.1939 | −0.0364 | 0.0617 | 0.1616 |
| | FF5_MODEL_ADJUSTED_CUMULATIVE_ABNORMAL_RETURN | 0.0506** | 0.1917 | −0.0432 | 0.0614 | 0.1724 |
| [−10, −1] | BUY_AND_HOLD_ABNORMAL_RETURN | 0.0103 | 0.0935 | −0.0229 | 0.0252 | 0.0728 |
| | MARKET_MODEL_ADJUSTED_CUMULATIVE_ ABNORMAL_RETURN | 0.0222** | 0.0976 | −0.0150 | 0.0324 | 0.0767 |
| | FF3_MODEL_ADJUSTED_CUMULATIVE_ABNORMAL_RETURN | 0.0151 | 0.0965 | −0.0229 | 0.0210 | 0.0726 |
| | FF5_MODEL_ADJUSTED_CUMULATIVE_ABNORMAL_RETURN | 0.0160 | 0.0973 | −0.0259 | 0.0241 | 0.0698 |
| [0, 10] | BUY_AND_HOLD_ABNORMAL_RETURN | 0.0600*** | 0.1106 | −0.0149 | 0.0495 | 0.1180 |
| | MARKET_MODEL_ADJUSTED_CUMULATIVE_ ABNORMAL_RETURN | 0.0682*** | 0.1112 | −0.0115 | 0.0600 | 0.1361 |
| | FF3_MODEL_ADJUSTED_CUMULATIVE_ABNORMAL_RETURN | 0.0575*** | 0.1045 | −0.0149 | 0.0536 | 0.1206 |
| | FF5_MODEL_ADJUSTED_CUMULATIVE_ABNORMAL_RETURN | 0.0541*** | 0.1025 | −0.0274 | 0.0544 | 0.1247 |

## B. Do Suspect IPs Profit on the Information?

We now examine whether the information proves to be profitable for SUSPECT_IPs. Given the extensive evidence on positive abnormal announcement returns to activist 13D filings, we expect the same to hold true in the subsample of suspect-linked campaigns. We next verify the value of information in suspect-linked campaigns by computing abnormal returns for our sample of suspect campaigns. We compute returns in four ways: a buy-and-hold abnormal return, a market-adjusted cumulative abnormal return, a Fama–French 3-factor model abnormal return, and a Fama–French 5-factor model abnormal return. We compute the abnormal returns across four time windows: [−1, 1], [−20, 20], [−10, −1], and [0, 10]. Table 6 reports the results.

Across nearly all specifications, we find significantly positive abnormal returns around the announcement. The abnormal return estimates for the [−1, 1] window average approximately 4%, while the longer-term [−20, 20] and [0, 10] windows average in approximately 6–7%. The sole exception to the significantly positive returns is in the [−10, −1] window, which only contains the returns *prior to* the announcement. The abnormal returns, therefore, appear to be primarily driven by the market response to the announcement rather than informed purchases leading up to it.

## C. Do Suspect IPs Increase Their Holdings Prior to the 13D Announcement?

We next turn our attention to the trading activity of SUSPECT_IPs, examining the changes in their ownership of the target firm around the campaign announcement. If SUSPECT_IPs indeed act on the valuable information, we anticipate an increase in their holdings of the target firm around the campaign announcement, relative to the other institutions in the same target firm without the information. Ideally, daily transaction-level data would provide the best evidence of informed trading activity; however, institutions are not required to report trades with this level of granularity, and to the extent that these data are available, the traders are anonymized. We, therefore, use quarterly 13F holdings to examine the SUSPECT_IP's trading activity.

We acknowledge that the quarterly reporting could allow the investor to earn the profit and liquidate the holding without ever reporting the ownership. However, our assertion is that this investor is providing voting support to the activist, which would require the investor to retain at least some shares of the stock through the duration of the campaign. We also acknowledge that quarterly reporting prevents us from knowing the exact date of share acquisition. Still, given the timing of when the information was acquired, we find it unlikely that any acquisitions were delayed until after the announcement, when the information no longer has value.

We are able to match SUSPECT_IPs to 13F holdings data for 51 out of 90 campaigns.[8] We measure the change of holdings for each institution between the quarter ending before and the quarter ending immediately after the campaign announcement. We then examine whether increases in holdings are more likely to occur within the institutions associated with a SUSPECT_IP. Specifically, we use the following logit model specification, using a dependent variable that is an indicator for whether the respective institutions increase their holdings.

$$(2)\qquad \Pr(\text{STAKE}_i) = \Lambda\left(\gamma_0 + \gamma_1 \text{SUSPECT\_IP}_i + \sum_{k=2}^{7} \gamma_k \text{CONTROL}_i + \varepsilon_i\right).$$

Table 7 reports the results of regression (2). While we employ an indicator for an increase in holdings in models 1 and 2, one may argue that small increases can result from portfolio rebalancing rather than informed investment. Thus, we also use an indicator for an increase greater than 5% in models 3 and 4. Our independent variable of interest across models 1 through 4 is a SUSPECT_IP indicator that is 1 if institution $i$ is associated with SUSPECT_IP access for the respective campaign, and 0 otherwise. Additionally, these regressions are at the institution level, and we add a set of control variables to models 2 and 4 that account for institutional portfolio construction and rebalancing.

In Table 7, we use the sample of campaigns having SUSPECT_IP access. In models 1 and 3 with no control variables, the estimate of $\gamma_1$ for SUSPECT_IP is positive and statistically significant at the 1% level. The $\gamma_1$ estimate 0.614 in model 1 implies that an institution with SUSPECT_IP access is 15.23% more likely to increase their holdings around the campaign announcement. The magnitude of this effect is comparable once our control variables are added in models 2 and 4, and positive and statistically significant at the 1% level. The results suggest that those institutions with suspicious research activities are indeed likely to trade on the information.

[8] 13F holdings are reported at the parent organization level. Therefore, if a SUSPECT_IP is a subsidiary of a different institution, we assess the holdings of the parent organization. The remainder of unmatched firms did not file Form 13F during the relevant quarters.

TABLE 7

Suspect IP Ownership Changes Around the Campaign Announcement

Table 7 displays the results of logit regressions that determine the effect of SUSPECT_IP access on the likelihood that an institution will increase its holdings in the target firm following the announcement of the campaign. The logit model specification is as follows:

$$\Pr(\text{STAKE}_i) = \Lambda\left(\gamma_0 + \gamma_1 \text{SUSPECT}_{\text{IP}\,i} + \sum_{k=2}^{7} \gamma_k \text{CONTROL}_i + \varepsilon_i\right).$$

We estimate this regression at the institution – target firm level, using the sample of campaigns having a SUSPECT_IP that file a form 13F. In models 1 and 2, the dependent variable, $\text{STAKE}_i$, is an indicator that is 1 if institution i increases their share ownership stake from the quarter-end before to the quarter-end following the campaign announcement date, and 0 otherwise. In models 3 and 4, the dependent variable, $\text{STAKE}_i$, is an indicator that is 1 if institution $i$ increases their share ownership by greater than 5% from the quarter-end before to the quarter-end following the campaign announcement date, and 0 otherwise. The independent variable of interest is a $\text{SUSPECT\_IP}_i$ indicator that is 1 if institution $i$ is associated with SUSPECT_IP access in the respective campaign, and 0 otherwise. We construct all control variables as described in Appendix B. We measure a target firm's market cap as of the firm's most recent fiscal year end. We measure a target firm's prior 12-month stock performance during the 12 months preceding the month of the firm's campaign announcement date. We measure institutional characteristics of Average Holding Market Cap, Portfolio Dollar Value, and Number of Portfolio holdings as of the quarter before the target firm's campaign announcement quarter. We compute $z$-statistics using heteroscedasticity-robust standard errors (White (1980)) and we cluster standard errors by year. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| | Holdings Increase | | 5% Holdings Increase | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| SUSPECT_IP | 0.614*** | 0.459** | 0.744*** | 0.712*** |
| | (2.85) | (2.09) | (3.59) | (3.40) |
| LOG_OF_MARKET_CAP | | 0.044 | | 0.017 |
| | | (1.59) | | (0.45) |
| BHAR [−1, 1] | | −1.937** | | −1.639 |
| | | (−2.48) | | (−1.46) |
| PRIOR_12_MONTH_RETURN | | −0.088 | | −0.160 |
| | | (−0.78) | | (−1.24) |
| AVERAGE_HOLDING_MARKET_CAP | | −0.301*** | | −0.340*** |
| | | (−4.20) | | (−4.06) |
| PORTFOLIO_DOLLAR_VALUE | | 0.047*** | | −0.004 |
| | | (2.99) | | (−0.27) |
| NUMBER_OF_PORTFOLIO_HOLDINGS | | −0.077 | | −0.094* |
| | | (−1.58) | | (−1.78) |
| No. of obs. | 15,325 | 15,325 | 15,325 | 15,325 |
| Pseudo-$R^2$ | 0.000 | 0.013 | 0.000 | 0.013 |

One may argue that the effects in Table 7 are attributable to an inherent tendency for suspect institutions to adjust their holdings more frequently. We address this endogeneity concern by limiting the regression sample to transient institutions with short-term trading strategies.[9] In models 1 through 4 of Panel A of Table C3 of the Supplementary Material, we continue to find a positive and statistically significant association between SUSPECT_IP access and the likelihood of holdings increase, suggesting that suspect institutions' trades are not merely driven by frequent turnover.

In Panel B of Table C3 of the Supplementary Material, we report a similar test but restrict the sample to only those investors classified as having SUSPECT_IP access at least once in our sample. We then examine whether their trading activity in campaigns in which they are labeled "suspect" is fundamentally different from other activist campaigns. The positive and significant coefficient on SUSPECT_IP in each model indicates that the institution is much more likely to acquire shares in a suspect campaign, where they are apparently informed, than in any other activist

[9]We use the classifications in Bushee and Noe (2000) and Bushee (2001) to find transient institutions. The institutional classification data is available at https://accounting-faculty.wharton.upenn.edu/bushee/.

https://doi.org/10.1017/S0022109022001156 Published online by Cambridge University Press

campaign. Such a result provides evidence against the suspect investors being serial predictors of activist campaigns.

The quarterly reporting of 13F prevents us from knowing exactly when the SUSPECT_IP acquired their shares. While the previous test provides evidence consistent with our conjecture of the informed investor acquiring shares when they were first informed of the campaign, we cannot conclusively state that the shares were purchased before the 13D filing. To mitigate this concern, we also run a similar test for the subset of campaigns in which the 13F quarter-end reporting date is within 10 days before the 13D filing, comparing these holdings within the event window to the holdings in the prior quarter. Although this is small-sample test, it provides a unique look at holdings during the period in which the information of the activist's campaign is still private but seemingly known by the SUSPECT_IPs. In Panel C of Table C3 of the Supplementary Material, all four specifications report that the SUSPECT_IP significantly increases their holdings in the target firm during the event window.

## D. Do Suspect IPs Affect the Activist's Trading Activity?

We next turn our attention to the effect of SUSPECT_IPs on the activist's trading activity. If the SUSPECT_IP and any other outside investors provide voting support to the activist, we would expect to find the activist less likely to need additional shares to augment voting support later in the campaign. Because the current regulation does not require the activist to report continuous changes in its holdings, we use a set of discrete outcomes to test this possibility. For each campaign, we follow the progression of amended 13D (Schedule 13D/A) filings made by each respective activist over the 3, 6, and 12-month horizons, separating our campaigns into three groups: i) the activist neither withdraws or increases their stake by 1% (Group 1); ii) the activist withdraws by decreasing its ownership below 5% (Group 2); iii) the activist increases its stake by greater than 1% (Group 3).[10] We use the following multilevel logistic regression:

$$\text{(3)} \quad \Pr(\text{STAKE}_i) = \Lambda\left(\gamma_0 + \gamma_1 \text{SUSPECT\_IP}_i + \sum_{k=2}^{15} \gamma_k \text{CONTROL}_i + \varepsilon_i\right).$$

The dependent variable in regression (3) is a categorical variable based on whether firm $i$ is a member of Group 1, 2, or 3. The independent variable of interest in regression (3) is our SUSPECT_IP indicator for firm $i$. Additionally, we choose Group 1 (i.e., the null group) as the baseline group with which to compare the effect of having SUSPECT_IP.

We display the results of regression (3) in Table 8. Models 1 through 3 report the estimates within the withdrawal group (Group 2), and within the 3, 6, and 12-month horizons we use to form our campaign groups. Across each of these models, our SUSPECT_IP indicator is statistically insignificant; activists of campaigns with suspicious IP activity are not more or less likely to withdraw from the

[10]SEC Rule 13d-2(a) requires a beneficial owner to amend a Schedule 13D promptly upon any material increase or decrease in the percentage of the class beneficially owned. An increase or decrease in beneficial ownership of 1% or more is considered a material change (please see the Administration Proceeding file No. 3–20020 at https://www.sec.gov/litigation/admin/2020/34-89914.pdf).

https://doi.org/10.1017/S0022109022001156 Published online by Cambridge University Press

TABLE 8

**Subsequent Activist Ownership Changes**

Table 8 displays the results of a multilevel logit regression we use to determine the effect of SUSPECT_IP access on subsequent ownership changes of the activist. The multilevel logit model specification is as follows:

$$\Pr(\text{STAKE}_i) = \Lambda\left(\gamma_0 + \gamma_1 \text{SUSPECT}_{\text{IP}\,i} + \sum_{k=2}^{15} \gamma_k \text{CONTROL}_i + \varepsilon_i\right).$$

We estimate this regression at the campaign – target firm level. The dependent variable $\text{STAKE}_i$ is 0, 1, or 2 if over the 3, 6, and 12 months following the announcement of a campaign, there is a 13D/A showing the activist does not withdrawal from the target or increase the stake to greater than 1% (Group 1), the activist has a withdrawal below 5% (Group 2), or the activist has an increase larger than 1% in a 13D/A (Group 3). We treat Group 1 as the base group in the regressions. The independent variable of interest is the SUSPECT_IP indicator variable that is 1 if the respective campaign has at least one SUSPECT_IP, and 0 otherwise. We construct all variables as described in Appendix B. We measure firm characteristic controls as of the target firm's most recent fiscal year end. We compute a target firm's institutional ownership as of the most recent quarter before the campaign announcement. We compute a target firm's Amihud (2002) illiquidity as the average of monthly illiquidity over the year prior to the campaign announcement year. Prior 12- and 36-month stock performance is measured in the months preceding the campaign announcement month. Models 1 through 3 display results for Group 2 and models 4 through 6 display results for Group 3. We compute $z$-statistics using heteroscedasticity-robust standard errors (White (1980)) and we cluster standard errors by year. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| | Group 2: Withdrawal | | | Group 3: Increase | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| | 3-Month | 6-Month | 12-Month | 3-Month | 6-Month | 12-Month |
| SUSPECT_IP | −0.336 | −0.415 | −0.265 | −0.531* | −0.529** | −0.539* |
| | (−0.68) | (−0.99) | (−0.65) | (−1.81) | (−2.00) | (−1.87) |
| TOTAL_IP | 0.079 | 0.128 | 0.131* | −0.146*** | −0.119* | −0.108* |
| | (0.54) | (1.24) | (1.67) | (−3.16) | (−1.90) | (−1.89) |
| BOARD_DEMANDS | −1.250** | −0.559 | −0.293 | 0.207 | 0.438*** | 0.250*** |
| | (−2.42) | (−1.31) | (−0.90) | (0.68) | (2.71) | (2.58) |
| GOVERNANCE_DEMANDS | 0.510 | −0.095 | −0.423 | 0.214 | 0.130 | 0.379* |
| | (1.54) | (−0.25) | (−1.28) | (0.71) | (0.70) | (1.68) |
| VALUE_DEMANDS | 0.198 | 0.164 | 0.126 | −0.376*** | −0.331** | −0.332* |
| | (1.19) | (1.13) | (0.60) | (−2.92) | (−2.49) | (−1.79) |
| LOG_OF_CAMPAIGNS | 0.029 | 0.019 | 0.138 | 0.261*** | 0.253*** | 0.358*** |
| | (0.23) | (0.21) | (0.90) | (5.91) | (5.24) | (3.79) |
| LOG_OF_MARKET_CAP | −0.280*** | −0.144 | −0.269 | −0.165 | −0.093 | −0.124 |
| | (−2.58) | (−0.93) | (−1.54) | (−1.36) | (−1.27) | (−1.32) |
| MARKET_LEVERAGE | 0.532 | 0.007 | 0.381 | −0.103 | −0.421 | 0.129 |
| | (0.79) | (0.01) | (1.11) | (−0.38) | (−1.60) | (0.51) |
| RETURN_ON_ASSETS | 0.686 | −0.539 | −0.325 | 0.093 | −0.344 | 0.059 |
| | (0.82) | (−0.90) | (−0.69) | (0.37) | (−1.64) | (0.31) |
| INSTITUTIONAL_OWNERSHIP | −0.310 | 0.233 | 0.399 | 0.115 | 0.311 | 0.287 |
| | (−0.56) | (0.54) | (1.16) | (0.41) | (1.05) | (0.82) |
| LOG_OF_AMIHUD_ILLIQUIDITY | −0.296*** | −0.241** | −0.282*** | −0.136* | −0.079 | −0.101** |
| | (−3.33) | (−2.11) | (−3.13) | (−1.90) | (−1.34) | (−2.01) |
| PRIOR_12_MONTH_RETURN | 0.966*** | 0.359* | 0.200 | −0.132 | −0.215 | −0.115 |
| | (4.18) | (1.73) | (1.05) | (−0.52) | (−1.00) | (−0.48) |
| PRIOR_36_MONTH_RETURN | −0.240* | 0.040 | 0.044 | 0.074 | 0.118 | 0.082 |
| | (−1.88) | (0.43) | (0.82) | (0.89) | (1.38) | (1.01) |
| OWNERSHIP_BY_ACTIVIST | −0.417*** | −0.306*** | −0.241*** | −0.033** | −0.042*** | −0.060*** |
| | (−8.14) | (−4.59) | (−6.66) | (−2.14) | (−2.65) | (−2.67) |
| BHAR [−1, 1] | 0.042 | −2.103* | −0.789 | −1.272 | −1.368 | −0.411 |
| | (0.02) | (−1.68) | (−0.58) | (−1.17) | (−1.42) | (−0.55) |
| No. of obs. | 1,286 | 1,286 | 1,286 | 1,286 | 1,286 | 1,286 |
| Pseudo-$R^2$ | – | – | – | 0.067 | 0.082 | 0.100 |

target firm, versus simply maintaining their position, in the months following the announcement of the campaign.

In models 4 through 6 of Table 8, we display the estimates of regression (3) within the group of campaigns for which the activist increases their stake (Group 3). The estimates of the SUPSECT_IP coefficients are negative and increase in statistical significance moving from models 4 to 6. Furthermore, the results suggest activists of campaigns with SUSPECT_IP activity are less likely to increase their position in the target firm when the alternative is to simply maintain their position. For example, using the average marginal effect, the $\gamma_1$ estimate of $-0.529$ in model 5 suggests that the probability of a suspect campaign activist having an increase in their ownership stake (greater than 1%) during the 6 months following the announcement decreases by 9.71%. When we consider the activist ownership activity in the subsequent 12 months, as shown in model 6, this probability decreases by 10.05%. Both effects are statistically and economically significant. More critical, these results are consistent with our conjecture that the necessity for activists to increase their stake is moderated by the support they garner from sharing information.[11]

## E. Do Suspect IPs Affect the Likelihood of a Proxy Fight?

A proxy fight requires support from other shareholders of the target firm. If suspicious IP access is a result of the activist's efforts to build a supportive shareholder base, it is likely that this activity happens more frequently for campaigns where the activist intends to initiate a proxy contest. We, therefore, determine whether SUSPECT_IP access is associated with a greater likelihood of initiating a proxy contest. To do this, we use the following logistic regression:

$$\text{(4)} \quad \Pr(\text{CONTEST}_i) = \Lambda\left(\gamma_0 + \gamma_1 \text{SUSPECT\_IP}_i + \sum_{k=2}^{16} \gamma_k \text{CONTROL}_i + \varepsilon_i\right).$$

The dependent variable in regression (4) is an indicator variable that is 1 if the activist begins a proxy contest for firm $i$ during the 3, 6, 12, and 18 months following the month of the campaign announcement. We consider the start of the proxy to be the occurrence of either of the following during the respective window we consider: i) the activist files a proxy statement with the SEC or ii) there is a proxy announcement in SharkRepellent. In addition to using the same independent variables of interest and controls in regression (3), we include the change in institutional ownership during the quarter in which the campaign is announced. If having SUSPECT_IP access increases the likelihood of a proxy contest, then we expect $\gamma_1$ to be positive and statistically significant.

We include the results of regression (4) in Table 9. Models 1 through 4 show $\gamma_1$ estimates of 1.393, 1.150, 0.602, and 0.607, statistically significant at the 1% and 10% levels. These estimates are economically significant; the average marginal effects of these coefficients suggest that SUSPECT_IP access increases the probability that a proxy contest is launched within 3, 6, 12, and 18 months of the campaign announcement by 3.48%, 3.97%, 2.13%, and 2.46%, respectively. Considering that proxy contests occur to roughly 17% of the total 1,286 campaigns, SUSPECT_IP access explains the likelihood of proxy contests in a significant

[11]We conduct a similar analysis to our multilevel logistic regressions by considering only the sample of campaigns where the activist either increases or maintains their stake in the target firm. In this setting, we use a traditional logistic regression having a dependent variable that is one if the activist increases their stake, and zero otherwise. These models suggest that the probability of an activist increasing their stake during the 3, 6, and 12 months of a campaign with a SUSPECT_IP decreases by 9.35%, 10.93%, and 12.61%. These results are available upon request.

TABLE 9

**Suspect IP Access and Proxy Contest Likelihood**

Table 9 displays the results of logit regressions that we use to determine the effect of Common IP access on the likelihood that the activist will launch a proxy contest. The logit model specification is as follows:

$$\Pr(\text{CONTEST}_i) = \Lambda\left(\gamma_0 + \gamma_1 \text{SUSPECT}_{\text{IP}\,i} + \sum_{k=2}^{16} \gamma_k \text{CONTROL}_i + \varepsilon_i\right).$$

We estimate this regression at the campaign – target firm level. The four dependent variables, $\text{CONTEST}_i$, are indicator variables that are either of the following occur: i) the activist files a proxy statement with the SEC in the 3, 6, 12, and 18 months following the announcement of the campaign or ii) there is a proxy announcement date during each respective time horizon in the SharkRepellent database. The independent variable of interest is the SUSPECT_IP indicator variable that is 1 if the respective campaign has at least one SUSPECT_IP, and 0 otherwise. Appendix B contains all variable descriptions. We measure firm characteristic controls as of the target firm's most recent fiscal year end. We compute a target firm's institutional ownership as of the most recent quarter before the campaign announcement. We compute the change in a target firm's institutional ownership from the quarter before to the quarter of the campaign announcement. We compute a target firm's Amihud (2002) illiquidity as the average of monthly illiquidity over the year prior to the campaign announcement year. Prior 12- and 36-month stock performance is measured in the months preceding the campaign announcement month. We compute *z*-statistics using heteroscedasticity-robust standard errors (White (1980)) and we cluster standard errors by year. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| | Contest 3 Months | Contest 6 Months | Contest 12 Months | Contest 18 Months |
| SUSPECT_IP | 1.393*** | 1.150*** | 0.602* | 0.607* |
| | (3.45) | (3.34) | (1.67) | (1.68) |
| TOTAL_IP | −0.186 | −0.208 | −0.238 | −0.273* |
| | (−1.01) | (−1.39) | (−1.46) | (−1.67) |
| BOARD_DEMANDS | 2.619*** | 3.537*** | 4.689*** | 4.764*** |
| | (3.73) | (4.00) | (4.57) | (5.40) |
| GOVERNANCE_DEMANDS | 2.604*** | 1.609 | 0.582 | 0.330 |
| | (3.27) | (1.60) | (0.57) | (0.29) |
| VALUE_DEMANDS | 0.184 | 0.440** | 0.661*** | 0.833*** |
| | (0.93) | (2.36) | (4.18) | (5.53) |
| LOG_OF_CAMPAIGNS | −0.320*** | −0.148 | −0.024 | −0.050 |
| | (−3.04) | (−1.46) | (−0.15) | (−0.29) |
| LOG_OF_MARKET_CAP | −0.679*** | −0.482*** | −0.461** | −0.495*** |
| | (−3.77) | (−2.63) | (−2.21) | (−2.66) |
| MARKET_LEVERAGE | −0.868* | −0.601 | −1.017** | −1.101*** |
| | (−1.73) | (−1.32) | (−2.49) | (−2.78) |
| RETURN_ON_ASSETS | −0.113 | −0.382 | −0.174 | −0.227 |
| | (−0.24) | (−0.71) | (−0.28) | (−0.34) |
| INSTITUTIONAL_OWNERSHIP | 0.885** | 0.344 | 0.103 | 0.125 |
| | (2.21) | (1.05) | (0.28) | (0.31) |
| Δ_INSTITUTIONAL_OWNERSHIP | 0.951 | −0.228 | −0.854 | −1.088 |
| | (1.20) | (−0.36) | (−1.10) | (−1.21) |
| LOG_OF_AMIHUD_ILLIQUIDITY | −0.320*** | −0.222** | −0.253** | −0.255** |
| | (−3.16) | (−2.32) | (−2.41) | (−2.52) |
| PRIOR_12_MONTH_RETURN | 0.724*** | 0.426 | 0.296 | 0.254 |
| | (3.44) | (1.43) | (1.19) | (1.09) |
| PRIOR_36_MONTH_RETURN | −0.011 | −0.061 | −0.053 | −0.024 |
| | (−0.14) | (−0.74) | (−0.71) | (−0.17) |
| OWNERSHIP_BY_ACTIVIST | −0.050* | −0.038 | −0.035 | −0.023 |
| | (−1.74) | (−1.61) | (−1.40) | (−1.20) |
| BHAR [−1, 1] | 2.902 | 2.033 | 1.281 | 1.318 |
| | (1.55) | (1.26) | (1.11) | (1.18) |
| No. of obs. | 1,286 | 1,286 | 1,286 | 1,286 |
| Pseudo-$R^2$ | 0.335 | 0.362 | 0.416 | 0.428 |

manner. The results in Table 9 emphasize the importance of our efforts to identify common IPs and highlight a clear, meaningful relation between the activist of a campaign and access by unique institutions.[12]

[12]In additional tests of proxy contest likelihood, we use the same model as in Table 9, excluding campaigns where we do not identify a SUSPECT_IP, but the activist of the respective campaign has at

https://doi.org/10.1017/S0022109022001156 Published online by Cambridge University Press

## F. Do Suspect IPs Affect the Outcome of a Proxy Fight?

Does the greater likelihood of a proxy contest from suspect campaigns lead to a greater likelihood of proxy contest success? An ideal test would examine voting patterns in SUSPECT_IP investors. However, these are only publicly disclosed for mutual funds through Form N-PX filings. After limiting our sample to the subset of campaigns that proceed to a proxy vote, and then the subset of SUSPECT_IPs within those campaigns that are mutual funds filing Form N-PX, we are left with only 4 campaigns in which a Suspect N-PX filer voted in a proxy. All 4 Suspect N-PX filers voted in favor of the respective activist in these campaigns, which supports our conjecture of the SUSPECT_IPs' role. Additionally, 3 of the 4 filers voted in support of the same activist in at least one other campaign for which they were not identified as suspect by our measure, which again suggests that our approach may under-identify the true level of pre-13D information sharing.

Given the small sample of individual voting records, we instead rely on a broader test focused on the activist's likelihood of success in a proxy contest. We use the following logit model specification on our sample of campaigns for which a proxy contest is pursued:

$$\Pr(\mathrm{WIN}_i) = \Lambda\left(\gamma_0 + \gamma_1 \mathrm{SUSPECT\_IP}_i + \sum_{k=2}^{13} \gamma_k \mathrm{CONTROL}_i + \varepsilon_i\right). \tag{5}$$

The dependent variable in regression (5), $\mathrm{WIN}_i$, is an indicator variable that is 1 if the activist has a successful outcome in the proxy contest involving target firm $i$, and 0 otherwise. We define the proxy contest outcome as successful for the activist if the activist either wins board representation or otherwise accomplishes an explicitly stated goal (such as a merger or spinoff). Control variables are similar to those we use in Table 9; however, we exclude our indicator variables for characteristics of the activist campaign because the Board Demand and Governance Demand indicators maintain a value of 1 for nearly every campaign. This frequency is to be expected given the frequent board and governance initiatives that motivate many activist proxy campaigns (Gow, Shin, and Srinivasan (2016), Fos (2017)).

If SUSPECT_IP access signals a stronger coalition of shareholders that will support the activist, we anticipate activists are more likely to have a successful proxy outcome. The results of regression (5) in Table 10 confirm our conjecture. The estimates of $\gamma_1$ in models 1 and 2 are 0.891 and 0.841 and statistically significant at the 10% and 5% levels, respectively. Moreover, the economic magnitude of these effects is large; the average marginal effects suggest that the probability of the activist having a successful proxy campaign increases by 17.25% and 16.25%, respectively, when there is suspicious IP activity leading up to the announcement of the campaign.

least one other campaign having a SUSPECT_IP. In this analysis, we find comparable increases in the probability that a proxy contest is launched within 3, 6, 12, and 18 months of the campaign announcement of 4.15%, 3.49%, 2.12%, and 2.57%. The persistence of these probabilities in this sample indeed supports our conjecture that we are not fully identifying SUSPECT_IP and therefore underestimating the effects of SUSPECT_IP access throughout the article. We also conduct a similar analysis to Table 8 using a linear probability model. Using an OLS framework allows us to include year, industry, and activist fixed effects that are problematic in logistic regressions. With this OLS specification, we continue to find a statistically significant increase in the probability that a proxy contest is started within the 3- and 6-month horizons of the announcement of campaigns with a SUSPECT_IP. The results of these additional tests are available from the authors.

TABLE 10

Suspect IP Access and Proxy Success Likelihood

Table 10 displays the results of logit regressions that we use to determine the effect of Common IP access on the likelihood of a successful proxy contest outcome. The logit model specification is as follows:

$$\Pr(\text{WIN}_i) = \Lambda\left(\gamma_0 + \gamma_1 \text{SUSPECT}_{\text{IP}\,i} + \sum_{k=2}^{13} \gamma_k \text{CONTROL}_i + \varepsilon_i\right).$$

We estimate this regression at the campaign – target firm level. The dependent variable is an indicator variable, $\text{WIN}_i$, that is 1 if the activist either wins board representation or otherwise accomplishes an explicitly stated goal (such as a merger or spinoff). The independent variable of interest is the SUSPECT_IP indicator variable that is 1 if the respective campaign has at least one SUSPECT_IP, and 0 otherwise. We construct all variables as described in Appendix B. We measure firm characteristic controls as of the target firm's most recent fiscal year end. We compute a target firm's institutional ownership as of the most recent quarter before the campaign announcement. We compute the change in a target firm's institutional ownership from the quarter before to the quarter of the campaign announcement. We compute a target firm's Amihud (2002) illiquidity as the average of monthly illiquidity over the year prior to the campaign announcement year. Prior 12- and 36-month stock performance is measured in the months preceding the campaign announcement month. We compute $z$-statistics using heteroscedasticity-robust standard errors (White (1980)) and we cluster standard errors by year. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| | Dependent Variable: WIN | |
|---|---|---|
| | 1 | 2 |
| SUSPECT_IP | 0.891* | 0.841** |
| | (1.79) | (2.02) |
| TOTAL_IP | | −0.042 |
| | | (−0.37) |
| LOG_OF_CAMPAIGNS | | 0.074 |
| | | (0.33) |
| LOG_OF_MARKET_CAP | | 0.063 |
| | | (0.21) |
| MARKET_LEVERAGE | | 0.005 |
| | | (0.01) |
| RETURN_ON_ASSETS | | 0.165 |
| | | (0.18) |
| INSTITUTIONAL_OWNERSHIP | | −0.453 |
| | | (−0.64) |
| Δ_INSTITUTIONAL_OWNERSHIP | | 2.957 |
| | | (0.83) |
| LOG_OF_AMIHUD_ILLIQUIDITY | | −0.062 |
| | | (−0.40) |
| PRIOR_12_MONTH_RETURN | | 0.436 |
| | | (1.10) |
| PRIOR_36_MONTH_RETURN | | −0.277 |
| | | (−1.14) |
| OWNERSHIP_BY_ACTIVIST | | 0.077 |
| | | (1.36) |
| BHAR [−1, 1] | | −1.482 |
| | | (−0.72) |
| No. of obs. | 216 | 216 |
| Pseudo-$R^2$ | 0.008 | 0.037 |

## G. Are Suspect Campaigns Fundamentally Different from Other Campaigns?

As a final test, we examine the determinants of a campaign having SUSPECT_IP access. We use two models to examine the likelihood of SUSPECT_IP access:

$$\text{(6)}\quad \Pr(\text{SUSPECT\_IP}_i) = \Lambda\left(\gamma_0 + \sum_{k=1}^{5} \gamma_k \text{CAMPAIGN\_CHARACTERISTICS}_i\right.$$
$$\left. + \sum_{k=6}^{14} \gamma_k \text{FIRM\_CHARACTERISTICS}_i + \varepsilon_i\right),$$

$$(7)\qquad \text{SUSPECT\_IP}_i = \beta_0 + \sum_{k=1}^{5} \gamma_k \text{CAMPAIGN\_CHARACTERISTICS}_i + \sum\nolimits_{k=6}^{14} \gamma_k \text{FIRM\_CHARACTERISTICS}_i + \varepsilon_i.$$

Regression (6) is a logit model controlling for various characteristics of the target firm, where the dependent variable is equal to 1 if the campaign has SUSPECT_IP access. Regression (7) is an OLS model where we also include industry, year, and activist fixed effects. In addition to the previous control variables, the presence of a poison pill and the Shapley value is included in these models. The presence of a poison pill may impose a deterrence effect on the activist's intention to acquire the target shares by itself, and the activist may invite other investors discreetly so that they can accumulate the target shares collectively without triggering the poison pill. Shapley value estimates the target's ownership concentration, using the generalized pivotal player approach for infinite person games like in Milnor and Shapley (1978) for each institutional shareholder owning a stake of at least 3%, and a higher Shapley value indicates that the activist may find it easier to garner support for their agendas (Boyson and Pichler (2019)), which in turn may decrease the activist's incentive to share information with other investors.

The results are reported in Table C4 of the Supplementary Material. We find very few differences between suspect and nonsuspect campaigns. The campaign characteristics exhibit no association with suspect IP access throughout the models in Table C4 of the Supplementary Material. In model 2, the OLS model including industry and year-fixed effects, market cap has a significantly positive impact on the likelihood of SUSPECT_IP access. This result is consistent with the activist needing more outside support to engage a larger firm, although the finding is not consistent across other specifications. We conclude that the target firms involved in suspect campaigns are largely similar to those in any other activist campaign. We also note that the lack of explanatory power in these tests provides further evidence against the SUSPECT_IPs using a model to predict activist campaigns.

## H. Additional Robustness Tests

Numerous investors download information from EDGAR each day. We recognize the possibility that our identification of SUSPECT_IPs could potentially arise from spurious download activity unrelated to the activist campaign. We next provide several robustness checks to ensure that our SUSPECT_IPs are different from other IP addresses.

We first verify the uniqueness of the activist campaign by employing two counterfactual scenarios. In the first test, we establish a placebo date, 1 year prior to the initial 13D filing, for each target firm in our sample. We rerun our primary SUSPECT_IP identification approach as of this date, maintaining the same event window and again looking for investment firm-linked IP addresses connected to multiple campaigns from the same activist during this window (exactly following the approach laid out in Section III.B). We identify a substantially smaller

36 placebo suspect campaigns through this approach.[13] We then run a placebo version of Table 4 (pre-13D turnover) and Table 8 (changes in target firm 13F ownership for the SUSPECT_IP) for these placebo suspects. The results are in columns 1–3 of Tables D1 and D2 of the Supplementary Material. We find no evidence of higher preplacebo event turnover for Suspect campaigns, and we find no evidence that the placebo Suspects have any abnormal trading in the targeted stock around this date. We also verify that these Suspects are unrelated to the activist's proxy fight in Table D3 of the Supplementary Material. In Panel A, the placebo Suspect has no significant effect on the likelihood of the activist pursuing a proxy fight, and in Panel B, the placebo Suspect has no effect on the likelihood of the activist winning the proxy fight.

We provide additional verification through a second placebo test. We propensity score match each activist target firm to another nontarget firm with a similar propensity for being an activist target in the respective year. The propensity score model that we use includes the core firm characteristics in the model of Table 4, including market cap, market leverage, ROA, institutional ownership, prior stock performance, and Amihud illiquidity. Using this model, each year we estimate a firm's propensity score and then match firms within the same Fama–French 48 industry with the closest propensity score during the respective target year. We then identify suspects among the sample of matched firms using the same approach as before, but on the sample of IP addresses downloading filings from the matched firms. This approach should result only in spurious matches. We again find a substantially smaller number of suspect campaigns (15). Further, as displayed in columns 4–6 of Tables D1 and D2 of the Supplementary Material, these 15 suspects have no significant effect on prefiling turnover in the matched stock, and we find no detectable trading activity of the match-identified SUSPECT_IPs in the targeted stock. Based on the evidence from both placebo tests, we conclude that the search activity prior to 13D disclosure is fundamentally different from other times, and that the Suspects we identify during this time are more likely to be trading on valuable nonpublic information.

While the above placebo tests focus on download activity during pre-13D windows, we next shift our analysis to the SUSPECT_IP's overall download activity across the entire time series of our sample. For this test, we aim to rule out the possibility of spurious downloads by examining whether sudden download activities by the SUSPECT_IPs are more predictive of pending 13D activity than other seemingly uninformed downloads across the entire sample period, including all access dates outside of the filing window for the respective campaign. We first identify every IP address, including both suspect and all other IPs, downloading target firm filings during pre-13D windows for any campaign in our sample. We then collect every access point, throughout the entire sample, from each of these IP addresses. The control group, therefore, consists of downloads from seemingly uninformed IP addresses that would not be classified as SUSPECT by our primary

[13]We note that in the 1-year prior placebo sample, 13F filings show that the activist has established a non-13D qualifying position prior to the placebo date for 10 of the 36 placebo suspect campaigns. The test is therefore not purely in the absence of the activist, and some of the Suspect activity could be a result of investors tracking activist 13F holdings.

measure. We then test whether the SUSPECT_IP's sudden downloads are more likely to occur within the 10 days prior to a 13D filing than downloads from the control group. We report three versions of this test: the first examines the impact of sudden downloads on the likelihood of a pending 13D from any activist. The second examines the likelihood of a pending 13D from a SUSPECT-associated activist (an activist ever associated in a campaign with a SUSPECT_IP), and the third examines the impact of sudden downloads on the likelihood of a 13D filing for a pending 13D from any of the nonassociated activists.

Our test, run at the IP access point level, uses a logit model, where the dependent variable is equal to 1 if the access point precedes a 13D filing by a SUSPECT-associated (nonassociated) activist within the subsequent 10 days. We include the same controls as our matching procedure from the placebo test above. We report the results in Table D4 of the Supplementary Material. We find that the sudden access points of a SUSPECT_IP are significantly more likely to precede a 13D filing in general (columns 1 and 2), and this is primarily driven by SUSPECT-associated activists (columns 3 and 4). The SUSPECT_IP's sudden access points have no measurable impact on the likelihood of subsequent 13D filings by nonassociated activists (columns 5 and 6). These results provide supporting evidence that the SUSPECT_IP has unique information pertaining only to one specific activist.

## V. Conclusion

We use the SEC log files to identify suspiciously timed downloads of firm financial and proxy statements ahead of activist campaigns. We find evidence of information about the activist's campaign spreading to outside investors, where the outside investor consistently accesses the target's statements immediately before the disclosures of a particular activist and appears to trade on this information.

Our empirical analysis examines the effects of this information sharing. Activist campaigns for which there is at least one SUSPECT_IP accessing the firm's important financial statements in the 10 days before the filing of a 13D have greater turnover during this time-period. Furthermore, we find target firm stock returns following the announcement to be significantly positive for SUSPECT_IP campaigns, creating a clear incentive for investors to act on this shared information.

Investors with access to this nonpublic information are not the only beneficiaries. By sharing information, the activist is better able to assemble a coalition of shareholders that will support them in more combative endeavors. To this end, we find that campaigns with SUSPECT_IP access have larger increases in institutional ownership and a doubling of the odds that the activist will pursue a formal proxy contest within 18 months of the campaign announcements. Most critical, we find that conditional on launching a proxy contest, activists of campaigns with SUSPECT_IP access have a greater likelihood of a successful outcome.

Our study is the first to report evidence of this information sharing and document its effect on campaign success. Our unique approach to using the EDGAR access logs shines a light on the darker, hidden corners of activist campaigns, allowing us to gain a greater understanding of what happens behind closed doors in the days before public disclosures.

https://doi.org/10.1017/S0022109022001156 Published online by Cambridge University Press

## Appendix A. Activist Campaign Data Construction Process

Appendix A provides the data construction process we use to assemble our activist campaigns. The process leaves us with 1,286 campaigns with a total of 236 unique activist CIK and 1,267 unique target firms.

| | |
|---|---|
| STEP 1: | Restrict to those campaign observations for which:<br>– The target has a valid permno / GVKEY and share code of 10 or 11 in CRSP<br>– 13D filed with SEC<br>– The SharkRepellent announcement date is not 10 days before the original 13D filing date listed in SharkRepellent<br>– Minimum of either the SharkRepellent announcement date or the 13D filing date falls between 1/1/2005 and 6/30/2017 |
| STEP 2: | Obtain Target firm CIK from Computstat. Delete campaigns where there is no matching Target CIK |
| STEP 3: | Limit to CAMPAIGN_ID's for which there is an activist 13D filing available in SEC. In cases where there are multiple CAMPAIGN_ID's for the same activist 13D filing, take the first one |
| STEP 4: | Eliminate Filer CIK that have only one Filer CIK – Target CIK match |
| STEP 5: | (13D Restriction) Eliminate campaign observations for which there is a 13D filed in previous 60 days with SEC |
| STEP 6: | (Proxy Filing Restriction) Eliminate campaign observations for which there is a DEFN14A, PREN14A, DEFC14A, PREC14C, DEFC14C, and PREC14A filing in previous 60 days with SEC |
| STEP 7: | (Risk Arbitrage Restriction 1) Eliminate campaign observations for which the target is part of a merger announcement in previous 60 days using SDC acquisition data. The merger announcement date in SDC is the date that we use to determine when the merger is public |
| STEP 8: | (Risk Arbitrage Restriction 2) Eliminate campaign observations where SharkRepellent lists a dissident tactic of "Block Acquisition/Agitate for Lower Price (Shareholder of Acquirer)" or "Block Merger/Agitate for Higher Price (Shareholder of Target)" |
| STEP 9: | (Risk Arbitrage Restriction 3) Use 8 K filings to identify campaigns with "Merger agreement" in the [−60, 0] window. This process involves searching Item 1.01 in 8 K filings |
| STEP 10: | (Control Variable Restriction) Drop campaign observations not having a complete set of control variables we use throughout our multivariate tests |
| STEP 11: | (BHAR Restriction) Drop campaign observations that do not have a complete set of BHAR spanning the [−20, 20] day window around the campaign announcement date |

## Appendix B. Variable Descriptions

Appendix B contains variable descriptions for all variables used throughout the study. We note that all continuous variables are winsorized at the 1% and 99% levels.

TOTAL_IP: Number of unique IP accessing a firm's major SEC filing such as 10-K, 10-Q, and proxy statements over the 13D filing window, unconditional on any filtering process. The campaign announcement date we use is the lesser of the ANNDATS in SharkRepellent or the date on the initial 13D filing.

COMMON_IP: Number of unique IPs accessing a firm's major SEC filing such as 10-K, 10-Q, and proxy statements over the [Event Date, − 1] day window of the campaign announcement date (day 0) that have accessed a SEC filing of other firms targeted by the same activist over the [Event Date, − 1] window prior to their respective campaign announcement date. The announcement date is the lesser of the ANNDATS in SharkRepellent or the date on the initial 13D filing.

COMMON_IP_NO_PRIOR_ACCESS: Subset of Common IP that do not access the target firm's major SEC filing such as 10-K, 10-Q, and proxy statements in the [−60, Event Date) day window of the campaign announcement date (day 0). The announcement date is the lesser of the ANNDATS in SharkRepellent or the date on the initial 13D filing.

SUSPECT_IP_INDICATOR: Indicator variable that is 1 if the firm has a Common IP No Prior Access identified as either a Bank or Investment firm, and 0 otherwise. For the identification of organization behind each IP, we use historical WhoIs data, provided by American Registry for Internet Numbers' (ARIN) WhoWas, as of the announcement date of each activism campaign. Because IPs from the EDGAR log file data have the first three octets only, we adopt a conservative identification approach that requires the entire IP block for the fourth octet to be assigned to the same organization. We exclude those cases when the identified organization is one of the activists in the respective activism campaign.

NUMBER_OF_CAMPAIGNS: Number of unique 13D filings that are filed by the activist in our sample.

LOG_OF_NUMBER_OF_CAMPAIGNS: Log of 1 plus the winsorized number of unique 13D filings that are filed by the activist.

BOARD_INDICATOR: Indicator variable that is 1 if the "Primary Campaign Type" or "Secondary Campaign Type" listed in SharkRepellent includes "Board Representation" or "Board Control," and 0 otherwise.

GOVERNANCE_DEMANDS_INDICATOR: Indicator variable that is 1 if the Governance Demands (Follow-through/Success) variable in SharkRepellent contains any of the following items: Remove Director(s), Board Seats (activist group), Remove Takeover Defenses, Remove Officer(s), Add Independent Directors, Compensation Related Enhancements, Other Governance Enhancements, or Social/Environmental/Political Issues.

VALUE_DEMANDS_INDICATOR: Indicator variable that is 1 if the Value Demands (Follow-through/Success) variable in SharkRepellent contains any of the following items: Block Acquisition/Agitate for Lower Price (Shareholder of Acquirer), Block Merger/Agitate for Higher Price (Shareholder of Target), Breakup Company, Divest Assets/Divisions Change Investment Strategy, Realize NAV/ Open-End a Closed-End Fund, Other Capital Structure Related, Increase Leverage, and so forth, Potential Acquisition (Friendly and Unfriendly), Return Cash via Dividends/Buybacks, Review Strategic Alternatives, Seek Sale/Merger/ Liquidation, Separate Real Estate/Create REIT, Holder Type, or Equity Assets.

BHAR [$n$, $m$]: Buy and Hold Abnormal Return (BHAR) of the target firm over the [$n$, $m$] day window centered at the nearest trading date of or following the activist's campaign announcement date. The announcement date is the lesser of the ANNDATS in SharkRepellent or the date on the initial 13D filing. We use the CRSP value-weighted index as a benchmark.

MCAR [$n$, $m$]: Market Adjusted Cumulative Abnormal Return of the target firm over the [$n$, $m$] day window centered at the nearest trading date of or following the activist's campaign announcement date. The announcement date is the lesser of the ANNDATS in SharkRepellent or the date on the initial 13D filing. We use a market model benchmark having the CRSP value-weighted index as the market return. We estimate this market model for each target over the [$-160$, $-61$] day relative to each target's respective activist campaign announcement (i.e., day 0).

FF3CAR [$n$, $m$]: Fama–French 3-factor model adjusted cumulative abnormal return of the target firm over the [$n$, $m$] day window centered at the nearest trading date of or following the activist's campaign announcement date. The announcement date is the lesser of the ANNDATS in SharkRepellent or the date on the initial 13D filing. We estimate the Fama–French 3-factor model for each target over the [−160, −61] day relative to each target's respective activist campaign announcement (i.e., day 0).

FF5CAR [$n$, $m$]: Fama–French 5-factor model adjusted cumulative abnormal return of the target firm over the [$n$, $m$] day window centered at the nearest trading date of or following the activist's campaign announcement date. The announcement date is the lesser of the ANNDATS in SharkRepellent or the date on the initial 13D filing. We estimate the Fama–French 5-factor model for each target over the [−160, −61] day relative to each target's respective activist campaign announcement (i.e., day 0).

TURNOVER [$n$, $m$]: Average of daily turnover of the target firm over the [$n$, $m$] daily window. We measure daily turnover as the target firm's daily trading volume divided shares outstanding.

MARKET_CAPITALIZATION: Market capitalization of the target firm as of the recent fiscal year end before the 13D filing quarter. We obtain the targets firm's quarter end share price and shares outstanding from the CRSP database.

MARKET_LEVERAGE: We calculate leverage as the book value of debt divided by the sum of book value of debt and market capitalization. We compute market capitalization and book value of debt from the target's most recent fiscal year financial statements before the target date.

RETURN_ON_ASSETS: We calculate ROA as Net Income from the most recent fiscal year end before the 13D filing date, divided by average of total assets from the prior two fiscal year ends.

INSTITUTIONAL_OWNERSHIP: We obtain the institutional ownership of each firm using the Thomson Reuters Institutional (13F) Holdings database. For each target firm, we use the institutional ownership percentage as of the most recent calendar quarter before the date of the initial 13D filing.

MONTHLY_AMIHUD_ILLIQUIDITY: We calculate illiquidity of each firm following Amihud (2002). Specifically, we calculate illiquidity for each stock as $\left(\frac{1}{N}\sum_{t=1}^{N}\frac{|R_t|}{\text{VOLD}_t}\right)\times 10^5$, where $N$ is the number of nonzero trading days in the respective calendar year before the campaign year, $R_t$ is the return on day $t$, and $\text{VOLD}_t$ is dollar volume on day $t$. We winsorize this illiquidity variable at the 1% level.

PAST_12_MONTH_RETURN: We compute each target firm's cumulative return over the prior 12 months before the month of the activist's campaign announcement using monthly return data in CRSP. The announcement date we use is the lesser of the ANNDATS in SharkRepellent or the date on the initial 13D filing.

PAST_36_MONTH_RETURN: We compute each target firm's cumulative return over the prior 36 months before the month of the activist's campaign announcement using monthly return data in CRSP. The announcement date we use is the lesser of the ANNDATS in SharkRepellent or the date on the initial 13D filing.

OWNERSHIP_BY_ACTIVIST (%): Activist's percent ownership of the target firm as of the 13D filing date. The percent ownership is listed in percent under the Dissident Group Ownership % at Announcement variable in SharkRepellent.

POISON_PILL_IN_RESPONSE_TO_THE_CAMPAIGN: Indicator variable in SharkRepellent that is 1 if the target firm adopted a poison pill – a defensive tool that creates a negative financial event triggered when the activist's stake in the target firm reaches a certain point – in response to this activist campaign.

POISON_PILL_IN_PLACE_PRIOR_TO_THE_CAMPAIGN: Indicator variable in SharkRepellent that is 1 if the target firm had a poison pill in place prior to the campaign.

SHAPELY_VALUE: An estimate for the target's ownership concentration, using the generalized pivotal player approach for infinite person games like in Milnor and Shapley (1978) for each institutional shareholder owning a stake of at least 3%.

HOLDINGS_AVERAGE_MARKET_CAP: We compute the average market capitalization of each institutional investor's portfolio holding within their respective quarterly 13F filing. We obtain 13F filings from the Thomson Reuter's 13F database.

PORTFOLIO_DOLLAR_VALUE: We compute the total dollar value of each institutional investor's portfolio, as reported in their quarterly 13F filing. We obtain 13F filings from the Thomson Reuter's 13F database.

NUMBER_OF_PORTFOLIO_HOLDINGS: We compute the total number of firms held by each institutional investor and as reported in their respective 13F filing. We obtain 13F filings from the Thomson Reuter's 13F database.

## Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109022001156.

## References


Aiken, A. L., and C. Lee. "Let's Talk Sooner Rather Than Later: The Strategic Communication Decisions of Activist Blockholders." *Journal of Corporate Finance*, 62 (2020), 101593.

Amihud, Y. "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects." *Journal of Financial Markets*, 5 (2002), 31–56.

Appel, I. R.; T. A. Gormley; and D. B. Keim. "Passive Investors, Not Passive Owners." *Journal of Financial Economics*, 121 (2016), 111–141.

Appel, I. R.; T. A. Gormley; and D. B. Keim. "Standing on the Shoulders of Giants: The Effect of Passive Investors on Activism." *Review of Financial Studies*, 32 (2019), 2720–2774.

Becht, M.; J. Franks; J. Grant; and H. F. Wagner. "Returns to Hedge Fund Activism: An International Study." *Review of Financial Studies*, 30 (2017), 2933–2971.

Boyson, N. M., and P. Pichler. "Hostile Resistance to Hedge Fund Activism." *Review of Financial Studies*, 32 (2019), 771–817.

Brav, A.; A. Dasgupta; and R. Mathews. "Wolf Pack Activism." *Management Science*, 68 (2022), 5557–6354.

Brav, A.; J. B. Heaton; and J. Zandberg. "Failed Anti-Activist Legislation: The Curious Case of the Browaw Act." *Journal of Business, Entrepreneurship, and the Law*, 11 (2018), 329–352.

Brav, A.; W. Jiang; T. Li; and J. Pinnington. "Picking Friends Before Picking (Proxy) Fights: How Mutual Fund Voting Shapes Proxy Contests." Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3101473 (2021).

Brav, A.; W. Jiang; F. Partnoy; and R. Thomas. "Hedge Fund Activism, Corporate Governance, and Firm Performance." *Journal of Finance*, 63 (2008), 1729–1775.

Bushee, B. J. “Do Institutional Investors Prefer Near-Term Earnings Over Long-Run Value?” *Contemporary Accounting Research*, 18 (2001), 207–246.
Bushee, B. J., and C. F. Noe. “Corporate Disclosure Practices, Institutional Investors, and Stock Return Volatility”. *Journal of Accounting Research*, 38 (2000), 171–202.
Chabakauri, G.; V. Fos; and W. Jiang. “Trading Ahead of Barbarians’ Arrival at the Gate: Insider Trading on Non-Inside Information.” Available at https://papers.ssrn.com/sol3/Papers.cfm?abstract_id=4018057 (2022).
Chen, H.; L. Cohen; U. Gurun; D. Lou, and C. Malloy. “IQ from IP: Simplifying Search in Portfolio Choice.” *Journal of Financial Economics*, 138 (2020), 118–137.
Collin-Dufresne, P., and V. Fos. “Do Prices Reveal the Presence of Informed Trading?” *Journal of Finance*, 70 (2015), 1555–1582.
Crane, A. D.; K. Crotty; and T. Umar. “Hedge Funds and Public Information Acquisition.” *Management Science*, forthcoming (2023).
Crane, A. D.; A. Koch; and S. Michenaud. “Institutional Investor Cliques and Governance.” *Journal of Financial Economics*, 133 (2019), 175–197.
Di Maggio, M.; F. Franzoni; A. Kermani; and C. Sommavilla. “The Relevance of Broker Networks for Information Diffusion in the Stock Market.” *Journal of Financial Economics*, 134 (2019), 419–446.
Dimson, E.; O. Karakaş; and X. Li. “Active Ownership.” *Review of Financial Studies*, 28 (2015), 3225–3268.
Edmans, A.; V. W. Fang; and E. Zur. “The Effect of Liquidity on Governance.” *Review of Financial Studies*, 26 (2013), 1443–1482.
Fos, V. “The Disciplinary Effects of Proxy Contests.” *Management Science*, 63 (2017), 655–671.
Gantchev, N. “The Costs of Shareholder Activism: Evidence from a Sequential Decision Model.” *Journal of Financial Economics*, 107 (2013), 610–631.
Gantchev, N., and C. Jotikasthira. “Institutional Trading and Hedge Fund Activism.” *Management Science*, 64 (2018), 2930–2950.
Gow, I.; Shin S.; and S. Srinivasan. “Consequences to Directors of Shareholder Activism.” Working Paper No. 14-071, Harvard Business School (2016).
Greenwood, R., and M. Schor. “Investor Activism and Takeovers.” *Journal of Financial Economics*, 92 (2009), 362–375.
He, Y., and T. Li. “Social Networks and Hedge Fund Activism.” *Review of Finance*, 26 (2022), 1267–1308.
Iliev, P.; J. Kalodimos; and M. Lowry. “Investors’ Attention to Corporate Governance.” *Review of Financial Studies*, 34 (2021), 5581–5628.
Kedia, S.; L. T. Starks; and X. Wang. “Institutional Investors and Hedge Fund Activism.” *Review of Corporate Finance Studies*, 10 (2021), 1–43.
Klein, A., and E. Zur. “Entrepreneurial Shareholder Activism: Hedge Funds and Other Private Investors.” *Journal of Finance*, 64 (2009), 187–229.
Krishnan, C. N. V.; F. Partnoy; and R. S. Thomas. “The Second Wave of Hedge Fund Activism: The Importance of Reputation, Clout, and Expertise.” *Journal of Corporate Finance*, 40 (2016), 296–314.
Loughran, T., and B. McDonald. “The Use of EDGAR Filings by Investors.” *Journal of Behavioral Finance*, 18 (2017), 231–248.
Milnor, J. W., and L. S. Shapley. “Values of Large Games II: Oceanic Games.” *Mathematics of Operations Research*, 3 (1978), 290–307.
Norli, Ø.; C. Ostergaard; and I. Schindele. “Liquidity and Shareholder Activism.” *Review of Financial Studies*, 28 (2015), 486–520.
Schoenfeld, J. “Contracts Between Firms and Shareholders.” *Journal of Accounting Research*, 58 (2020), 383–427.
White, H. “A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity.” *Econometrica*, 48 (1980), 817–838.
Wong, Y. T. F. “Wolves at the Door: A Closer Look at Hedge Fund Activism.” *Management Science*, 66 (2020), 2347–2371.

https://doi.org/10.1017/S0022109022001156 Published online by Cambridge University Press