Shining a Light in a Dark Corner: EDGAR Search Activity Reveals the Strategically Leaked Plans of Activist Investors*

Ryan Flugum
Department of Finance
College of Business Administration
University of Northern Iowa
Cedar Falls, IA 50613
ryan.flugum@uni.edu

Choonsik Lee
College of Business
University of Rhode Island
Kingston, RI 02881
choonsiklee@uri.edu

Matthew E. Souther
Department of Finance
Darla Moore School of Business
University of South Carolina
Columbia, SC 29208
matthew.souther@moore.sc.edu

Abstract

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Keywords: Activist campaigns, Investor coordination, Investor search activity, Proxy fights
JEL Classification: G14, G30, G34, G38

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1. Introduction

On October 12th, 2015, activist hedge fund John Doe Management 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 October 9th, 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 one year later, on September 15th, 2015, 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 September 18th, 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 that 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.

What reason might our anonymized activist hedge fund have for sharing its pending campaign information with outsiders? 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 in order to get their slate of directors elected by shareholders. By leaking the pending campaign information, and allowing certain informed shareholders to build positions in the targeted stock ahead of the disclosure-related price surge, activists like John Doe Management may 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; Brav, Jiang, Li, and Pennington, 2019; Li and Hi, 2020). 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 with non-public 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 leaking and potential informed trading. Rarely in finance research 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 has non-public information pertaining to that activist.

We investigate search activity on the SEC's EDGAR website during the 10 days prior to an activist campaign disclosure (once passing the five percent 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 that download information pertaining to the activist's target during this 10-day period, 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 prior to a 13D filing.

We find that certain institutional investors are especially adept at predicting the targets of a specific activist, downloading information pertaining to multiple campaign targets from that activist during the 10-day window prior to public disclosure. This pattern of informed EDGAR access suggests that these investors have information pertaining to 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 on the activist's strategy.

We first define our measure of interest. We consider an IP address to be a *Suspect IP* if 1) it downloads information pertaining to a campaign target during the 10-day window for at least two campaigns belonging to a single activist, 2) it has not accessed information on that same target firm for the 50 days preceding the 10-day window, and 3) it belongs to an investment firm, which includes hedge funds, mutual funds, and investment banks. Our variable of interest in our main tests, run at the activist campaign level, takes a value of one if a *Suspect IP* is present at the campaign.

Our analysis begins by examining the market trading activity in the 10-day pre-13D window. We note that prior research (see, for example, Brav, Jiang, Partnoy, and Thomas, 2008; Becht, Franks, Grant, and Wagner, 2017) documents heightened turnover and returns in the pre-13D window. However, if the activist has leaked the plans for the 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 significantly 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 note that this finding is consistent with Wong (2019), who shows abnormal trading volume to be a good, albeit indirect, measure of coordinated activism.

We next examine the post-13D returns associated with the *Suspect IP* campaigns. If the leaked campaign information has any value for the receiving party, we would expect to see evidence of that here. We find that 13D filings associated with a *Suspect IP* earn significantly higher returns than other 13D filings during the ten days following the filing. Returns are 2.5-3.8% higher when a *Suspect IP* is present. 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.

Institutional investors, particularly those classified as hedge funds or investment banks, have a variety of tools to profit on 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 for evidence of 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.

We recognize that the opacity of portfolio holdings makes it difficult to conclusively state that any campaign-level effects of *Suspect IP* are driven solely by the identified investors. We interpret the presence of a *Suspect IP* in a campaign as an indicator that the activist has likely leaked information about the campaign to other investors, including, but not limited to, the *Suspect IP* investor. If other informed investors are purchasing stakes in the target firm, we would also expect an increased overall level of institutional ownership after the 13D disclosure. Using 13F filings, we indeed find that institutional ownership increases more for *Suspect IP* campaigns between the quarter before and the quarter after the 13D filing than for non-leaked campaigns. The increase in institutional ownership is approximately 3.0-3.3% higher for campaigns with a *Suspect IP* than those without a *Suspect IP*.

We next focus on the activist's incentives for sharing the information. If the activist is 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, their leaked 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 9% when a *Suspect IP* is present.

Finally, we examine the possible benefits of leaked plans for the activist's subsequent campaign strategy. If an activist has additional voting support from investors who entered the stock prior to the 13D disclosure, they should have a higher degree of confidence in spending the formidable resources towards 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 campaign. 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 speak to the activist's incentives for leaking the plans; they allow other firms to share in the profits in exchange for additional voting support.

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 no obligation to keep this information internal, as there would be with, for example, a pending earnings report. However, the SEC does require disclosure of alliances between investors to be included on the 13D filing. 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.[1]

Prior work by Di Maggio, Franzoni, Kermani, and Sommavilla (2019) suggests leaking by the activist's brokers. Because activists typically spread their trades around multiple brokers, the study uses network centrality measures to identify the brokers most central, and therefore most informed, to the activist's trades. The study documents elevated pre-13D trading activity in the targeted stock by other clients of the activist's most central brokers, indicating that the broker shares information about a campaign as a way to reward its best clients. The authors note that this type of information sharing is in the broker's, and not that activist's, interests, due to the increased competition from other traders in the stock. Because the study relies on anonymized Abel Noser trading data, only the brokers, and not the identities of the traders, are known.

By contrast, our measure is more direct; we are uniquely able to identify the exact trader that has information. We further document that this trader has similar information across multiple campaigns from the same activist, indicative of an ongoing relationship between the two parties. Contrary to the broker leaking documented by Di Maggio, Franzoni, Kermani, and Sommavilla (2019), we find that these informed traders serve the activist's interests, providing voting support that increases their odds of success in a proxy contest. We acknowledge the possibility that the broker could be the source of some information leakage, but, as stated by Di Maggio, Franzoni, Kermani, and Sommavilla (2019), leaked information from the broker is a detriment to the activist, since the outside trader has no obligation to provide voting support to the activist. We therefore

[1] https://www.wsj.com/articles/sec-probes-activist-funds-over-whether-they-secretly-acted-in-concert-1433451205

conclude that the spread of information identified by our measure is fundamentally different (but not mutually exclusive) from that of Di Maggio, Franzoni, Kermani, and Sommavilla (2019).

We note that our estimation measure likely underestimates the true extent of leaked plans. If, for example, the informed investor downloads the target firm's filings 11 days before the 13D disclosure instead of 10 days, they would not show up in our estimate. We use 10 days because it aligns with the timeline of when the activists have to disclose their stake after passing the 5% threshold, although a less conservative approach would yield higher numbers of *Suspect IP*s. We also note that we are only focusing on one narrow channel in which an investor can do research on the firm. If the investor instead downloads target firm information from other data sources such as Bloomberg or FactSet, they would also not appear in our data; the nature of our dataset requires research through EDGAR. Given these limitations, the fact that we find any evidence at all of leaking and informed trading suggests that the true extent is likely larger than estimated in our tests.

The activist does face tradeoffs in leaking campaign information prior to the 13D. Our study documents the benefits in the form of a stronger voting base in a proxy fight and higher 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 prior to the 13D filing. Regardless of their motivations, our evidence suggests that at least some activists are willing to accept this tradeoff.

Several recent published and working papers make use of the EDGAR log files in different ways. Many of these studies use aggregate log data to make inferences about investor attention (see, for example, Loughran and McDonald, 2017; Iliev, Kalodimos, and Lowry, 2019). Chen, Cohen, Gurun, Lou, and Malloy (2020) and Crane, Crotty, and Umar (2019) look specifically at information-gathering by institutional investors, showing that investors that access certain EDGAR documents outperform those who do not. Similarly, Drake, Johnson, Roulstone, and Thornock (2020) note that EDGAR downloads of more sophisticated investors predict strong future performance. 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 these announcement returns to be a function of factors such as the target's acquisition likelihood, the activist's reputation, and early engagement between the target and the activist (Greenwood and Schor, 2009; Krishnan, Partnoy, and Thomas, 2016; Aiken and Lee, 2020). Regarding coordination between the activist and other investors, Brav, Dasgupta, and Mathews (2018) provides 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. Numerous studies including Becht, Franks, Grant, and Wagner (2017), Crane, Koch, and Michenaud (2019), Wong (2019), Kedia, Starks, and Wang (2020), and He and Li (2020) 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 prior to 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 direct evidence of leaked information from activists to outside parties.

2. Data and Methodologies

2.1.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 the investors with an 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 non-trivial 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 two 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 prior to the 13D disclosure. The EDGAR Log File data set contains information on internet search traffic for EDGAR filings from February 14, 2003 through June 30, 2017, and 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 with 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 prior to 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 own Form 8-K[2] filing in the 60-day window prior to the activism announcement. We also exclude campaigns with explicit intent of merger arbitrage in the SharkRepellent database, because this indicates that the filing activist targeted the firm due to an ongoing merger deal.

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 period 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.

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[2] 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 August 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 January 1, 2005.

2.2.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 over the 10-day window [-10, -1] prior to the announcement date of activist campaign. We use the 10-day window because it is consistent with the current regulation for Schedule 13D filing. An activist must disclose its holdings and intent within 10 calendar days after passing the 5% threshold. Similar to 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 that have more than 50 filing requests in a given day. We use this procedure to identify search activities by regular, non-robot 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 prior to the 13D for more than one campaign by the same activist. Considering these search activities consistently occur prior to the announcement, the *Common IP*s 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 announcement. Thus, we investigate search activities of the same IP in the preceding 50-day window [-60, -11], and eliminate any *Common IP*s that have search activity in this 50-day window. Our attention is therefore exclusively in investors that display a sudden interest in the target firm immediately prior to the announcement of activist campaigns by the same activist. This type of sudden attention is highly unlikely to occur by coincidence. Figure 1 depicts our methods to identify a *Common IP* with no prior access graphically.

[Figure 1 about here]

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 collect all the historical registration details to identify the organization owning the IP address as of the time of the activist campaign.[3]

While a variety of 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, non-profit 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 participants in the campaign. This approach leaves us with a small

[3] 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, Cohen, Gurun, Lou, and Malloy (2020) to map the hidden octet with an actual octet.

subset of *Suspect IP*s. 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 the potential information leaking from the filing activist.

2.3. 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.

[Table 1 about here]

In Panel B of Table 1 we present yearly statistics for the number of campaigns with at least one *Suspect IP*. While the number of campaigns decreased in 2008 from the previous year, the number of campaigns with suspicious activities increased. This trend could be due to the 2008 financial crisis: funds have higher incentive to leak the information to other associates during the difficult times. Another interesting trend appears during the period of 2011 through 2014. While the number of activist campaigns generally increased in this period, the number of campaigns with suspicious activities were proportionally higher than the prior period. One possible explanation is that more activist funds tended to target larger firms during this period, and strategic alliance may be more valuable when the activism is more costly with larger target firms. Figure 2 shows these yearly statistics graphically.

[Figure 2 about here]

Table 2 provides summary statistics for our key variables and further details of *Suspect IP* access activity. In Panel A of Table 2, *Total IP* reports that the average campaign has 39.25 unique IPs conducting search activities on a target firm's major filings during the 10-day window [-10, -1] prior to each activist campaign, unconditional on any filtering process. We then identify IPs conducting research for more than one campaign by the same activist, denoting this group as *Common IP*. The average number of *Common IP* is 1.05, much less than the 39.25 for *Total IP*. The difference between *Total IP* and *Common IP* confirms that having the same IP appear on multiple campaigns by the same activist is highly unusual. Next, we apply another restriction to exclude those IPs showing interest in the target firm well before the 10-day window. This set of IPs, which we denote as *Common IP No Prior Access*, do not access the target firm's major filings during the preceding 50-day window [-60, -11]. The average of *Common IP No Prior Access* is 0.66, 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 one if, within the set of *Common IP No Prior Access* for a campaign, we identify the owner of the IP address as an investment management firm or an investment bank. The *Suspect IP* indicator has an average of 0.09, reflective of the stringent identification process we utilize.

[Table 2 about here]

Buy-and-hold abnormal returns show positive returns centered around the announcement date, which is consistent with the consensus in the shareholder activism literature (see, for example, Brav, Jiang, Partnoy, and Thomas, 2008). Based on *Market Cap, Leverage, ROA, and Institutional Ownership*, our sample shows meaningful cross-section variations. 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.

Some may argue that *Suspect IP* could simply follow the stock holdings in the activist's portfolio. Thus, in Panel B of Table 2, we display *Suspect IP* access activity of the activist's other holdings to further 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 immediate before the activist's announcement of a campaign. The activists of the 115 campaigns we identify as having a *Suspect IP* hold an average of 279 firms in their portfolios. During the same 10-day 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 equates to a mere 1.41% of holdings and clearly shows the uniqueness of the connections we identify.

3. Empirical Findings

3.1. Suspect IP Access and Market Effects

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 prior to the campaign disclosure. Further, if there is incentive for investors to act on this shared information, we would also expect to find higher levels of returns following the campaign disclosure.

Figure 3 and 4 show preliminary evidence that there is indeed a discernable difference in market activity among campaigns that have *Suspect IP* access. In Figure 3, we split our campaign sample based on the presence of *Suspect IP* access. We then plot the daily relative turnover during the [-20, 20] trading days centered at the campaign announcement date (day zero). Specifically, on each event day, and within the suspect (115 campaigns) and non-suspect (1,171 campaigns) campaign groups, we compute the average of daily turnover as the daily volume divided by shares outstanding. We then normalize these values by dividing by the group's average daily turnover during the [-120, -61] day window. Figure 3 shows that campaigns with *Suspect IP* access have greater relative turnover, mainly during the 10 days leading up to the announcement – exactly when we identify *Suspect IP* activity.

[Figure 3 about here]

Figure 4 documents the differences in returns. We plot average cumulative buy-and-hold abnormal returns (BHAR) of the suspect versus non-suspect campaigns over the same [-20, 20] trading day window. We compute the daily BHAR of each target firm using the CRSP value-weighted index as a benchmark. Figure 4 shows little difference in performance among these campaign groups during the pre-announcement window.[4] Following the campaign announcement, however, the spread among the BHAR of each group widens, with the BHAR of the *Suspect IP* campaigns eventually outperforming the non-suspect campaigns by 3.71%, confirming the informed investors' incentives to trade on this information.

[Figure 4 about here]

We continue to test whether these differences in turnover and return performance persist in a multivariate setting using the following OLS model specifications:

[4] The difference in the mean BHAR during the [-10, -1] day pre-target window is 0.83% and statistically indistinguishable from zero.

$$Share\ Turnover_i = \beta_0 + \beta_1 Suspect\ IP_i + \Sigma_{k=2}^{16} \beta_k Control_i + \varepsilon_i \quad (1)$$

$$BHAR_i = \beta_0 + \beta_1 Suspect\ IP_i + \Sigma_{k=2}^{14} \beta_k Control_i + \varepsilon_i \quad (2)$$

The dependent variable in regression (1) is firm i's average daily turnover during the [-10, -1] day window from the campaign announcement (day zero). The dependent variable in regression (2) is the BHAR of firm *i* over the [0, 10] day window of the campaign announcement date. The independent variable of interest in both regressions is the *Suspect IP* indicator variable. If suspicious IP activity is associated with increased trading activity and greater stock returns, we expect a positive and statistically significant coefficient, β_1, throughout these regressions.

The remaining independent variables in regressions (1) and (2) 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 in the 10 days before the campaign is announced. We control for the activist's campaign characteristics by using indicator variables that are one 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 the campaign experience of each activist (Log of Campaigns) by including natural log of one 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. In regression (1), we also include the market reaction on the campaign announcement (BHAR [-1, 1]) to control for the market's assessment on the prospects of a successful campaign.

Our set of firm characteristic controls include log of each firm's market cap as of the most recent quarter 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[5] and 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; Norli, Ostergaard and Schindele, 2014; 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). In regression (1), we also include each target's average daily turnover during the [-120, -61] day window so that we may interpret β_1 on the *Suspect IP* indicator as a change in turnover during the [-10, -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 3. In each of the models, the coefficient estimate of β_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 β_1 in models (1) through (3) equate to an increase in turnover

[5] See for example Appel, Gormley, and Keim (2016), Gantchev and Jotikasthira (2018), Appel, Gormley, and Keim (2019), Hi and Li (2020), Brav, Jiang, Li, and Pinnington (2020), He and Li (2020), and Kedia, Starks, and Wang (2020).

of 0.50% and 0.30% of total shares outstanding during the [-10, -1] day window of the campaign announcement. Put differently, these effects show turnover increases by roughly 55.56% and 33.33% from the turnover of the average target firm in the [-120, -61] day window.

[Table 3 about here]

In models (4) through (6) of Table 3, we also find a positive association between suspicious IP activity and campaign returns. The estimates of β_1 in these models ranges from 0.025 to 0.038, each statistically significant at the 5% and 1% levels. Moreover, the effects in models (5) and (6) are robust to the inclusion of our comprehensive set of controls and activist fixed effect. Most important, the magnitude of these effects are economically meaningful. For example, β_1 of 0.029 and 0.038 in models (5) and (6) suggest that suspect campaigns generate BHAR over the [0, 10] window that are 2.90% and 3.80% larger than non-suspect campaigns, on average.

Throughout the models in Table 3, the coefficient estimates on our set of controls identify market effects that are consistent with our expectations. For example, greater IP access in the days leading up to the announcement, greater ownership by the activist, and greater liquidity of the target firm's shares are positively associated with the change in turnover during the days leading up to a campaign. Campaign BHAR is also greater among smaller target firms with recent poor stock performance, likely due to investor's belief that the activist will be more effective at increasing firm value. Moreover, investors react more strongly to campaigns where the activist has a greater initial ownership stake and some form of value demand associated with their campaign agenda. Taken together, the results of Table 3 demonstrate a heightened level of trading and better stock performance among campaigns having *Suspect IP* access.

3.2. Target Firm Ownership Changes

We next assess changes in ownership of the target firm around the campaign announcement. We first focus on the trading activity of the *Suspect IP*. If the *Suspect IP* indeed acts on the valuable leaked information, we anticipate an increase in its 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 time for 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, but 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 IP*s to 13F holdings data for 72 out of 115 campaigns.[6] We measure the change of holdings for each institution between the quarter ending prior to and the quarter ending immediately after the campaign announcement. We then examine whether

[6] 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.

increases in holdings are more likely to occur within the institutions that are 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.

$$\Pr(Stake_i) = \Lambda(\gamma_0 + \gamma_1 Suspect\ IP_i + \Sigma_{k=2}^{7} \gamma_k Control_i + \varepsilon_i) \qquad (3)$$

Table 4 reports the results of regression (3). While we employ an indicator for an increase in holdings in models (1) and (2), one may argue that small increases can be a result of 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 one if institution *i* is associated with suspect IP access, and zero otherwise. Additionally, these regressions are at the institution level, and we therefore add a set of control variables to model (2) and (4) that account for institutional portfolio construction and rebalancing.

[Table 4 about here]

In models (1) and (3) with no control variables, the estimate of γ_1 for *Suspect IP* is positive and statistically significant at the 1% level. The γ_1 estimate 0.644 in model (1) implies that an institution with suspect IP access is 15.95% more likely to increase their holdings around the campaign announcement. The magnitude of this effect is smaller once our control variables are added in models (2) and (4), yet positive and statistically significant at the 10% and 1% levels, respectively. Overall, the results suggest that those institutions with suspicious research activities are indeed likely to trade on the information.

If the activist has leaked their plans to get additional support for the campaign, we might also expect an increase in the overall institutional ownership base of target firms as other informed investors, beyond those identified by EDGAR search activity, acquire shares. We test these hypotheses using the aggregate institutional holdings in the quarters around the announcement date of the activist campaign. We use the following OLS regression:

$$\Delta Institutional\ Ownership_i = \beta_0 + \beta_1 Suspect\ IP_i + \Sigma_{k=2}^{14} \beta_k Control_i + \varepsilon_i \qquad (4)$$

The dependent variable in regression (4) is the change in firm i's institutional ownership percentage, in decimal form, from the end of the quarter before to the end of the quarter during which the activist's campaign is announced. As before, the independent variable is our *Suspect IP* indicator and the control variables follow our prior specifications. If *Suspect IP* access is associated with greater increases in aggregate institutional ownership, we expect β_1 to be positive and statistically significant.

The results of regression (4) in Table 5 indeed show an increase in target firm institutional ownership for our suspect campaigns. Using no control variables, the estimate of β_1 in model (1) is positive and statistically significant at the 5% level. The β_1 estimate 0.033 suggests that, on average, the increase in institutional ownership of a target firm is 3.30% for campaigns having suspicious IP activity. The magnitude of this effect is similar once we add our control variables; the estimate of β_1 in models (2) and (3) are 0.032 and 0.030, statistically significant at the 5% and 10% levels. These estimates suggest that institutional ownership of suspect campaigns increases by 3.20% and 3.00%, on average.

[Table 5 about here]

We next turn our attention to the effect of *Suspect IP*s on the activist's trading activity. If the *Suspect IP* and any other outside investors are providing 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: (1) the activist neither withdraws or increases their stake by 1% (Group 1); (2) the activist has a decrease in ownership below 5% (Group 2); (3) the activist increases their stake by greater than 1% (Group 3). Our aim is to determine the propensity for an activist to increase their ownership of the target firm, conditional on having a *Suspect IP* associated with the campaign. We therefore use the following multilevel logistic regression:

$$\Pr(Stake_i) = \Lambda(\gamma_0 + \gamma_1 Suspect\ IP_i + \Sigma_{k=2}^{15} \gamma_k Control_i + \varepsilon_i) \qquad (5)$$

The dependent variable in regression (5) 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 (5) 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 (5) in Table 6. 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 target firm, versus simply maintaining their position, in the months following the announcement of the campaign.

[Table 6 about here]

In models (4) through (6) of Table 6 we display the estimates of regression (5) within the group of campaigns for which the activist increases their stake (Group 3). There is a distinguishable difference in the effects of *Suspect IP* access in these models. The estimates of the *Suspect 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 γ_1 estimate of -0.469 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 campaign announcement decreases by 8.48%. When we consider the activist ownership activity in the subsequent 12 months, as in shown in model (6), this probability decreases by 7.33%. Both effects are statistically and economically significant. More critical, these results are consistent with our conjecture that the necessity for activists of suspect campaigns to increase their stake is moderated by the support they garner from sharing information.[7]

3.3. Likelihood of Proxy Contest

[7] 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 6 and 12 months of a campaign with a *Suspect IP* decreases by 10.10% and 10.61%. These results are available upon request.

Activist initiatives often require a collective effort from new and existing shareholders. It is therefore critical for the activist to gather support from either existing or potential shareholders of the target firm. One activist tactic that is particularly reliant on this support is a proxy contest. If suspicious IP access is due to 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:

$$\Pr(Contest_i) = \Lambda(\gamma_0 + \gamma_1 Suspect\ IP_i + \Sigma_{k=2}^{16} \gamma_k Control_i + \varepsilon_i) \quad (6)$$

The dependent variable in regression (6) is an indicator variable that is one 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: (1) the activist files a proxy statement with the SEC or (2) there is a proxy announcement in SharkRepellent. In addition to using the same independent variables of interest and controls that we use 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 γ_1 to be positive and statistically significant.

We include the results of regression (6) in the Table 7. Models (1) through (4) show γ_1 estimates of 1.310, 1.237, 0.608, 0630, statistically significant at the 1% and 5% 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 3.18%, 4.38%, 2.17%, and 2.62%, 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 manner. Moreover, these effects are identified while controlling for critical determinants of proxy contests such as seeking board nominations, value initiatives related to M&A and payout policy, and the target's level of institutional ownership. Overall, the results in Table 7 emphasize the importance of our efforts to specifically identify common IPs and highlights a clear, meaningful relation between the activist of a campaign and access by unique institutions.[8]

[Table 7 about here]

3.4 Likelihood of Proxy Contest Success

Does the greater likelihood of a proxy contest from suspect campaigns lead to a greater likelihood of proxy contest success? We make this assessment using the following logit model specification on our sample of campaigns for which a proxy contest is pursued:

$$\Pr(Win_i) = \Lambda(\gamma_0 + \gamma_1 Suspect\ IP_i + \Sigma_{k=2}^{13}\gamma_k Control_i + \varepsilon_i) \qquad (7)$$

The dependent variable in regression (7), Win_i, is an indicator variable that is one if the activist has a successful outcome in the proxy contest involving target firm *i,* and zero otherwise. We

[8] In additional tests of proxy contest likelihood, we use the same model as in Table 7, excluding campaigns where we do not identify a *Suspect IP*, but the activist of the respective campaign has at 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 3.34%, 2.89%, 1.70%, and 2.23%. The persistence of these probabilities in this sample indeed support our conjecture that we are not fully identifying *Suspect IP* and therefore underestimating the effects of *Suspect IP* access throughout the paper. We also conduct a similar analysis to Table 7 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 upon request.

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). Our independent variable of interest is *Suspect IP* and the remaining controls are similar to those we use in the models of Table 7. We do, however, exclude our indicator variables for characteristics of the activist campaign because the Board Demand and Governance Demand indicators maintain a value of one for nearly every campaign. This frequency is to be expected given the frequent board and governance initiatives that motivate many activist proxy campaigns.

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 (7) in Table 8 confirm our conjecture. The estimates of γ_1 in models (1) and (2) are 1.191 and 1.134 and statistically significant at the 5% and 1% levels, respectively. Moreover, the economic magnitude of these effects is large as the average marginal effects of these estimates suggest that the probability of the activist having a successful proxy campaign increase by 21.73% and 20.67%, respectively, when there is suspicious IP activity leading up to the announcement of the campaign.[9]

[Table 8 about here]

4. Conclusion

[9] We conduct further analysis of our results in Table 8 using a linear probability model with activist fixed effects. Including these fixed effects does mitigate the predictive content of suspect IP access, but we interpret this result with caution. Our sample of 216 campaigns used in Table 8 has 116 unique activists, causing the fixed effects to reduce our degrees of freedom by a considerable margin that makes the analysis relatively uninformative.

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 leaked information from the activist to outside financial institutions, where the outside institution consistently accesses target's statements immediately prior to 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 to be greater for *Suspect IP* campaigns in the 10 days that follow the campaign announcement; this group of campaigns outperforms all others by 2.5-3.8%, creating a clear incentive for investors to act on this shared information.

Investors with access to this non-public 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 identify direct 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.

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Table 1: Campaign Summary Statistics

This table 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. *Common IP No Prior Access* and *Suspect IP* are as defined in Appendix B. Displayed in Panel B are the number of campaigns by year and the number of campaigns with various Common IP classifications by year. For those campaigns with a Common IP or *Suspect IP*, we display the average number of IP respectively.

Panel A: Campaign Activist Types

Holder Type	Campaigns with this Holder Type	Unique Activist CIK	Average Observations 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	# of Campaigns	# of Campaigns with Suspect IP	Average Suspect IP	Median Target Size
2005	88	3 (3.41%)	1.00	199.22
2006	119	6 (5.04%)	1.00	243.84
2007	169	9 (5.33%)	1.33	257.79
2008	138	17 (12.32%)	1.29	189.46
2009	73	7 (9.59%)	1.14	68.50
2010	69	5 (7.25%)	1.80	196.69
2011	78	11 (14.10%)	1.27	208.30
2012	100	10 (10.00%)	1.70	264.12
2013	98	12 (12.24%)	1.33	208.00
2014	131	16 (12.21%)	1.38	304.94
2015	115	10 (8.70%)	1.30	280.09
2016	93	6 (6.45%)	1.33	213.28
2017	15	3 (20.00%)	1.00	865.71

Table 2: Variable Summary Statistics

This table includes the summary statistics of our sample of 1,286 campaigns and the variables we use throughout our multivariate tests. Panel A display variable summary statistics where variables are constructed as described in Appendix B. Panel B displays summary statistics regarding Suspect IP access of other holdings of the respective activist for which the *Suspect IP* is identified. Specifically, during the 10-day window in which we identify and IP as *Suspect*, we determine the number of the activist's other holdings that are accessed by this same IP and in the same 10-day window.

Panel A: Variable Summary Statistics

Variable	Mean	Std Dev	25th Pctl	50th Pctl	75th Pctl
Total IP	39.249	60.003	11.000	23.000	46.000
Common IP	1.054	1.774	0.000	0.000	1.000
Common IP No Prior Access	0.656	1.280	0.000	0.000	1.000
Suspect IP Indicator	0.089	0.285	0.000	0.000	0.000
Number of Campaigns	18.896	27.186	3.000	9.000	19.000
Log of Number of Campaigns	2.388	1.031	1.386	2.303	2.996
BHAR [-1, 1]	0.032	0.078	-0.007	0.022	0.060
BHAR [0, 10]	0.009	0.117	-0.712	-0.040	0.010
BHAR [-10, -1]	0.037	0.127	-0.024	0.024	0.086
Market Cap	1365.640	4283.670	80.901	228.359	891.143
Market Leverage	0.172	0.224	0.000	0.064	0.296
ROA	0.041	0.261	0.014	0.076	0.136
Institutional Ownership	0.575	0.284	0.351	0.623	0.804
Log of Amihud Illiquidity	-6.144	3.199	-8.667	-6.302	-4.066
Prior 12 Month Return	-0.052	0.500	-0.352	-0.110	0.151
Prior 36 Month Return	0.124	0.939	-0.424	-0.062	0.398
Turnover [-10, -1]	0.012	0.013	0.004	0.008	0.015
Turnover [-120, -61]	0.009	0.010	0.003	0.006	0.011
Ownership by Activist (%)	8.350	4.598	5.400	6.700	9.670

Panel B: Suspect IP Access of Activist's Other Holdings

Variable	Mean	Std Dev	25th Pctl	50th Pctl	75th Pctl
Total Activist's Other Holdings	279.809	502.942	10.000	19.000	642.000
Suspect IP Access of Activist's Other Holdings	3.600	7.739	0	0	3.000
Suspect IP Access of Activist's Other Holdings (%)	1.412	2.676	0	0	1.504

Table 3: Suspect IP Access and Market Effects

This table displays the results of OLS regressions that we specify as follows:

$$Share\ Turnover_i = \beta_0 + \beta_1 Suspect\ IP_i + \Sigma_{k=2}^{16} \beta_k Control_i + \varepsilon_i \qquad (1)$$

$$BHAR_i = \beta_0 + \beta_1 Suspect\ IP_i + \Sigma_{k=2}^{14} \beta_k Control_i + \varepsilon_i \qquad (2)$$

The dependent variable in regression (1) is firm i's average daily turnover during the [-10, -1] day window from the announcement of the activist campaign (day zero). We measure daily turnover as daily volume divided by shares outstanding. The dependent variable in regression (2) is the Buy-and-Hold Abnormal Return (BHAR) of firm i over the [0, 10] day window around the announcement of the activist campaign (day zero). The independent variable of interest is the *Suspect IP* indicator variable. We construct all variables as described in Appendix B. Additionally, in models (1) through (3) 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 determined using the 48 Fama – French industries, and activist fixed effects. We compute t-statistics using standard errors that are robust to the effects of heteroscedasticity (White (1980)). We denote significance at the 1%, 5%, and 10% levels by ***, **, and * respectively.

	(1) Turnover [-10, -1]	(2) Turnover [-10, -1]	(3) Turnover [-10, -1]	(4) BHAR [0, 10]	(5) BHAR [0, 10]	(6) BHAR [0, 10]
Suspect IP	**0.005*****	**0.003****	**0.003***	**0.025****	**0.029****	**0.038*****
	(2.80)	**(1.99)**	**(1.72)**	**(2.32)**	**(2.49)**	**(2.95)**
Total IP		0.002***	0.002***		-0.001	0.004
		(3.54)	(2.98)		(-0.15)	(0.78)
Board Demands		0.001	0.000		0.012	0.012
		(1.47)	(0.44)		(1.04)	(0.79)
Governance Demands		-0.001	-0.001		-0.014	-0.017
		(-1.29)	(-0.68)		(-1.14)	(-1.14)
Value Demands		-0.001	-0.000		0.026***	0.021**
		(-0.81)	(-0.19)		(3.39)	(2.38)
Log of Campaigns		-0.001**	0.036*		-0.003	0.044
		(-2.04)	(1.79)		(-0.67)	(0.20)
Log of Market Cap		-0.001	-0.001		-0.016**	-0.028***
		(-1.41)	(-0.97)		(-2.06)	(-3.17)
Market Leverage		-0.001	-0.001		0.037	0.037
		(-0.76)	(-0.25)		(1.45)	(1.40)
Return on Assets		-0.000	0.001		-0.002	0.014

		(-0.27)	(0.30)		(-0.05)	(0.35)
Institutional Ownership		0.004*	0.004**		-0.013	-0.012
		(1.92)	(2.27)		(-0.68)	(-0.63)
Log of Amihud Illiquidity		-0.001**	-0.001**		-0.007*	-0.007*
		(-2.20)	(-2.32)		(-1.77)	(-1.85)
Prior 12 Month Return		0.001	0.001		-0.024**	-0.023**
		(0.68)	(0.63)		(-2.18)	(-2.17)
Prior 36 Month Return		0.001	0.001**		0.007	0.010
		(1.60)	(2.33)		(0.90)	(1.11)
Ownership by Activist		0.000**	0.000***		0.002*	0.003**
		(2.37)	(3.39)		(1.80)	(2.25)
BHAR [-1, 1]		0.009*	0.008*			
		(1.83)	(1.65)			
Turnover [-120, -61]	0.755***	0.526***	0.496***			
	(5.12)	(3.55)	(3.24)			
Intercept	0.005***	0.001	-0.046*	0.035***	0.008	0.066
	(4.38)	(0.43)	(-1.67)	(9.28)	(0.27)	(0.23)
Industry Fixed Effects	No	Yes	Yes	No	Yes	Yes
Year Fixed Effects	No	Yes	Yes	No	Yes	Yes
Activist Fixed Effects	No	No	Yes	No	No	Yes
N	1,286	1,286	1,286	1,286	1,286	1,286
Adj. R-sq	0.332	0.400	0.466	0.002	0.052	0.102

Table 4: Suspect IP Ownership Changes Around the Campaign Announcement

This table displays results of logit regressions we use to determine the likelihood that *Suspect IP* will increase their holdings in the target firm following the announcement of the campaign. The logit model specification is as follows:

$$\Pr(Stake_i) = \Lambda(\gamma_0 + \gamma_1 Suspect\ IP_i + \Sigma_{k=2}^{7}\gamma_k Control_i + \varepsilon_i)$$

That sample contains 72 unique campaigns with 3,138 unique institutions. In models (1) and (2), the dependent variable, $Stake_i$, is an indicator that is one if institution i increases their share ownership from the quarter before to the quarter of the campaign announcement date, and zero otherwise. In models (3) and (4), the dependent variable, $Stake_i$, is an indicator that is one if institution i increases their share ownership by greater than 5% from the quarter before to the quarter of the campaign announcement date, and zero otherwise. The independent variable of interest is the *Suspect IP* indicator variable. We construct all variables as described in Appendix B. We compute z-statistics using standard errors that are robust to the effects of heteroscedasticity (White (1980)) and we cluster standard errors by firm. We denote significance at the 1%, 5%, and 10% levels by ***, **, and * respectively.

	(1) Holdings Increase	(2) Holdings Increase	(3) 5% Holdings Increase	(4) 5% Holdings Increase
Suspect IP	**0.644*****	**0.461***	**0.726*****	**0.668*****
	(2.70)	(1.90)	(3.20)	(2.85)
Log of Market Cap		-0.011		-0.047*
		(-0.49)		(-1.83)
BHAR [-1, 1]		-1.778**		-1.518
		(-2.04)		(-1.38)
Prior 12 Month Return		-0.078		-0.084
		(-1.00)		(-0.94)
Average Holding Market Cap		-0.256***		-0.277***
		(-5.73)		(-5.21)
Portfolio Dollar Value		0.051***		-0.003
		(4.29)		(-0.25)
Number of Portfolio Holdings		-0.084***		-0.100***
		(-2.75)		(-3.09)
Intercept	-0.290***	1.814***	-0.626***	3.270***
	(-5.35)	(3.24)	(-9.54)	(5.20)
N	19,695	19,695	19,695	19,695
Pseudo R-sq	0.000	0.012	0.000	0.012

Table 5: Institutional Ownership Changes Around the Campaign Announcement

This table displays results of OLS regressions we use to determine the effect of Common IP access on changes in a target firm's level of institutional ownership around the announcement of an activist campaign. The OLS model specification is as follows:

$$\Delta Institutional\ Ownership_i = \beta_0 + \beta_1 Suspect\ IP_i + \Sigma_{k=2}^{14}\beta_k Control_i + \varepsilon_i$$

The dependent variable is the change in firm i's institutional ownership percentage, in decimal form, from the end of the quarter before to the end of the campaign announcement quarter. The independent variable of interest is the *Suspect IP* indicator variable. We construct all variables as described in Appendix B. We include year fixed effects and industry fixed effects determined using the 48 Fama – French industries. We compute t-statistics using standard errors that are robust to the effects of heteroscedasticity (White (1980)). We denote significance at the 1%, 5%, and 10% levels by ***, **, and * respectively.

	(1) ΔInstitutional Ownership	(2) ΔInstitutional Ownership	(3) ΔInstitutional Ownership
Suspect IP	**0.033****	**0.032****	**0.030***
	(2.54)	**(2.36)**	**(1.83)**
Total IP		0.004	0.008*
		(1.15)	(1.66)
Board Demands		0.004	0.007
		(0.34)	(0.63)
Governance Demands		-0.001	0.002
		(-0.05)	(0.17)
Value Demands		0.007	0.010
		(1.36)	(1.58)
Log of Campaigns		0.009***	0.156
		(2.92)	(0.97)
Log of Market Cap		-0.001	-0.005
		(-0.27)	(-0.69)
Market Leverage		-0.016	-0.025
		(-1.29)	(-1.49)
Return on Assets		-0.022*	-0.022*
		(-1.96)	(-1.76)
Log of Amihud Illiquidity		0.000	-0.000
		(0.09)	(-0.10)
Prior 12 Month Return		0.016**	0.017*
		(2.37)	(1.94)
Prior 36 Month Return		0.004	0.004
		(1.05)	(0.80)
Ownership by Activist		-0.000	-0.000
		(-0.06)	(-0.12)
BHAR [-1, 1]		-0.045	-0.029
		(-1.18)	(-0.69)
Intercept	-0.004	-0.060***	-0.208
	(-1.29)	(-2.71)	(-1.00)
Industry Fixed Effects	No	Yes	Yes
Year Fixed Effects	No	Yes	Yes
Activist Fixed Effects	No	No	Yes
N	1,286	1,286	1,286
Adj. R-sq	0.008	0.050	0.035

Table 6: Subsequent Activist Ownership Changes

This table 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 multi-level logit model specification is as follows:

$$\Pr(Stake_i) = \Lambda(\gamma_0 + \gamma_1 Suspect\ IP_i + \Sigma_{k=2}^{15} \gamma_k Control_i + \varepsilon_i)$$

The dependent variable $Stake_i$ is zero, one, or two 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. Models (1) through (3) display results for Group 2 and models (4) through (6) display results for Group 3. We construct all variables as described in Appendix B. We compute z-statistics using standard errors that are robust to the effects of heteroscedasticity (White (1980)) and we cluster standard errors by year. We denote significance at the 1%, 5%, and 10% levels by ***, **, and * 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	**-0.436**	**-0.516**	**-0.335**	**-0.364**	**-0.469***	**-0.426***
	(-1.14)	**(-1.37)**	**(-0.95)**	**(-1.26)**	**(-1.66)**	**(-1.83)**
Total IP	-0.011	-0.022	-0.053	-0.088***	-0.207***	-0.192***
	(-0.09)	(-0.23)	(-0.53)	(-2.61)	(-3.05)	(-2.63)
Board Demands	-1.121**	-0.503	-0.255	0.219	0.442***	0.261**
	(-2.19)	(-1.18)	(-0.76)	(0.69)	(2.81)	(2.45)
Governance Demands	0.501	-0.066	-0.387	0.180	0.091	0.334
	(1.55)	(-0.17)	(-1.16)	(0.57)	(0.46)	(1.44)
Value Demands	0.190	0.140	0.122	-0.397***	-0.348***	-0.332*
	(1.07)	(1.02)	(0.61)	(-3.24)	(-2.58)	(-1.85)
Log of Campaigns	0.035	0.036	0.162	0.257***	0.255***	0.370***
	(0.26)	(0.37)	(1.05)	(5.43)	(5.01)	(3.77)
Log of Market Cap	-0.170	-0.067	-0.244	-0.189*	-0.085	-0.142
	(-1.60)	(-0.55)	(-1.54)	(-1.65)	(-1.08)	(-1.38)
Market Leverage	0.319	0.148	0.461	-0.200	-0.492*	-0.006
	(0.49)	(0.30)	(1.22)	(-0.75)	(-1.76)	(-0.02)
Return on Assets	1.561	-0.058	0.063	0.457*	0.175	0.492***
	(1.62)	(-0.11)	(0.18)	(1.84)	(0.88)	(3.46)
Institutional Ownership	0.808	0.625	0.781***	0.632**	0.557*	0.815**
	(1.41)	(1.45)	(2.65)	(1.98)	(1.78)	(2.44)
Log of Amihud Illiquidity	-0.174**	-0.204**	-0.280***	-0.098	-0.068	-0.085
	(-2.45)	(-2.27)	(-3.66)	(-1.52)	(-1.24)	(-1.58)
Prior 12 Month Return	0.917***	0.377*	0.316	-0.012	-0.121	-0.006
	(4.73)	(1.94)	(1.38)	(-0.05)	(-0.56)	(-0.02)
Prior 36 Month Return	-0.281*	-0.022	-0.030	0.078	0.090	0.051
	(-1.95)	(-0.24)	(-0.61)	(1.00)	(1.07)	(0.72)
Ownership by Activist	-0.415***	-0.303***	-0.229***	-0.025**	-0.020	-0.032*
	(-7.52)	(-4.67)	(-6.41)	(-2.27)	(-1.62)	(-1.93)
BHAR [-1, 1]	-0.411	-2.012	-1.006	-1.711**	-1.713**	-1.044*
	(-0.16)	(-1.60)	(-0.82)	(-1.99)	(-2.19)	(-1.79)
Intercept	-0.472	-0.437	0.244	-1.216***	-1.218***	-1.000***
	(-0.85)	(-0.77)	(0.41)	(-2.95)	(-4.53)	(-2.64)
N	1,286	1,286	1,286	1,286	1,286	1,286
Pseudo R-sq	-	-	-	0.070	0.083	0.101

Table 7: Suspect IP Access and Proxy Contest Likelihood

This table 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:

$$\Pr(Contest_i) = \Lambda(\gamma_0 + \gamma_1 Suspect\ IP_i + \Sigma_{k=2}^{16}\gamma_k Control_i + \varepsilon_i)$$

The four dependent variables, $Contest_i$, are indicator variables that are either of the following occur: (1) the activist files a proxy statement with the SEC in the 3, 6, 12, and 18 months following the announcement of the campaign or (2) 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. We construct all variables as described in Appendix B. We compute z-statistics using standard errors that are robust to the effects of heteroscedasticity (White (1980)) and we cluster standard errors by year. We denote significance at the 1%, 5%, and 10% levels by ***, **, and *, respectively.

	(1) Contest 3 Months	(2) Contest 6 Months	(3) Contest 12 Months	(4) Contest 18 Months
Suspect IP	**1.310*** **	**1.237*** **	**0.608** **	**0.630** **
	(3.92)	**(4.16)**	**(2.16)**	**(2.25)**
Total IP	0.117	0.040	0.014	0.028
	(1.23)	(0.38)	(0.17)	(0.32)
Board Demands	2.763***	3.724***	4.915***	5.019***
	(3.59)	(3.90)	(4.71)	(5.69)
Governance Demands	2.353***	1.360	0.261	-0.041
	(2.61)	(1.39)	(0.30)	(-0.04)
Value Demands	0.166	0.426**	0.639***	0.803***
	(0.84)	(2.12)	(3.68)	(4.64)
Log of Campaigns	-0.330***	-0.140	-0.001	-0.028
	(-2.58)	(-1.27)	(-0.01)	(-0.18)
Log of Market Cap	-0.555***	-0.495***	-0.441***	-0.487***
	(-3.61)	(-4.12)	(-2.94)	(-3.55)
Market Leverage	-0.989	-0.697	-1.078**	-1.168***
	(-1.63)	(-1.38)	(-2.42)	(-2.72)
Return on Assets	-0.061	-0.310	-0.196	-0.162
	(-0.19)	(-0.76)	(-0.36)	(-0.27)
Institutional Ownership	1.488***	1.200**	0.749	0.741
	(2.77)	(2.33)	(1.37)	(1.29)
Δ Institutional Ownership	0.898	0.058	-0.516	-0.916
	(1.57)	(0.13)	(-0.82)	(-1.13)
Log of Amihud Illiquidity	-0.170*	-0.127*	-0.155**	-0.155**
	(-1.79)	(-1.74)	(-2.00)	(-2.02)
Prior 12 Month Return	0.663***	0.479**	0.372**	0.337**
	(3.90)	(2.43)	(2.23)	(2.04)
Prior 36 Month Return	-0.018	-0.071	-0.063	-0.013
	(-0.28)	(-0.83)	(-0.74)	(-0.09)
Ownership by Activist	-0.055	-0.047	-0.041	-0.032
	(-1.48)	(-1.56)	(-1.52)	(-1.38)
BHAR [-1, 1]	2.283	1.341	0.700	0.681
	(1.57)	(1.02)	(0.85)	(0.81)
Intercept	-3.943***	-3.936***	-4.125***	-3.674***
	(-3.96)	(-4.13)	(-3.44)	(-3.35)
N	1,286	1,286	1,286	1,286
Pseudo R-sq	0.330	0.363	0.411	0.422

Table 8: Suspect IP Access and Proxy Success Likelihood

This table 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:

$$Pr(Win_i) = \Lambda(\gamma_0 + \gamma_1 Suspect\ IP_i + \Sigma_{k=2}^{13}\gamma_k Control_i + \varepsilon_i)$$

The dependent variable is an indicator variable, Win_i, that is one if the proxy outcome is "Settled / Concessions Made", "Dissident", or "Split", and zero otherwise. The independent variable of interest is the *Suspect IP* indicator variable. We construct all variables as described in Appendix B. We restrict the sample to campaigns for which a proxy contest is started within 18 months of the campaign announcement. We compute z-statistics using standard errors that are robust to the effects of heteroscedasticity (White (1980)) and we cluster standard errors by year. We denote significance at the 1%, 5%, and 10% levels by ***, **, and * respectively.

	(1) Win	(2) Win
Suspect IP	**1.191****	**1.134*****
	(2.25)	**(2.59)**
Total IP		0.038
		(0.22)
Log of Campaigns		0.086
		(0.41)
Log of Market Cap		-0.036
		(-0.12)
Market Leverage		-0.098
		(-0.14)
Return on Assets		0.031
		(0.03)
Institutional Ownership		0.468
		(0.56)
Δ Institutional Ownership		2.809
		(0.75)
Log of Amihud Illiquidity		-0.015
		(-0.11)
Prior 12 Month Return		0.470
		(1.28)
Prior 36 Month Return		-0.287
		(-1.15)
Ownership by Activist		0.053
		(1.06)
BHAR [-1, 1]		-1.161
		(-0.56)
Intercept	0.544***	-0.102
	(5.01)	(-0.08)
N	216	216
Pseudo R-sq	0.015	0.041

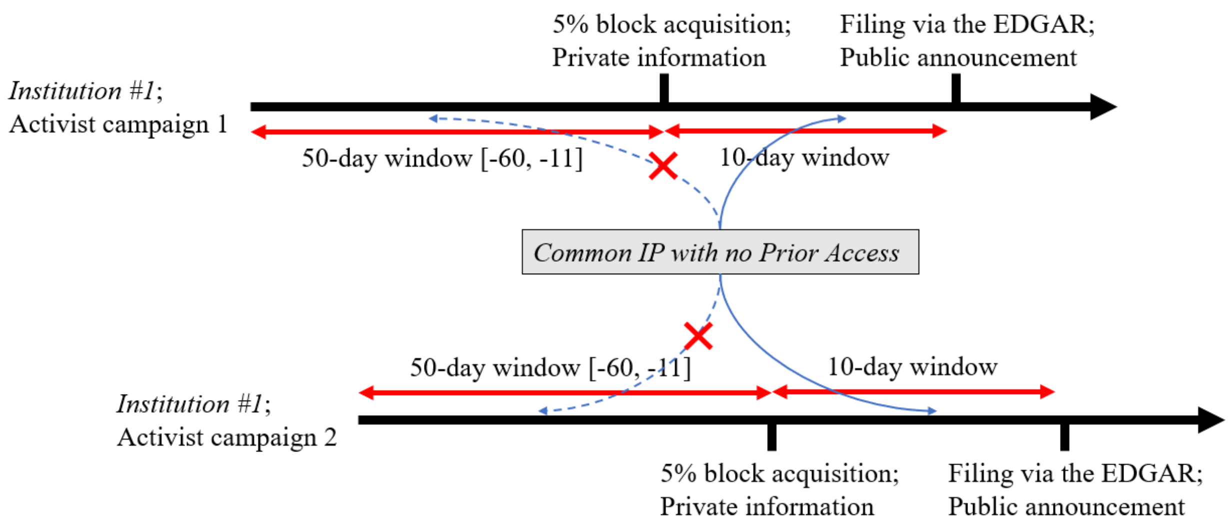

Figure 1: Illustration of Common IP with No Prior Access

This figure provides a graphic illustration of our methods to identify a *Common IP* with no prior access. We first define a '*Common IP'* as one conducting search activity prior to the 13D filing for more than one campaign by the same activist. We then investigate search activities of the same IP in the preceding 50-day window [-60, -11] and define a '*Common IP* with no prior access' as a *Common IP* that have no search activity in this 50-day window.

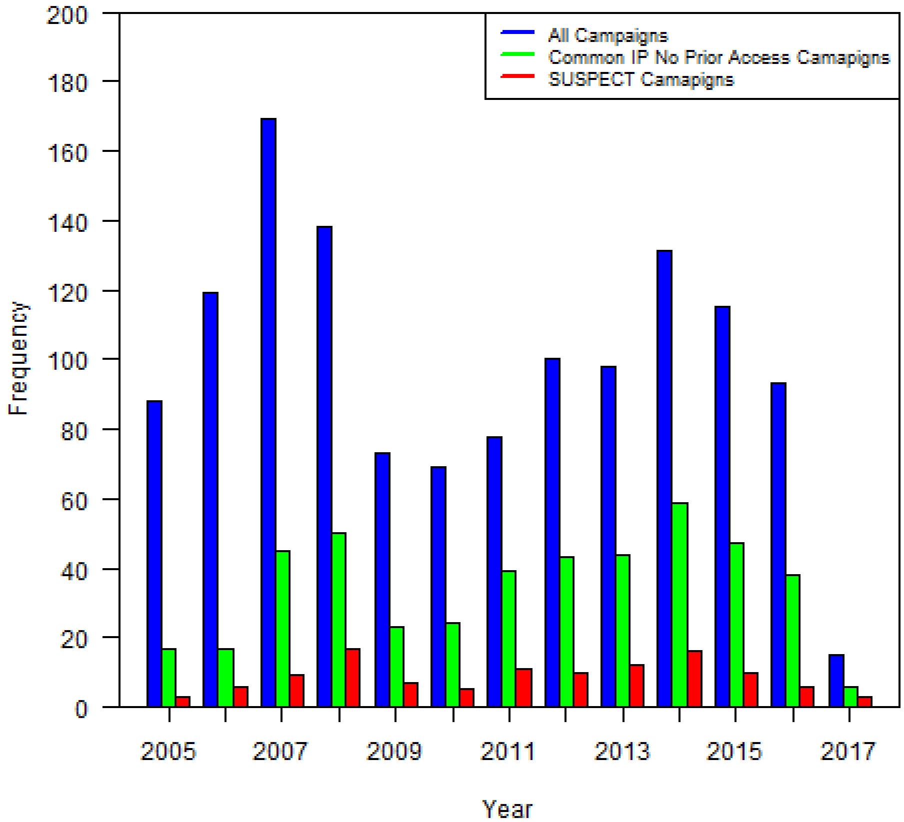

Figure 2: Campaigns Frequencies by Year

This figure plots the yearly frequencies of all activist campaigns, campaigns with at least one *Common IP No Prior Access*, and campaigns with at least one *Suspect IP*. *Common IP No Prior Access* and *Suspect IP* are as described in Appendix B.

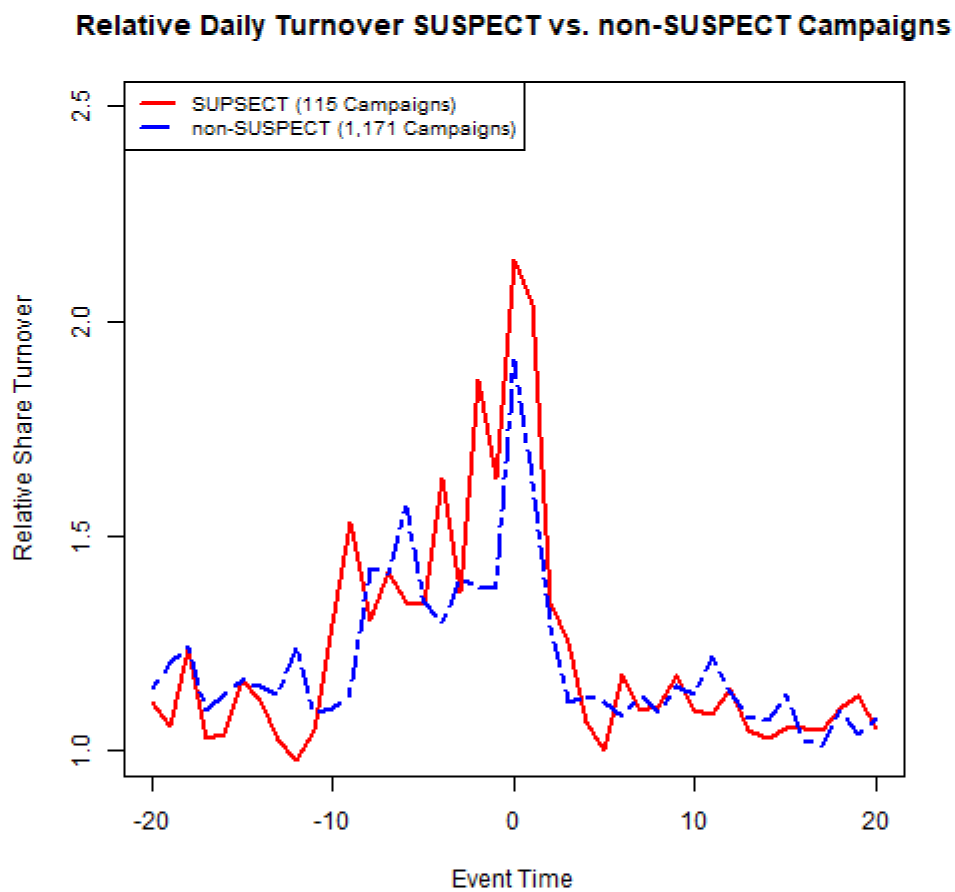

Figure 3: Suspect IP Access and Relative Daily Turnover

This figure plots the relative daily share turnover for the group of campaigns that have a *Suspect IP* and those that do not. We compute relative turnover on each event day, and within each campaign group, as the average of daily turnover scaled by the groups average daily turnover during the [-120, -61] day window from the campaign announcement date. The announcement date we use is the lesser of the ANNDATS in SharkRepellent or the date on the initial 13D filing.

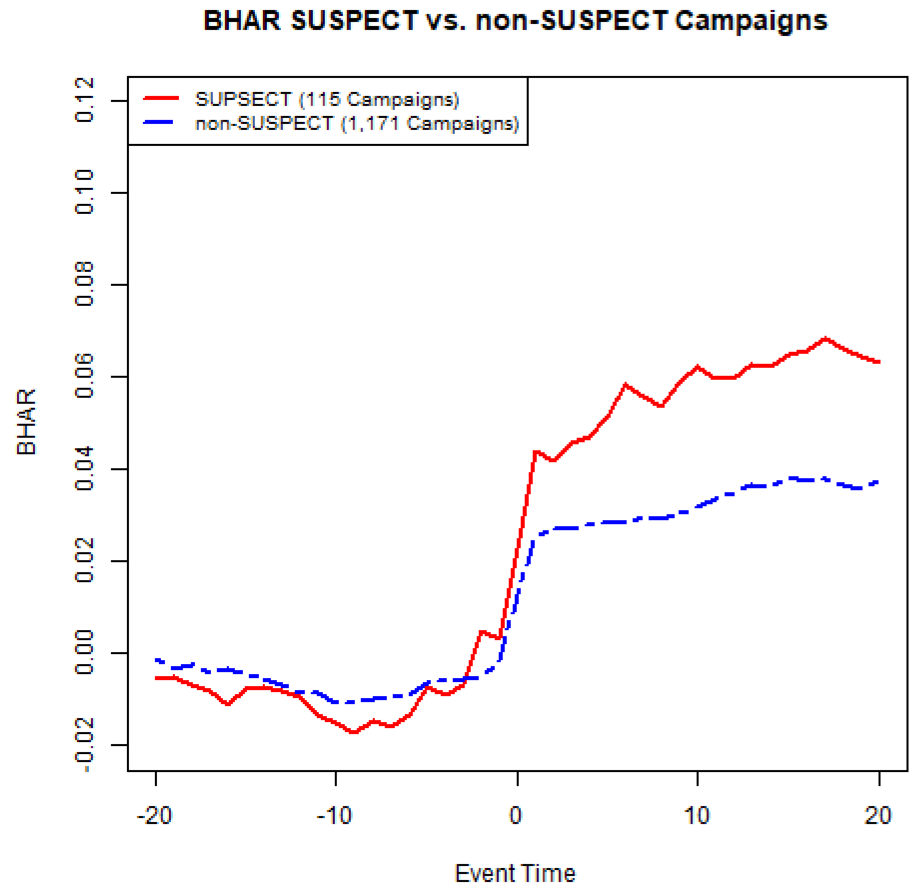

Figure 4: Suspect IP Access and Buy-and-Hold Abnormal Returns

This figure plots the average Buy-and-Hold Abnormal Return (BHAR) for the group of campaigns that have a *Suspect IP* and those that do not. We compute BHAR over the [-20, 20] day window centered at the announcement date of the activist campaign. The announcement date we use is the lesser of the ANNDATS in SharkRepellent or the date on the initial 13D filing.

Appendix A: Activist Campaign Data Construction Process

This table 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: - The target has a valid permno / GVKEY and share code of 10 or 11 in CRSP - 13D filed with SEC - The SharkRepellent announcement date is not 10 days before the original 13D filing date listed in SharkRepellent. - 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, 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 8K filings to identify campaigns with "Merger agreement" in the [-60, 0] window. This process involves searching Item 1.01 in 8K 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

Variable Name	Description
Total IP	This is the number of unique IP accessing a firm's major SEC filing such as 10-K, 10-Q, and Proxy Statements over the [*t* - 10, *t* - 1] day window, where *t* denotes the lesser of the ANNDATS in SharkRepellent or the date on the initial 13D filing. We obtain IP data from the SEC log files over the years 2005 to 2017. In our multivariate regressions, we normalize Total IP by year to mitigate the time-varying nature of the total number of accesses.
Common IP	This is the number of unique IPs accessing a firm's major SEC filing such as 10-K, 10-Q, and Proxy Statements over the [*t* - 10, *t* - 1] day window, where *t* is the announcement date of the activism campaign, that have accessed a SEC filing of other firms targeted by the same activist over the 10-day 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. We obtain IP data from the SEC log files over the years 2005 to 2017.
Common IP No Prior Access	This is the 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 [*t* - 60, *t* -11] day window, where *t* denotes the announcement date of the activism campaign. The announcement date is the lesser of the ANNDATS in SharkRepellent or the date on the initial 13D filing. We obtain IP data from the SEC log files over the years 2005 to 2017.
Suspect IP Indicator	This is an indicator variable that is one if the firm has a Common IP No Prior Access identified as either a Bank or Investment firm, and zero 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	This is the number of unique 13D filings that are filed by the activist.
Log of Number of Campaigns	This is log of one plus the number of unique 13D filings that are filed by the activist.
Board Indicator	This is an indicator variable that is one if the "Primary Campaign Type" or "Secondary Campaign Type" listed in SharkRepellent includes "Board Representation" or "Board Control," and zero otherwise.
Governance Demands Indicator	This is an indicator variable that is one 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	This is an indicator variable that is one 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, etc., 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.

Appendix B (Continued): Variable Descriptions

Variable Name	Description
BHAR [n, m]	This is the 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.
Turnover [n, m]	This is the 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	This is the market capitalization of the target firm as of the most recent quarter end before the 13D filing quarter. We obtain the targets firm's quarter end share price and shares outstanding from the Compustat 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 EBITDA from the most recent fiscal year end before the 13D filing date, divided by total assets from the most recent fiscal year.
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 $(\frac{1}{N}\sum_{t=1}^{N}\frac{\lvert R_t \rvert}{VOLD_t}) \times 10^5$, where N is the number of non-zero trading days in the respective calendar year before the campaign year, R_t is the return on day *t*, and $VOLD_t$ 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 (%)	This is the 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.
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 firm held by each institutional investor and as reported in their respective 13F filing. We obtain 13F filings from the Thomson Reuter's 13F database.