Detecting Opportunistic Behavior in Public Short Campaigns

Abstract

The high hurdles in proving short campaigns to be illegal manipulation, as well as the possibility of the transgressor claiming "honest errors," leave room for opportunistic short campaign behavior. Motivated by the theory of Benabou and Laroque (1992), this paper proposes an empirical approach to detect such behavior. Using comprehensive data on short campaigns and linking them to daily short-sale metrics and post-campaign stock market performance, I find a greater presence of opportunistic behavior when campaigns are clustered, that is, when multiple campaigns are published on the same target at the same time. I further find that the evidence suggesting clustered campaigns are more opportunistic concentrates in the subsamples where target firms are more prone to price manipulation, campaign authors are better connected, and authors' reputation concerns are lower.

Keywords: opportunistic behavior, short campaigns, reputation, network

Detecting Opportunistic Behavior in Short Campaigns

> "Anti-corporate campaigners have taken to the digital world like ducks to the water... Opportunists have also joined the ducks in the water: there is money to be made by 'shorting' a stock (that is, betting that its price will go down) and then unleashing a value-destroying digital storm." —*The Economist*, October, 2014

1. Introduction

There have long been controversies regarding the role of short sellers in the market. On one hand, the market benefits and becomes more efficient when the prices incorporate the negative information acquired and provided by short sellers (Senchack and Starks 1993; Chang, Cheng, and Yu 2007; Karpoff and Lou, 2010, Hirshleifer, Teoh, and Yu 2011, Beber and Pagano 2013, Massa, Qian, Xu, and Zhong, 2015). On the other hand, short sellers pose threats for potential price manipulation and self-fulfilling bear raids (Goldstein and Guembel 2008). Public short campaigns—in which short sellers voluntarily announce their short reports on target firms—can amplify both the beneficial and detrimental roles of short sellers.

Academic research argues that short campaigns, used as a tool to convince the long side to sell, can enable the constrained short side to overcome the limits of arbitrage (Ljungqvist and Qian 2016). Legal practitioners and firm managers, however, have become increasingly concerned about the potential negative effect of short campaigns that can make a firm's stock price plunge without grounded facts.[1] One reason for the concern is that regulators' legal enforcement in this area has been rare. This is partly due to the difficulty in proving short campaigns contain false information, a necessary condition to charge against campaigns as illegal manipulation. This difficulty in legal enforcement creates room for opportunistic campaigns, that is, campaigns that

[1] See J. Katz and A. Hancock, "Short Activism: the Rise in Anonymous Online Short Attacks," Harvard Law School Forum on Corporate Governance and Financial Regulation, November 27,2017; P.M. Weiner, R. Weber, and K. Hsu, "The Growing Menace of 'short and distort' campaigns," August 31, 2017, Westlaw Journal Securities Litigation and Regulation.

are not driven by information but published to artificially drive down prices to benefit previously built short positions. While opportunistic campaigns may not necessarily contain false information, they can however add excessive price movements to the market, causing losses for investors and diverting managers' attention from improving real efficiency. The goal of this paper is to find *ex ante indicators* for opportunistic behavior in short campaigns. These indicators can help investors become less prone to opportunistic campaigns, thus reducing their effectiveness, and hopefully, acting as a substitute for weak legal enforcement, discipline opportunistic behavior in short campaigns.

Opportunistic campaigns might be effective, because investors, without systematic and statistical analyses of historical campaign data, may not be able to separate them out from the informative ones. First, opportunistic authors have incentives to make opportunistic campaigns appear as informative as possible, making it difficult for investors to differentiate them ex ante. Second, even a campaign is proved wrong ex post, the possibility of honest errors encumbers investors to immediately conclude the campaign author as the opportunistic type.[2] In addition, campaign authors who are the opportunistic type may not always act opportunistically but may at times incur information discovery effort to publish informative reports to pool with the non-opportunistic type. Finally, even if the opportunistic campaigns can sometimes be seen through by some sophisticated investors, because of the unpredictable timing of the campaign publication, the price correction may require extra liquidity, and thus not be timely enough to completely foil the opportunistic effort.

A systematic analysis of historical campaign data has the potential to identify indicators for opportunistic campaigns, as opportunistic campaigns will in the end exhibit a statistically higher

[2] The limited number of illegal manipulative short campaigns in the past decades indicates that it is also hard to summarize characteristics of manipulative campaigns from the past litigation data.

likelihood of errors than honest information-driven campaigns (Benabou and Laroque 1992). However, if the time series of data is not long enough, or if the opportunistic type authors have successfully implemented a mixed strategy, a statistically reliable indicator for opportunistic campaigns may not be identifiable from the data.

My methodology adopts a cross-sectional approach that is consistent with the idea in Benabou and Laroque (1992). The empirical strategy is to detect campaigns that systematically and statistically deviate from normal campaigns in a way that suggests they are more likely to be opportunistic. This approach is similar to how accounting literature identifies earnings management where the normal earnings process is estimated from the sample and only the residual is attributed to possible earnings management (Jones 1991; Dechow and Dichev 2002). In my paper, the market performance of normal short campaigns and short-sale activities before normal campaign publications are estimated from the sample and only the residuals are exploited to find indicators for opportunistic behavior.

In particular, the goal is to find whether certain short campaigns, compared to normal campaigns, (1) are more likely to be wrong ex post with their targets performing better in the long run, and (2) are also associated with higher abnormal short-sale activities prior to campaign publication aiming to capitalize on the short-term price declines. Condition (1) is included to detect a greater likelihood of errors, which suggests opportunistic behavior as in the theory of Benabou and Laroque (1992). If Condition (1) is satisfied, Condition (2) helps understand the incentive behind a greater likelihood of errors, and higher short-sale activities before campaign publication imply greater profits from the short-term price declines.

For opportunistic short sellers who do have material bad news, clustered campaigns can be a desirable persuasion tool to increase market impact. A network of non-information driven authors may intentionally collude and coordinate publications, or opportunistic authors, without disclosing their opportunistic incentive, may successfully convince others to publish together with them. Clustered campaigns can amplify market reaction based on both behavioral and rational theories. First, clustered campaigns can direct more investors' limited attention to the target firm by increasing saliency (Hirshleifer 2015). Second, DeMarzo, Vayanos, and Zwiebel (2003)'s model shows that individuals with bounded rationality are subject to persuasion bias; that is, they fail to account for possible repetition in the information they receive. Following this argument, investors would be more predictably swayed toward short sellers' views, the more short campaigns they see.

On the contrary, clustered short campaigns could reflect a simultaneous discovery of multiple independent bearish signals or multiple negative independent interpretations triggered by the arrival of one common event. Assume the likelihood of a stand-alone, information-driven campaign being wrong is 0.1, and then the likelihood of two independent and information-driven campaigns being wrong would be even lower at 0.01.[3] Thus, ex ante, it is not clear whether clustered campaigns are more informative or more opportunistic.

By studying short campaigns collected by Activist Insights (AI) and published on Seeking Alpha (SA) from 2010 to 2015, I find that clustered campaigns are systematically and statistically different from regular non-clustered campaigns in a way that suggests a greater likelihood of opportunistic behavior among clustered campaigns. While experiencing greater short-term price declines, targets of clustered campaigns exhibit significant better long-run performance that those of non-clustered campaigns, which suggests clustered campaigns are more likely to contain errors. In addition, clustered campaigns are associated with abnormally higher per-campaign short sale

[3] Clustered campaigns could also arise from information sharing initiated by information-driven authors. However, as long as the first author is independently informed, the likelihood of clustered campaigns being wrong should be no greater than 0.1, which should still be lower than the likelihood of an opportunistic campaign being wrong.

volume right before campaign publication, aiming to profit from the greater negative market reaction. Together, these two findings suggest a greater presence of opportunistic behavior among clustered campaigns.

One alternative explanation could be that clustered campaigns are driven by higher competition among short sellers due to the arrival of a common information event, which in turn triggers the clustering of short-sale trades and the clustering of short reports that are premature, contributing to a greater likelihood of errors. Using news releases from Dow Jones Equity provided by the Raven Pack News Analytics, my results show that in the subsample of campaigns immediately preceded by news release, there is neither evidence that clustered campaigns are more likely to be errors nor evidence that clustered campaigns are associated with higher per-campaign abnormal short-sale volume. Rather, the better long-run performance and higher per-campaign abnormal short-sale volume associated with clustered campaigns only exist in the subsample of campaigns with no preceding news release. The evidence provides some comfort that clustered campaigns' greater likelihood of errors are not due to the arrival of common news events and the resulting competition among short sellers.

I conduct several cross-sectional tests to provide corroborative evidence for my main findings. Specifically, I expect to find clustered campaigns more likely to exhibit opportunistic patterns in the subsamples in which the incentive or ability to engage in opportunistic clustering is higher. First, prior research shows that smaller firms are more likely to be targets of manipulation (e.g., Leuz, Meyer, Muhn, Soltes, and Hackethal 2017). Consistent with the literature, I find that clustered campaigns are opportunistic only in the subsample of smaller firms, which are, ex ante, more likely to be the target of price manipulation due to their poor information environments. Second, I divide the sample based on the campaign authors' network position. A well-connected network position makes both collusion and spreading short ideas easier for an opportunistic campaign author. The analyses demonstrate that clustered campaigns indicate a higher likelihood of opportunistic behavior only in the subsample in which campaign authors are well-connected, whereas clustered campaigns in the low-connectedness subsample do not. Finally, I exploit the variation in the transparency of authors' real identities. Authors with more transparent real identities have greater concerns of their reputation, and are thus less likely to be opportunistic. Consistently, the stock-return pattern and abnormal short-sale pattern associated with clustered campaigns that are suggestive of opportunistic behavior do not exist in the subsample where authors' real identities are publicly available; they only concentrate in the subsample where authors only have their online accounts publicly available.

In robustness analyses, I find that my inferences hold after adding additional controls such as campaign authors' past performance, number of followers, an indicator for author-reported short positions in target firms, and campaign reports' textual features including readability, specificity, and the amount of negative information in financial context. In addition, I find my results robust to author fixed effects. Furthermore, my inferences hold if I define clustered campaigns at month level. Finally, I explore the predictability of title and text similarity of clustered campaigns. The results indicate that higher title similarity scores predict lower long-run returns. This evidence implies that among clustered campaigns, more similar titles suggest a greater consensus among short sellers, which has information content, whereas seemingly different tiles might be a result of opportunistic authors' deliberate effort to make them so.

This paper is motivated by and contributes to three strands of literature. First, it is related to the literatures on persuasion bias (DeMarzo, Vayanos, and Zwiebel 2003; DellaVigna and Gentzkow 2010) and limited attention (Hirshleifer 2015; Michaely, Rubin, and Vedrashko 2016;

Chakrabarty, Moulton, and Wang 2016). My study adds to this literature by providing empirical evidence on how sophisticated investors, such as short sellers, capitalize on persuasion bias or saliency for their own benefit. Second, the paper contributes to the literature on price manipulation (Goldstein and Guembel 2008; Blocher, Engelberg, and Reed 2009; Leuz, Meyer, Muhn, Soltes, and Hackethal 2017). Specifically, to the best of my knowledge, this is the first study to propose an empirical approach to identify opportunistic behavior in public short campaigns. Future research can use this approach to explore other potential indicators for opportunistic behavior in addition to clustering. Finally, this study adds to the emerging literature on the disclosure of short positions and the publication of short campaigns (Jones, Reed, and Waller 2016; Ljungqvist and Qian 2016; Chen 2014; Zhao 2017). By comparing target firms and non-target firms, Ljungqvist and Qian (2016) find short campaigns help overcome limits of arbitrage; and Zhao (2017) conclude that firms with certain characteristics such as overvaluation and greater uncertainties are more likely to be targets of activist short-selling. Different from these papers, my paper focuses on short-seller's campaign strategy and identifies indicators for opportunistic behavior.

2. Related Literature

2.1 Literature on Price Manipulation

Stock market manipulation—activities to artificially influence stock prices—has been an important issue since the start of Amsterdam Stock Exchange in the seventeenth century. Depending on what deceptive tools are involved to change actual or perceived asset values, Allen and Gale (1992) classify price manipulation into three categories: action-based manipulation that involves real economic actions such as the opening or closing of factories, trade-based manipulation that involves artificial trading activities, and information-based manipulation that involves false information.

More recently, Kyle and Viswanathan (2008, 275) point out the difficulty in defining "illegal price manipulation," as "definitions of price manipulation have long reflected a tension between subjective approaches ("the smell test") and more scientific approaches based on economic efficiency." In their framework, information-based manipulation, however, meets the definition of illegal price manipulation. If a short campaign contains false information and is published to artificially dampen the target's stock price, it is one form of information-based manipulation. In particular, former SEC Chairman Christopher Cox labeled such schemes as "distort and short." They violate both the Securities Exchange Act Antifraud Provisions and SEC's Rule 10b-5 (Weiner, Weber, and Hsu 2017). Nonetheless, only a handful of cases against "distort and short" have been enforced by the SEC to date. The legal review of Walker and Forbes (2013, 1) concludes that "the SEC has appropriately brought enforcement cases only in clear-cut instances of fraud."

The very limited number of enforced cases makes it difficult to do a large scale examination of illegal short campaigns similar to what Leuz, Meyer, Muhn, Soltes, and Hackethal (2017) do with pump-and-dump schemes in Germany. The high hurdle in proving short campaigns as illegal manipulation leaves room for opportunistic campaign behavior. This paper contributes to the literature by proposing an empirical approach motivated by the theory of Benabou and Laroque (1992) to identify ex ante indicators for opportunistic campaign behavior. Hopefully these indicators, by increasing investors' awareness of and scrutiny over the opportunistic behavior, can work as a substitute for the weak legal environment to discipline opportunistic short campaigns.

2.2 Literature on Short-Selling Transparency

Recently, regulators have enhanced the disclosure of short-sale activities as a policy response to the financial crisis. For example, after September 2009, the Financial Industry Regulatory Authority (FINRA) began publishing daily aggregate short-sale volumes for each stock on its website. Internationally, the U.K., Spain, and France have adopted a requirement (that later became a pan-European requirement) that large short positions must be disclosed. By using that European setting, Jones, Reed, and Waller (2016) suggest that the *mandatory* short-position disclosure requirement is not used as a coordinating mechanism among short sellers. While their research focuses on the relation between short-selling behavior and mandatory disclosure of short positions, this paper investigates how short-selling behavior is associated with voluntarily published short campaigns.

Relatedly, Karpoff and Lou (2010) study the short-selling pattern before the announcement by securities authorities of financial misconduct. Khan and Lu (2013) find that short sellers front-run insider sales. Christophe, Ferri, and Angel (2004) and Christophe, Ferri, and Hsieh (2010) show that short sellers front-run analyst downgrades and negative earnings announcements. My setting is different from those examined in these papers in two ways. First, financial misconduct announced by authorities or other information events examined in the literature are negative events without much uncertainty. By contrast, short campaigns only reflect short sellers' opinions, which could be either correct or incorrect ex post. Second, short sellers cannot control the timing of other external information events, but they are better able at controlling the timing of short campaign publications.

Other studies, including Ljungqvist and Qian (2016) and Zhao (2017), also examine short-campaign data. By using campaigns from arbitrageurs, whose real identities are mostly available, Ljungqvist and Qian (2016) examine how the publication of short reports relaxes the constraints on arbitrage. By comparing target firms with non-target firms, Zhao (2017) finds that firms with certain characteristics such as overvaluation and greater uncertainties are more likely to be targets of activist short-selling. Different from these studies, this paper studies short-seller's campaign strategies, and aims to detect opportunistic behavior.

2.3 Literature on Persuasion, Limited Attention, and Social Finance

This paper is also related to the literature on investors' limited attention. Previously, studies have shown that investors "tend to neglect low salience signals and overreact to salient or recent news" (e.g., Hirshleifer 2015, 140). For example, when news appears on the front page of *The New York Times*, it helps correct investors' underreaction to changes in the value of underlying assets of country funds (Klibanoff, Lamount, and Wizman 1998). In addition, previous research shows that investors pay less attention on Fridays (DellaVigna and Pollet 2009). Other papers find evidence that managers take advantage of investors' low attention to hide bad news (Doyle and Magilke 2009; deHaan, Shevlin, and Thornock 2015; Michaely, Rubin, and Vedrashko 2016). Chakrabarty, Moulton, and Wang (2016) find that high-frequency trading, following low-attention earnings announcements, reduces price inefficiencies.

Another strand of literature has examined the effect of persuasion. DellaVigna and Gentzkow (2010) summarize that persuasive messages can affect behavior either by changing beliefs or by changing preference independently of beliefs. DeMarzo, Vayanos, and Zwiebel (2003) develop a theory in which bounded rationality leads to persuasion bias; that is, individuals fail to account for possible repetition in the information they receive. While prior research has focused on how firm managers and financial analysts persuade investors (Hirshleifer, Hou, and Zhang 2004; Malmendier and Shanthikumar 2007), this paper sheds lights on the behavior of short sellers and short-campaign authors. Most importantly, this paper adds to both the literatures on investor behavior or persuasion by providing empirical evidence on how sophisticated investors such as short sellers capitalize on persuasion bias or saliency for their own benefits.

In addition, my article is also related to the literature on social finance, particularly the emerging literature on information networks. Prior research has shown that social networks affect investment decisions (Ivković and Weisbenner 2005; Kaustia and Knüpfer 2012) and that traders with more connections earn higher profits (Ozsoylev, Walden, Yavuz, and Bildik 2014). Similarly, the social network effect has been identified in insider trading (Ahern 2017) and among sell-side analysts and mutual-fund managers (Hong, Kubik, and Stein 2005; Cohen, Frazzini, and Malloy 2008; Cohen, Frazzini, and Malloy, 2010). Jones, Reed, and Waller (2016) find that mandatory short-position disclosures from large or centrally located discloser are likely to be followed by other disclosures. This paper adds to the literature by introducing an empirical measure of networks among short sellers, and studies how short sellers' connectedness in the network is related to opportunistically clustered campaigns.

3. Hypothesis Development

Clustered campaigns can increase market impact according to both behavioral and rational theories. According to the behavioral theory, investors "tend to neglect low salience signals and overreact to salient or recent news" (Hirshleifer 2015, 140). If clustered campaigns make the short sellers' opinions more salient, they can direct more investors' limited attention to the target firm. Even without any behavioral bias, bounded rationality, as shown by DeMarzo, Vayanos, and Zwiebel (2003), can result in a persuasion bias; that is, individuals fail to account for possible repetition in the information they receive. Therefore, the more short campaigns investors see, the more likely they will be persuaded by the short side. For opportunistic campaign authors who are not driven by information but would like to move the market for the benefit of previously built positions, clustered campaigns are a desirable tool. A network of non-information driven authors can collude and coordinate publications, or opportunistic authors, without being honest about their opportunistic incentives, can convince others to publish with them.

In an extreme case, one Seeking Alpha contributor used multiple aliases to submit different reports on the same firm at the same time in an effort to gain market impact. Even though such behavior is not permitted by Seeking Alpha and triggered an investigation later by both Seeking Alpha and the SEC, it indicates how clustering reports together can be a desirable way to artificially affect stock prices.[4]

On the contrary, clustered short campaigns can reflect a simultaneous discovery of multiple independent bearish signals or multiple negative independent interpretations triggered by the arrival of one common event. Assume the likelihood of a stand-alone, information-driven campaign being wrong is 0.1, then the likelihood of two independent and information-driven campaigns being wrong would be 0.01. Even if there could be information sharing or herding among informative authors, as long as the first campaign is independently driven by information, the likelihood of clustered campaigns being wrong should be no greater than 0.1. If clustered campaigns, however, are more likely to involve opportunistic authors who are not driven by information, the likelihood of clustered campaigns being wrong would be greater than 0.1.

[4] Seeking Alpha's term of use includes a requirement that "one author may maintain only one account." Thus, an individual maintaining different aliases and releasing reports on the same firm at the same time is expressly prohibited. For more details on the investigation, please see "https://www.thestreet.com/story/12327045/1/galena-biopharma-pays-for-stock-touting-campaign-while-insiders-cash-out-millions.html?kval=dontmiss. Thus, same author publishing under different aliases is very risky and can be detected by Seeking Alpha. As the underlying mapping of alias and real identities are not public available, however, the paper assumes each different alias is a different author and cannot completely rule out the possibility of same author having different aliases

Based on the above discussion, it is not obvious ex ante whether clustered campaigns are more opportunistic or more informative than non-clustered campaigns. I state my hypothesis as the following (in the alternative form):

H1: *Clustered campaigns are more likely to be opportunistic than non-clustered campaigns.*

4. Data and Sample

My sample of short campaigns is from two data sources, similar to Zhao (2017). The first source is Activist Insights (AI), a data firm that profiles hedge funds, individuals, and shareholder groups that employ activist investment strategies. AI recently bought Activist Short Research, which is dedicated to tracking activist short campaigns. Activist short campaigns are initiated by those who have such negative views on target firms that they publicly announce their short campaigns instead of shorting the firm quietly. The short campaign data collected by AI is available from 2010 to 2015.

My second data source is Seeking Alpha (SA), a crowd-sourced investment research website. My choice of SA is motivated by its large user base, and prior studies show that the linguistic sentiment of SA articles and commentaries is useful in predicting future stock returns (Chen, De, Hu, and Hwang 2014). In addition, even though most authors publish anonymously on SA, SA short campaigns can have immediate and prolonged negative market impact.[5] To match the sample period of the AI sample, I downloaded all the articles published from 2010 to 2015 under the short-

[5] Katz and Hancock (2017) collect examples of SA short campaigns that have triggered 30% to 50% price declines in their target firms. See J. Katz and A. Hancock, “Short Activism: the Rise in Anonymous Online Short Attacks,” Harvard Law School Forum on Corporate Governance and Financial Regulation, November 27,2017

idea section of SA, a section of articles dedicated to short ideas. When a short-idea article contains multiple tickers, I manually identify the firm associated with the short campaign. I exclude a short campaign if it is not focused on a single firm or if it targets an industry rather than a firm. Combining the AI and SA data gives me a more comprehensive sample, as campaign authors who are proactively followed by AI do not usually contribute articles to SA, and campaign authors who publish on SA are usually not covered by AI. A more comprehensive sample reduces the risk of misclassifying a campaign as non-clustered when it is in fact clustered. In addition, AI campaign authors are usually hedge funds or research firms with transparent real identities, whereas SA authors only have their online accounts publicly available. Thus, another reason I include both data sources is to explore the difference in the transparency of authors' real identities, and consequently study how variation in authors' concerns of reputation affects their opportunistic behavior.

I then link the data to CRSP/COMPUSTAT to calculate abnormal stock returns and necessary control variables. Next, I download the daily short transaction data from FINRA's website. Pursuant to the SEC's request, FINRA started to report daily short-sale transaction data, which are available from August 2009. The Monthly Short Sale Transaction Files provide detailed trade activity for all off-exchange short-sale trades reported to a consolidated tape via NASDAQ's or NYSE's reporting facilities. Daily short interest, which aggregates uncovered short positions across different trading venues, is proxied by the number of shares on loan from a network of brokers covered by Markit securities lending data, consistent with Ljungqvist and Qian (2016).

One limitation of the short-sale data I use is that it is aggregated at daily level and lacks detail to trace each individual short seller's positions. This problem is worsened by the anonymity of SA campaigns. Hence I assume that each campaign author and those who join the process of building short positions before the campaign publication are one short entity, and investigate how certain campaign strategies benefit that one short entity. For example, some hedge fund short sellers may hire people to write and publish short campaign reports on the target firms they have shorted or plan to short. Alternatively, some campaign authors can also grant short sellers early access to the campaign reports, which will enable these short sellers to join the process of building short positions before the campaign publication. Due to data limitations, the detailed profit-sharing mechanisms are outside the scope of this paper.[6]

To be included in the final sample, each observation must have a non-missing publication date and non-missing PERMNO and GVKEY identifiers, resulting in 9,514 campaigns. I further require non-missing abnormal return on the publication date and in the first five days after the campaign publication and non-missing return and volume data from 90 days to 10 days prior to campaign publication. These filters result in 7,983 unique campaigns. Finally, the regression analyses further require non-missing short-sale metrics and non-missing long-run returns, leaving about 6,838 observations in the regressions.

5. Empirical Results

5.1 Descriptive Evidence

I first show the short-term and long-term stock market performance of short campaigns based on the entire sample. To measure the short-term market performance, I focus on the abnormal return on the publication day, *AR[0]*, and the buy-and-hold abnormal return in the [1,5] and [1,20] windows after the campaign publication, *BHAR[1,5]* and *BHAR[1,20]*. The daily abnormal return is adjusted using DGTW benchmark portfolios (Daniel, Grinblatt, Titman, and Wermers 1997)

[6] In additional analyses, I collect an indicator that indicates whether authors have short positions in the target firms, which is available for campaigns published on Seeking Alpha. This provides some insights on whether authors themselves benefit from opportunistic campaigns. The short-position indicator, however, is self-reported and does not show the size of the positions.

consistent with Ljungqvist and Qian (2016). In Table 1, I show that there is significant negative market reaction to short campaigns—the abnormal return on the publication is ranging from 30 to 100 basis points. The median one-year DGTW-adjusted return after campaign publication (i.e., *BHAR[1,250]*) is -4%, significant at 5.6%, indicating short campaigns' predictability of lower long-term return. The mean of the one-year DGTW-adjusted return is however insignificant at 1.1%. The fact that the median is smaller than the mean suggests that the distribution of *BHAR[1,250]* is right skewed; that is, *BHAR[1,250]* is negative for most campaigns but there must be some campaigns whose *BHAR[1,250]* is very positive and lies in the right tail of the distribution. Those are the short campaigns that are proved wrong in the long run ex post.

I then decompose my sample into clustered and non-clustered campaigns and examine whether the *BHAR[1,250]* of clustered campaigns is more likely to lie in the right tail of the distribution. Clustered campaigns are defined as multiple campaigns published by different authors on the same target firm and on the same date. The main advantage of defining clustered campaigns as multiple campaigns published on the same *date* is to obtain a clear definition of the publication date, so that the short-term market reaction as well as the short-sale volume right before the publication date can be measured with greater accuracy. In addition, defining clustered campaigns as campaigns published on the same date reduces the likelihood that the clustering is driven by one campaign author copying another.[7] In additional analyses, I explore the robustness of my results by measuring clustered campaigns at month level (see Section 6).

In panel B of Table 1, I find that average *BHAR[1,250]* for clustered campaigns is very positive at 5.8%, and close to zero (i.e., 0.6%) for non-clustered campaigns, with the difference

[7] According to Seeking Alpha, articles will normally be published within 24 hours of submissions if no major revisions are needed. Because of the 24-hour delay for an article to go through the publication process and get published on Seeking Alpha, it is unlikely that one campaign author can simply copy others and publish his or her campaign on the same date.

between the two significant at 5%. In addition, even though clustered campaigns are more likely to be errors ex post, they are reacted more negatively on the publication day and in the first five days after campaign publication. The difference of *AR[0]* and *BHAR[1,5]* between clustered and non-clustered campaigns are both negative and significant at 1%.[8]

In Figure 1, I plot DGTW-adjusted buy-and-hold returns for firms targeted by clustered and non-clustered campaigns in the [1,250] window after campaign publication. Consistent with the evidence in Panel B of Table 1, firms targeted by clustered campaigns perform worse in the short run, but the buy-and-hold abnormal returns start to reverse around 40 days after the campaign publication. At about 50 days after campaign publication, targets of clustered campaigns perform similar to those of non-clustered campaigns, and at the end of a one-year holding period, clustered-campaign targets show better performance than non-clustered campaign targets.

The return analyses above suggest that clustered short campaigns are more likely to be wrong ex post, but they generate greater short-term price declines that would potentially benefit short positions built before campaign publication. Next, I examine the short-sale activities prior to campaign publication. *Absale[-1]adj* is the abnormal short-sale volume one day prior to the campaign publication date, divided by the number of reports published by different authors on the campaign publication date. The reason I examine the abnormal short-sale volume on the last day *before* campaign publication is to capture the latest short-sale trades that can be executed prior to the campaign publication. In addition, I divide the abnormal short-sale volume by the number of campaigns published by different authors to ensure that a higher volume before clustered campaigns is not a mechanical result from a greater number of different campaign authors.

[8] The reason that I use DGTW-adjusted abnormal return is to make sure that the better long-run performance of clustered campaigns is not due to certain firm characteristics or certain pricing/risk factors. I obtain similar inferences using raw returns.

Abnormal short-sale volume is defined as the short-sale volume on a given day minus the normal short-sale volume in the [-60,-11] window relative to the publication date. Daily short-sale volume is the aggregate volume of the executed short-sale trades reported on FINRA's website standardized by shares outstanding. While short-sale volume on the last day before campaign publication reflects the amount of trading activities that are just in time to capitalize on the short-term market reaction to the publication, the cumulative uncovered short positions—short interest—indicate the overall negative beliefs on firms. The idea that short interest is informative and can predict lower future returns is supported by both theoretical and empirical studies (Diamond and Verrecchia 1987; Desai, Ramesh, Thiagarajan, and Balachandran 2002; Asquith, Pathak, and Ritter 2005). I measure daily short interest by the "quantity on loan" variable from the Markit Lending database, standardized by shares outstanding. "Quantity on loan" measures how many shares are on loan from lenders that borrowers borrow for short-sale purpose. *ABSI[-1]*, abnormal short interest on the last day before campaign publication date, is defined as the short interest on the last day before campaign publication date minus the normal short interest in the [-60,-11] window relative to the publication date.

Panel A of Table 2 shows that abnormal short interest measured right before campaign publication is significantly positive, indicating there are abnormal uncovered short positions prior to short campaign publication. This is consistent with both informative and opportunistic short sellers' incentive to profit from the negative market reaction to the campaign publication.

Regarding the per-campaign abnormal short-sale volume on the last day (i.e., *Absale[-1]adj*), the mean is significantly positive while the median is close to zero (from the negative side) and insignificant. This implies that the distribution of *Absale[-1]adj* is right skewed—a median campaign does not have significant and positive abnormal short-sale volume right before campaign publication but there must be some campaigns that do.

Panel B of Table 2 shows the differences in short-sale metrics between clustered and non-clustered campaigns. In particular, per-campaign abnormal short-sale volume right before campaign publication is significantly higher for clustered campaigns than non-clustered campaigns. The difference in abnormal short interest—the cumulative uncovered short positions—measured right before campaign publication, is not significant. The evidence seems to suggest that clustered campaigns are associated with *a concentration of higher short-sale volume right before* campaign publication, even though their total uncovered short positions prior to campaign publication is not higher than that of non-clustered campaigns.

To gain a more complete picture of short-sale patterns, I plot the abnormal short-sale metrics on each day in the twenty-day window around campaign publication for both clustered and non-clustered campaigns. In Figure 2(a), I plot the pattern of per-campaign abnormal short-sale volume. Prior to campaign publication, clustered campaigns are associated with a concentration of higher per-campaign short-sale abnormal volume on the last day before campaign publication than non-clustered campaigns. Before the last day, clustered campaigns have slightly lower per-campaign abnormal short-sale volume than non-clustered campaigns. In Figure 2(b), I plot the pattern of abnormal short interest. Clustered campaigns are associated with a quicker rise and fall of short interest around publication dates, whereas the increase of short interest before campaign publication is more gradual for non-clustered campaigns and there is not much decline in short interest after non-clustered campaign publication.[9]

[9] The daily short-sale volume may not match up exactly with the daily increase in short interest for the following reasons. First, the executed short-sale volume may include fail-to-deliver trades, which may not affect the short interest proxy in the Markit dataset. Note that the short interest proxy from Markit is based on the number of shares on loan and does not include the number of shares that are failed to deliver. Second, the trades covered by FINRA may be

It is worthwhile to discuss why clustered campaigns are associated with a higher short-sale volume only on the last day but not on other days before campaign publication, given all short positions built before publication date will benefit from price declines on or after the campaign publication date. First, a higher short-sale volume only on the last day before campaign publication may be driven by the difference in the short-selling strategy between opportunistic and information-driven authors. To short and immediately publish reports ("SIP") is a strategy more appealing to opportunistic authors who are not driven by information. SIP allows the short side to cover short positions within a shorter period of time, thus it reduces the cost and risk of carrying short positions (Engelberg, Reed, and Ringgenberg 2018). SIP strategy suggests an establishment of short-sale positions *only when it is very close to* campaign publication. Information-driven authors, by contrast, will spend time in improving the signals they receive and only publish reports when the signals are above certain precision threshold. During the process of improving the signals, if the risk of being front run by other short sellers who may have received the same signal is more important than the cost of carrying a short position, the information-driven authors will start building short positions earlier and not wait until the last minute before campaign publication. It follows that a campaign from an information-driven author is more likely to be preceded by a gradual increase of short positions rather than by a concentration of short-sale volume right before the publication date. Thus, the fact that clustered campaigns are associated with a higher per-campaign short-sale volume only on the last day before campaign publication may suggest that clustered campaigns are more likely to be published by opportunistic authors.

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outside the broker network of Markit. Third, it is also possible that some short-sale trades might be covered within the same day. In Appendix C, I show that fail-to-deliver trades increase to a very high level one or two days before clustered-campaign publication, which might be one reason why the high short-sale volume on those days does not translate to an exact amount of increase in short interest on those days.

Alternatively, it could also be that information regarding the upcoming clustered campaigns only gets shared or leaked not until the last day before campaign publication.[10] If the higher per-campaign short-sale volume on the last day before clustered campaign publication is due to information sharing or leakage, it could either be driven by clustered campaigns' greater information content, or by the anticipation of a greater market reaction caused by the clustering independent of the campaigns' information content.

To summarize, the univariate and descriptive analyses suggest that clustered campaigns are more likely to be wrong ex post than non-clustered campaigns, but they are associated with a higher per-campaign abnormal short-sale volume just in time to capitalize on the immediate negative market reaction to the campaign publication. Taken together, there is preliminary evidence suggesting that there is a greater presence of opportunistic behavior involved in clustered campaigns than non-clustered campaigns.

5.2 Determinants and Abnormal Short Sales Prior to Campaign Publication

I formally examine the relation between clustered campaigns and abnormal short-sale activities before campaign publication using the following empirical model:

$$Clustered = \beta_1 Absale[-1]adj + \beta_2 AbSI[-1] + \gamma X + e \qquad (1)$$

I first explore the determinants of clustered short campaigns, as there is no prior literature examining them. *Clustered* is an indicator that equals one if there is at least one other campaign report published by a different author on the same target firm and on the same date, zero otherwise. As the dependent variable is an indicator, I use logit regressions.

[10] The benefits of sharing or leaking information right before campaign publication but after campaign authors having built most of their own positions are three folds. First, if more short sellers are convinced to build positions, the higher abnormal short-sale activities may send another bearish signal along with the short campaign that can potentially increase the campaign's market impact. Second, sharing information can help campaign authors establish and maintain relationship with other short sellers who may share their campaign reports in the future. Third, campaign authors may obtain direct compensation for the early access they grant other short sellers.

First, I check whether the data source affects the likelihood of clustering. The results in column (1), (2), and (6) indicate that campaigns in the SA sample are more likely to be clustered. Second, I examine the effect of the arrival of news events, and find that the arrival of news event increases the likelihood of campaigns clustering together. Third, I test whether having an author who has previously published short reports on the target firm affects the likelihood of clustering. The analyses demonstrate that *PreAuthor,* an indicator that equals one if the author has previously published short reports on the target firm, is significantly positive. This implies that clustering is more likely when there is preexisting bearish views. This could be either because the preexisting bearish views attract other short sellers' attention, or because the preexisting bearish authors make strategic coordination easier by letting other short sellers know whom to coordinate with. Finally, as shown in column (6), whether the campaign is published in the second half of the year does not significantly affect the likelihood of clustering.[11]

In column 4, the results show that clustered campaigns are significantly and positively related to per-campaign abnormal short-sale volume on the last day before campaign publication (*Absale[-1]adj*). To ensure that the association between clustered campaigns and the abnormal short-sale volume is not due to firm characteristics, I include several control variables, including size, book-to-market ratio, and proxies for a firm's information environment such as institutional ownership, analyst coverage, trading volume, earnings news (i.e., earnings surprise), as well as earnings quality (i.e., total accruals), and voluntary disclosure policy (i.e., an indicator for the existence of a management forecast accompanying earnings news). In addition, Zhao (2017) shows that higher valuation and greater uncertainties attract activists short-selling, consequently I also include target

[11] There is anecdotal evidence that short sellers time their short claims and short-sale activities to be in the second half of the fiscal year, because managers have less discretion in earnings management as it is closer to the fiscal year end when financial statements need to go through a formal audit rather than a periodic review.

firms' cumulative stock returns in the past 90 days to 10 days prior to the campaign publication and uncertainty proxies such as return volatility and analyst forecast dispersion as additional controls. Among firm characteristics, I find that larger firms and firms with better past stock market performance (i.e., lower book-to-market ratio and higher past stock returns) and higher past trading volume are more likely to attract clustered campaigns. Most importantly, *Absale[-1]adj* remains significantly positive in both column 5 and 6 with all controls added. None of the coefficients of *ABSI [-1*] is significant in column 4, 5, and 6. Overall, the regression analyses confirm results from the univariate analyses, that is, clustered campaigns are associated with a significantly higher short-sale volume on the last day before campaign publication.

5.3 Stock Market Reactions and Long-Run Performance

I next examine the stock market reactions and long-run performance of clustered campaigns using the following model:

$$Stock\ Market\ Performance = \beta_1 Clustered + \beta_2 Absale[-1]adj + \beta_3 AbSI[-1] + \gamma X + e \quad (2)$$

In addition to all short-term and long-term return measures defined in section 5.1, I also examine the abnormal short-sale volume on the publication date, *Absale[0]*, as an alternative way to measure short-term market reaction. All determinants of clustered campaigns discussed in section 5.2 including short-sale activities prior to campaign publication are included. If clustered short campaigns are less informative and more likely to be wrong ex post than non-clustered campaigns, β_1 should be positive for *BHAR[1,250]*, which means clustered campaigns predict better long-run performance than non-clustered campaigns. This would be indirect evidence of the opportunistic incentives of clustered campaigns, as Benabou and Laroque (1992) discuss how a manipulative strategy will result in a higher likelihood of errors in the end than a non-manipulative one even though errors are unavoidable for both.

The first column in Table 5 shows the results of short-sale volume on the publication date. The coefficient of *Clustered* is 0.47 and significant at 1% level. This suggests that the abnormal short-sale volume is higher by 0.47% when campaigns are clustered together. The coefficient of *Clustered* is -0.871 and -1.244 for *BHAR[1,5]* and *BHAR[1,20]* respectively, with p-value at 2.5% and 5.2% respectively. Economically, for one unit of short positions, clustered short campaigns generate profits that are 87 basis points higher than non-clustered campaigns during the first five days after campaign publication and 124 basis points higher in the first twenty days after campaign publication. If clustered campaigns are more informative than non-clustered campaigns, the greater market reaction may reflect a more efficient revelation of bad news. However, if clustered campaigns are more likely a result of opportunistic behavior, with their targets performing better rather than worse in the long run, then the greater short-term price declines suggest greater profit for the short sellers who are able to build their positions prior to campaign publications. The campaigns' long-term predictability is presented in the last column with *BHAR[1,250]* as the dependent variable. *Clustered* is significantly positive at 6.44, suggesting that the DGTW-adjusted one-year return of clustered campaigns is 6.44% higher than that of non-clustered campaigns.

In sum, the above analyses based on stock market performance suggest that clustered campaigns contain a higher likelihood of errors than non-clustered campaigns, which is indirect evidence that there is a greater presence of opportunistic behavior among clustered campaigns. The higher abnormal short-sale volume on the last day before clustered campaign publication, as shown in section 5.2, is consistent with an opportunistic incentive to profit from the greater negative reaction to the clustered campaign publications.

5.4 Alternative Explanations and Cross-Sectional Analyses

5.4.1 Common Information Events

One alternative explanation could be that the arrival of public information events results in greater competition among short sellers, triggering both the clustering of short-sale volume and the clustering of premature short reports soon after the events. Under this alternative explanation, clustered reports are of lower quality because of competition rather than short sellers' opportunistic incentives. To mitigate the possibility that clustered campaigns' higher likelihood of errors is not driven by the arrival of public information events and the resulting competition, I repeat the analyses after restricting my sample to campaigns that are immediately preceded by a news release. The results are shown in Panel A of Table 6. The coefficients of *Clustered* for all stock return metrics measured in different windows are negative, even though not statistically significant, which suggests that in the subsample of campaigns with immediately preceding news events, clustered campaigns, if not more informative than non-clustered campaigns, are at least not more likely to be errors. By contrast, in Panel B of Table 6 where the subsample includes campaigns with no preceding news release, *Clustered* is negative for all short-term market return metrics but is significantly positive for *BHAR[1,250]*. In addition, I confirm in panel C of Table 6 that the significant association between clustered campaigns and the higher abnormal per-campaign short-sale volume does not exist in the subsample of campaigns with preceding news release and only exists in the subsample of campaigns without. The finding suggests that the greater likelihood of errors and higher abnormal short-sale volume associated with clustered campaigns are not driven by the arrival of news event, contradictory to the alternative explanation.

Next, I use cross-sectional analyses to provide further corroborative evidence for my main findings. In particular, I expect to find clustered campaigns more opportunistic primarily in the subsamples where the incentive or ability to engage in opportunistic clustering is higher; that is, where firms are more prone to price manipulation (i.e., smaller firms), where campaign authors are better connected, and where authors' concerns of reputation are lower.

5.4.2 Likelihood of Price Manipulation

For my first cross-sectional test, I partition my sample based on the likelihood of a firm being the target of price manipulation. There is ample anecdotal and empirical evidence that smaller firms, such as penny stocks, are often the targets of manipulation due to their poor information environment (e.g., Leuz et al. 2017). Spreading rumors is more difficult with a more transparent information environment, which is one of the reasons why firms are required to issue periodic reports to the public (Allen and Gale 1992). Accordingly, smaller firms should be the more likely targets of opportunistic campaigns. In Table 7, I divide the sample into two groups based on the median market capitalization. Panel B of Table 7 shows market reactions and long-term stock market performance for the subsample of smaller firms. Targets of clustered short campaigns perform significantly better than those of non-clustered campaigns in the long run, with *BHAR[1,250]* being 16.244% higher than those non-clustered campaign. In Panel C of Table 7, in the subsample of smaller targets, clustered campaigns are associated with a significantly higher per-campaign abnormal short-sale volume on the last day before campaign publication. This evidence suggests that clustered campaigns are more likely to be opportunistic than non-clustered campaigns when target firms are smaller.

In the subsample of larger target firms, as shown in Panel C of Table 7, clustered campaigns are also associated with a significantly higher per-campaign abnormal short-sale volume. However, there is no evidence that clustered campaigns contain a greater likelihood of errors than non-clustered campaigns in the subsample of larger target firms. Specifically, Panel A of Table 7 shows that, in the subsample of larger firms, clustered campaigns are associated with a significantly greater negative market reaction in the short run, but there is no evidence of significant better performance in the long run. Thus, the higher short-sale volume before clustered campaign publication in the subsample of larger target firms might be related to the campaigns' information content and compensate short sellers for identifying material bad news. In sum, the analyses based on firm size indicate that clustered campaigns are more opportunistic only in the subsample with smaller targets firms, which are, ex ante, more prone to price manipulation.

5.4.3 Author Connectedness

For opportunistic campaign authors who are not driven by information to cluster short campaigns on the exact same date, private communication is required. Connected campaign authors can simply collude to cluster campaigns together even when all participants know there is not much real information. Alternatively, opportunistic campaign authors can proactively share short ideas and convince others to cluster short campaigns with them, without necessarily being honest about their opportunistic incentives. Either of the above clustering strategies requires the ability to engage in private communication and is easier for those that are better connected to the network.

Given that private communication is ultimately unobservable, I implement a PageRank algorithm to measure authors' observed connectedness, and use it as a proxy for the ability to engage in clustering coordinated by private communication. A higher PageRank score means that an author (i.e., a node) is better connected to others in the network (See details in Appendix B). An advantage of using PageRank to measure author connectedness is that it does not require much demographical information or geographical location of the campaign authors. This strategy suits my research setting because SA authors may not have demographical or geographical information that is publicly available.

The analyses in Panel C of Table 8 demonstrate that clustered campaigns are associated with abnormally higher per-campaign short-sale volume right before campaign publication only in the subsample of campaigns with well-connected authors (i.e., authors with PageRank score in the top quartile). In addition, clustered campaigns from well-connected authors predict better performance in the long run, implying they are more likely to be wrong ex post. The greater negative market reactions they generate however benefit the higher abnormal short-sale volume built right before campaign publication. The evidence suggests that when authors are well connected, clustered campaigns are more likely to be opportunistic than non-clustered campaigns. On the contrary, there is neither a higher likelihood of errors nor higher abnormal short-sale volume associated with clustered campaigns in the subsample of campaigns with low-connected authors (i.e., authors with PageRank in the bottom quartile). Overall, the evidence suggests that only clustered campaigns from well-connected authors are more likely to involve opportunistic behavior.

5.4.4 Reputation as a Disciplining Mechanism

Finally, I study the disciplining effect of reputation. First, when authors' real identities are more transparent, they are less likely to be opportunistic and better motivated to protect their reputation. Whereas campaigns collected by AI are primarily from hedge funds or research firms with real identities, campaigns published on SA are from authors with only online accounts publicly available. The reputation damage is thus of higher stake to AI campaign authors than SA campaign authors. Therefore, AI campaign authors have less incentive or less ability to be opportunistic.

In Table 9, I divide the sample into campaigns from AI and campaigns from SA. In the subsample of SA campaigns, in Panel A of Table 9, clustered campaigns are associated with a significantly lower short-term return but significantly higher return in a one-year period, which suggests that clustered campaigns in SA are more likely to be errors ex post. In Panel C of Table 9, clustered campaigns in SA subsample are associated with a higher per-campaign abnormal short-sale volume right before campaign publication, consistent with an opportunistic incentive to capitalize on the greater negative market reaction to clustered campaigns.

By contrast, in the subsample of AI campaigns, in Panel B of Table 9, the coefficients of *Clustered* are negative for all stock return metrics (not significant). This pattern seems to suggest that, in the AI sample, clustered campaigns, if not more informative than non-clustered campaigns, are at least not more likely to be errors. In Panel C of Table 9, clustered AI campaigns are associated with higher per-campaign abnormal short-sale volume right before campaign publication than non-clustered AI campaigns. The higher short-sale volume might be a way to compensate the identification of bad news, as there is no evidence of greater opportunistic behavior involved in clustered AI campaigns. In sum, the analyses suggest that when campaign authors' real identities are more transparent to the investors, their clustered campaigns are less likely to be opportunistic, as the authors care more about their reputation.[12]

[12] The results only suggest that AI authors care more about their reputation than SA authors, and do *not* indicate that SA authors do not care about their reputation. If each SA authors may maintain only one account according to SA' s term of use, they have incentives to maintain their reputation. However, reputation damage is of lower stake to SA authors than to authors with real identities publicly available, because SA authors can always register another online account in another platform or open another new blog whereas it is much harder for authors to change their real identities.

6. Additional Analyses and Robustness Tests

First, I show my results are robust to the inclusion of campaign reports' textual features, self-reported short-position disclosure, and additional author characteristics. I do not include these controls in my main analyses, because these controls add additional restrictions on my sample. First, textual data for AI campaigns are not readily available because the campaign can take the form of a presentation in an investor conference. Second, the data on number of followers as well as self-reported short-position disclosure are only available for SA campaigns.[13] Third, to calculate the record of an author's past campaigns requires the existence of at least one campaign published 12 months prior to the current campaign publication, so that the past campaign's long-term performance can be measured. In Table 10, I first add textual features according to prior literature, including frequency of negative words in financial context (Loughran and McDonald 2011), readability (Li 2008; Loughran and McDonald (2014), specificity (Hope, Hu, and Lu (2016). I then add the author's number of followers, author's past campaign performance, and an indicator for whether the author reports a short position on target firm. I find that my results hold after including these additional controls.[14] In addition, I find my results robust to author fixed effects in Table 11, which suggests that even within the same author, clustered campaigns are more likely to be errors than non-clustered campaigns. This further indicates that my results are not driven by time-invariant author characteristics.

Second, I make use of the author-reported position disclosure included in SA campaign reports to examine whether authors themselves are more likely to build positions when they cluster

[13] Research firms, such as Citron Research and Muddy Waters Research, may provide a general legal disclaimer on their websites but omit indicating their positions on each of their short reports. Due to this reason, I did not collect position disclosure for AI campaigns.

[14] Using either length or file size as a proxy for readability does not affect my inference. To avoid a potential collinearity issue, I only include file size in the regression.

their campaigns opportunistically. Even though it is impossible to exactly trace how much of the short positions prior campaign publication are built by authors, this test at least provides some insights on whether authors themselves benefit from opportunistic clustering. Disclosure statements are automatically scripted from SA campaign reports and coded using a computer program. *Position Disclosure* is equal to one if authors disclose they are shorting the stocks and zero otherwise. Table 12 shows that clustered campaigns are associated with a higher likelihood of authors reporting short positions in the target stock only in the subsamples where they are more opportunistic; that is, where target firms are smaller and where authors are more connected. The evidence suggests that, by building short positions, authors themselves do benefit from opportunistically clustered campaigns.[15]

In addition, I explore whether stock market performance varies with the text similarity and title similarity of clustered campaigns. It is not very obvious ex ante whether a higher similarity score implies a greater or lower opportunistic incentive. On one hand, a higher similarity score might be an indication that the clustered campaigns are repetitive, being driven by correlated information. On the other hand, a higher similarity score can also be driven by a stronger consensus among short sellers, which indicates clustered short campaigns' worse information content. In addition, opportunistic campaign authors may act strategically and intentionally make their clustered campaigns look different from each other, in which case a lower similarity score might reflect a greater opportunistic incentive. To test this question empirically, I restrict my sample to clustered campaigns only and calculate the similarity score for their texts and titles using term frequency–inverse document frequency and the Gensim python library.

[15] Campbell, DeAngelis, and Moon (2017) find that author-reported long (short) positions increase the credibility of long (short) SA articles. Thus, the results is also consistent with authors using the position disclosure to increase the credibility of their reports when they are more opportunistic.

In Table 13, I find that clustered campaigns with higher similarity scores based on the campaign report title are associated with lower future returns in one-year period. The evidence suggests that a stronger consensus has information content; and clustered campaigns with more different titles might be a result of opportunistic authors intentionally making their campaigns look different.

Finally, I test the robustness of my results using an alternative proxy for clustering in Table 14. Specifically, I relax the definition of clustered campaigns to be campaigns published on the same day and examine the number of campaigns published by different authors on the same target within a month. The analysis is at the firm–month level. I examine the target's stock-market performance in the following month, six months, and twelve months. I benchmark the target firm's return on its benchmark DGTW portfolio (Daniel, Grinblatt, Titman, and Wermers 1997). Panel A shows the results of the full sample. In particular, targets with multiple short campaigns perform significantly better rather than worse in the six- and twelve-month periods following the campaign publication. To make sure the results are not due to differences in the campaigns across SA and AI samples, I further restrict my sample to SA campaigns only. In Panel B of Table 14, targets with multiple campaigns within a month perform significantly worse in the following month, implying a greater short-term market reaction to clustered campaigns, but they show a significantly better long-run performance by outperforming targets of non-clustered campaigns by 2.4% percent in the six-month period and by 7.8% in the twelve-month period. The analyses using the alternative proxy provide further support that campaigns clustered together are more likely to be errors ex post, indicating a greater presence of opportunistic incentives.

7. Conclusion

Publicly announced short campaigns have become more and more popular in recent years, as investment research platforms provide short sellers with instant access to a wide audience at very low cost. While short campaigns can help the revelation of bad news, they can also cause excessive short-term price declines of their target firms even though they may be proved wrong ex post.

This paper proposes an empirical approach to detect opportunistic campaign behavior in public short campaigns. Specifically, I examine (1) whether certain types of campaigns are more likely to contain errors than normal campaigns, and (2) whether the same types of campaigns are also associated with abnormally higher short positions built right before campaign publication to capitalize on the immediate negative market reactions. Condition (1) is included to detect a greater likelihood of errors, which suggests opportunistic behavior as in the theory of Benabou and Laroque (1992). If Condition (1) is satisfied, Condition (2) implies that the short side generate more profit from the opportunistic campaigns.

My empirical analyses indicate that clustered short campaigns exhibit a higher likelihood of errors than non-clustered campaigns, and they are also associated with abnormally higher per-campaign short-sale volume right before campaign publication aiming to profit more from the excessive short-term price decline. The evidence suggests that there is a greater presence of opportunistic behavior among clustered campaigns. Cross-sectional analyses further show that clustered campaigns indicate a greater likelihood of opportunistic behavior only in the subsamples where the incentive and ability to engage in opportunistic clustering is higher—where target firms are more prone to price manipulation, authors are better connected, and authors' reputation concerns are lower.

Opportunistic behavior—while perhaps falling in a legal grey area—is detrimental to both target firms and investors. Target firms, attacked by opportunistic campaigns, are often caught in a dilemma. They need to respond to the campaign to stop the price declines but defensive actions such as suing the short attackers might draw more attention and further amplify the negative impact of the attack. Thus, to deal with opportunistic short attacks often requires a significant amount of time and resources that could be better spent on other projects to improve real efficiency. For investors who long the target firm, opportunistic short campaigns can make them sell at a very low price that later reverses; and opportunistic campaigns can cause losses for other investors who do not own but short sell the target firm following the campaign reports and are later caught up in the process of return reversals.

This paper illustrates that, with a time-series of short campaign data that is long enough and short-sale data at daily level, it is possible to identify ex ante indicators for opportunistic behavior. These indicators would help investors to become less prone and regulators pay more attention to opportunistic campaign strategies, and hopefully in the long run can discipline opportunistic campaign behavior, reducing deadweight losses in real efficiency and unnecessary volatility in the market.

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Appendix A: Variable Definitions

Abnormal Return	
AR[0]	Abnormal return on the publication date. Daily abnormal return is the raw return adjusted by the return of DGTW benchmark portfolios.
BHAR[a,b]	The buy-and-hold abnormal returns during the event window [a, b] relative to publication date 0. Daily abnormal return is the raw return adjusted by the return of DGTW benchmark portfolios.
Abnormal Short Sale	
Absale[0]	Abnormal short-sale volume on the campaign publication date. Short-sale volume is standardized by shares outstanding. Abnormal short-sale volume is defined as the short-sale volume on a given day in the event window minus the normal short-sale volume in the [-60,-11] window.
ABSI[-1]	Abnormal short interest measured on the last day before campaign publication. Short interest is standardized by shares outstanding. Abnormal short interest is defined as the short interest on a given day in the event window minus the normal short interest in the [-60,-11] window before the event window.
Absale[-1]adj	Abnormal short-sale volume one day prior to the campaign publication date, divided by the number of reports published on the campaign publication date.

Variables of Interest and Controls	
Clustered	Indicator that equals one if there is at least another report by a different author on the same target firm and same date, zero otherwise.
SA	Indicator that equals one when a campaign report is from Seeking Alpha sample and zero when a campaign report is from Activist Insights sample.
Size	Log of total assets.
BtM	Book value of equity to market value of equity.
PriorRet	Cumulative daily returns in the [-90, -10] window relative to the campaign publication date.
PriorVolatility	Standard deviation of daily returns in the [-90, -10] window relative to the campaign publication date.
NumAnalysts	The natural log of one plus the number of analysts following the firm.
Dispersion	The standard deviation of the analyst EPS estimates.
Institutional	The percentage of institutional ownership.
Volume	The trading volume in the [-90, -10] window relative to the campaign publication date. standardized by shares outstanding.
Second	Indicator that equals one if the short-campaign report is published during the second half of the fiscal year.
PreAuthor	Indicator that equals one if the campaign author has published short reports on the target firm before.
Connectedness	A graph is constructed with each node corresponding to one author. An edge connecting two authors is added if they publish articles about the same company in the same month. *Connectedness* of an author is computed as the

	PageRank score of the node using Page et al. (1999). A node in the graph with a higher score indicates that it is connected to more nodes.
NewsRelease	Indicator that equals one if there are news releases during the two days prior to the campaign publication date. Information-release events are obtained from Dow Jones Equity product provided by the Raven Pack News Analytics. Consistent with the way Raven Pack News Analytics measures firms' news sentiment, I exclude the group "insider-trading" and "order-imbalances." I also exclude the group "stock-prices" to ensure there is material information rather than generic news on prices.
Accrual	Absolute value of the difference between net income and net cash flow from operating activities divided by total assets.
SUE	Earnings surprise estimated using a seasonal random-walk model.
Bundle	Indicator that equals one if a forecast is provided in a five-day window around earning announcement date at the most recent earnings announcement.
Length	Log of the total number of words in the campaign report.
LogFileSize	Log of the file size of the campaign reports following Loughran and McDonald (2014) to measure readability for financial context.
Negative	Log number of negative words in the campaign report. Negative words are identified according to the dictionary developed by Loughran and McDonald (2011) for financial context.
Readability	Following Li (2008) and De Franco et al. (2015) who study the readability of analyst reports, I calculate three linguistic measures shown to proxy for readability, including the Fog index, Flesch-Kincaid index, and FleschReading Ease index. I then rank each of them from 1 to 100, and then use the average of the three ranks as the aggregate readability measure.
Specificity	Log number of specific words in the campaign report. Following Hope, Hu, and Lu (2016), I use the Stanford Entity Name Recognition program to identify specific entity names belonging to seven entity categories: (1) names of persons, (2) names of locations, (3) names of organizations, (4) quantitative values in percentages, (5) money values in dollars, (6) time, and (7) dates.
Follows	Log of the number of followers collected for authors who publish on Seeking Alpha.
Record	The weighted average of the DGTW-adjusted one-year return of the all campaigns published by the author prior to the current campaign publication. To avoid look-ahead bias, only campaigns that are published more than 12 months earlier are included. The weight is the inverse of the number of days between a past campaign publication and the current campaign publication, so that a more recent campaign gets a higher weight.
Position Disclosure	An indicator that is equal to one if authors disclose they are shorting the target firms' stocks and zero otherwise. If disclosure statement is missing, then *Position Disclosure* is coded as missing and the observation is thus not included in the regression.

Appendix B: PageRank Calculation

Specifically, each author constitutes one node in the graph. An edge connecting two authors is added if they publish articles about the same company in the same month. I compute the PageRank value of each node in the graph following Brin and Page (1998). In particular, the PageRank value $PR(n)$ of a node n in a graph G satisfies the following equations:

$$PR(n) = \frac{1-d}{N} + d\left(\sum_{v \in adj(n)} \frac{PR(v)}{Deg(v)}\right) \quad (3)$$

N is the total number of nodes in the graph; $adj(n)$ indicates the set of all adjacent nodes, which are the nodes connected to node n with an edge; $Deg(v)$ indicates the degree of node v, i.e., the number of edges connecting v to any other nodes in the graph; and d is so-called damping factor, which is set to 0.85 as suggested in Brin and Page (1998).

Clearly, the PageRank value of one node depends on the values of other nodes in the same graph. To compute this value effectively, an iterative approach is used. Initially, I initialize $PR^0(n) = \frac{1}{N}$ for all nodes. Then, we iteratively compute

$$PR^{i+1}(n) = \frac{1-d}{N} + d(\sum_{v \in adj(n)} \frac{PR^i(v)}{Deg(v)})$$

It is easy to prove that after several iterations, the value $PR^i(n)$ approximates $PR(n)$, which is the fix-point of PageRank equations (3). In my calculation, I compute 100 iterations.

Table 1 Stock Market Performance

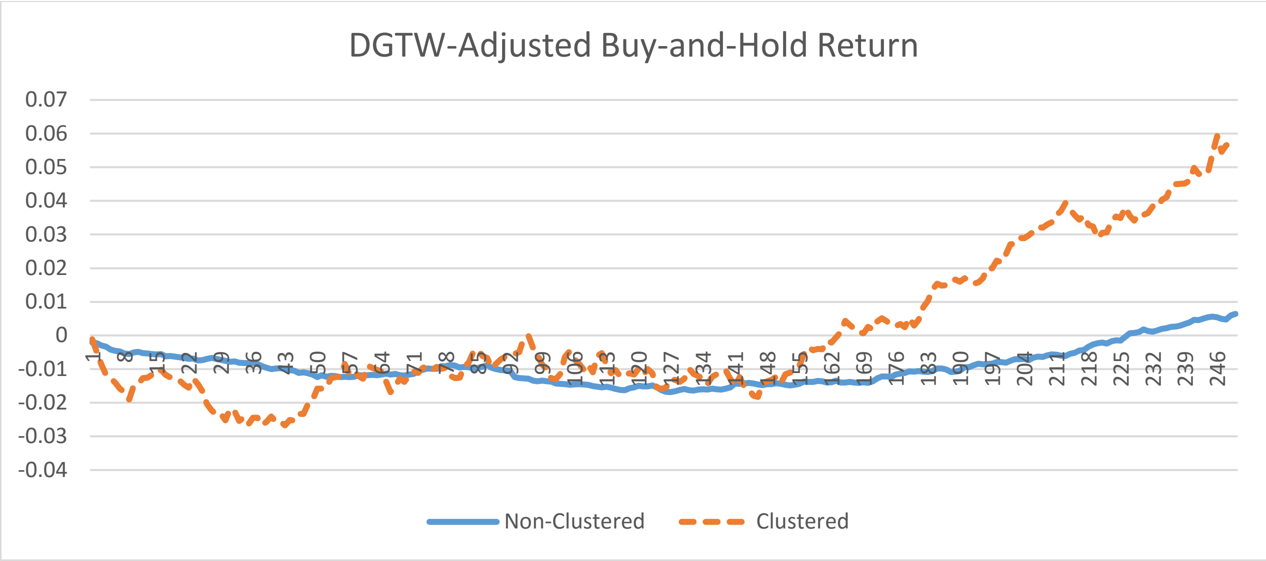
Panel A of Table 1 shows the short-term and long-term returns of short campaigns based on the entire sample. Daily abnormal return is defined as the difference between raw return and DGTW-portfolio return. Standard errors are clustered by firm and publication date.

Panel A	Median	Mean
AR[0]	-0.003***	-0.010***
	(0.000)	(0.000)
BHAR[1,5]	-0.004***	-0.005***
	(0.000)	(0.000)
BHAR[1,20]	-0.008***	-0.007***
	(0.000)	(0.003)
BHAR[1, 250]	-0.03996*	0.011
	(0.056)	(0.709)

Panel B of the table 1 shows the differences in short-term and long-term returns between clustered and non-clustered campaigns. P-value is from a two-sided t test of the difference of the group means. ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.

Panel B	Clustered	Non Clustered	Diff
AR[0]	-0.017	-0.009	-0.008***
BHAR[1,5]	-0.013	-0.004	-0.009***
BHAR[1,20]	-0.013	-0.007	-0.006
BHAR[1, 250]	0.058	0.006	0.052**

Figure 1: Stock Market Performance



The graph shows the average (equal weighted) DGTW-adjusted buy-and-hold return in the [1, 250] window after campaign publications for clustered and non-clustered campaigns.

Table 2 Short-Sale Activities

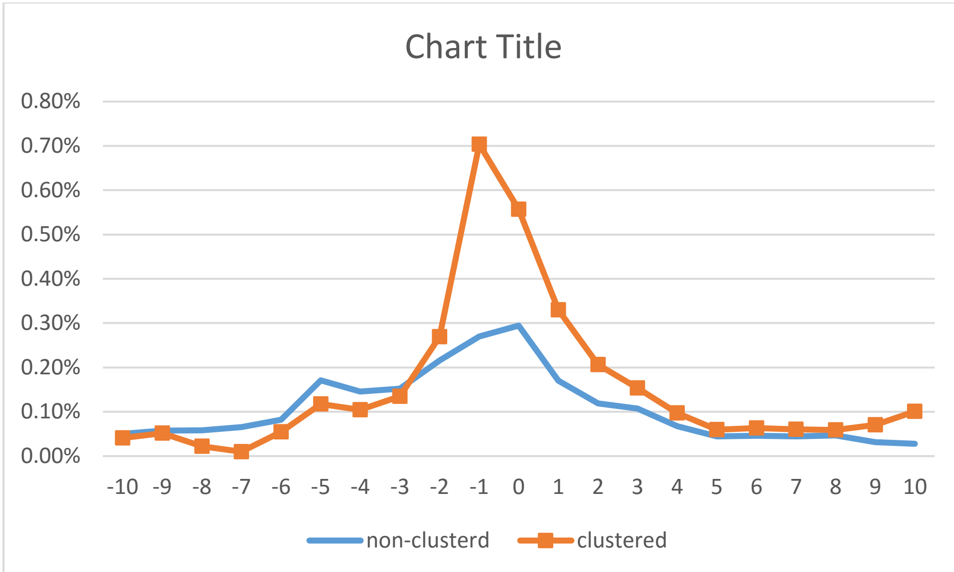
This table shows the short-sale activities before campaign publication. Panel A presents results based on the entire sample. Standard errors are clustered by firm and publication date.

Panel A	Median	Mean
Absale[-1]adj	-0.000	0.002***
	(0.875)	(0.000)
ABSI[-1]	0.037***	0.003***
	(0.044)	(0.000)

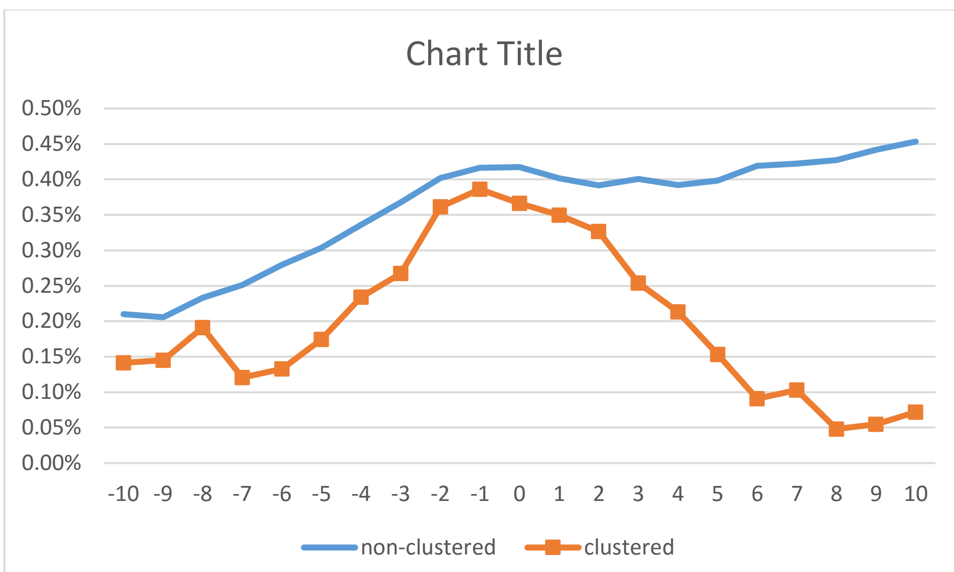
Panel B shows the differences in short-sale activities prior to campaign publication between clustered and non-clustered campaigns. P-value is from a two-sided t test of the difference of the group means. ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.

Panel B	Clustered	Non Clustered	Diff
Absale[-1]adj	0.004	0.002	0.002***
ABSI[-1]	0.004	0.005	-0.001

Figure 2: Abnormal Short-Sale Pattern for Clustered and Non-Clustered Campaigns



(a) This figure shows the pattern for abnormal short-sale volume for clustered and non-clustered campaigns. Abnormal short-sale volume is defined as the daily short-sale volume minus normal short-sale volume estimated in the [-60,-10] window relative to the publication date. I adjust the short-sale volume by dividing it by the number of campaigns. Daily short-volume is collected from FINRA and the number is standardized by the number of shares outstanding.



(b) This figure shows the pattern of abnormal short interest for clustered and non-clustered campaigns. Abnormal short interest is defined as the daily short interest ratio minus normal short interest ratio estimated in the [-60,-10] window relative to the publication date. Daily short interest is from Markit and the number is standardized by the number of shares outstanding.

Table 3 Summary Statistics

These tables present summary statistics for variables used in the regression analyses.

Variable of Interest and Controls						
	Obs.	Mean	Std.	P25	P50	P75
Cluster	7,983	0.089	0.285	0.000	0.000	0.000
SA	7,983	0.950	0.219	1.000	1.000	1.000
Connectedness	7,983	0.002	0.002	0.000	0.001	0.002
NewsRelease	7,983	0.421	0.494	0.000	0.000	1.000
PreAuthor	7,983	0.863	0.343	1.000	1.000	1.000
Second	7,983	0.506	0.500	0.000	1.000	1.000
Size	7,983	8.426	2.426	6.89	8.401	10.036
BtM	7,983	0.433	0.604	0.103	0.268	0.540
PriorRet	7,983	0.061	0.38	-0.123	0.017	0.161
PriorVolatility	7,983	0.029	0.017	0.017	0.025	0.037
NumAnalysts	7,983	2.343	1.218	1.609	2.773	3.296
Dispersion	7,983	0.068	0.150	0.010	0.030	0.080
Volume	7,983	0.025	0.030	0.008	0.014	0.029
Institutional	7,983	0.561	0.312	0.355	0.628	0.801
SUE	7,983	0.075	0.083	0.019	0.049	0.103
Accrual	7,983	-0.006	0.067	-0.004	0.000	0.003
Bundle	7,983	0.560	0.496	0.000	1.000	1.000

Table 4 Determinants of Clustering and Pre-Campaign Short-Sale Pattern

This table presents results on the determinants of clustering, and shows how clustered campaigns are associated with the short-selling activities before campaign publication. A logit regression is run with *Clustered* as the dependent variable. *AbSale[-1]adj* is the per-campaign abnormal short-sale volume one day prior to publication, divided by the number of reports published on publication date. *AbSale[-1]* is abnormal short interest measured at one day before publication. Other variables are defined in Appendix A. Standard errors are two-way clustered by publication date and firm. P-values are in parentheses. ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.

	1	2	3	4	5	6
	Clustered	*Clustered*	*Clustered*	*Clustered*	*Clustered*	*Clustered*
Absale[-1]adj				0.201***	0.191***	0.154**
				(0.005)	(0.006)	(0.033)
ABSI[-1]				-0.002	0.012	0.024
				(0.955)	(0.734)	(0.496)
SA	0.585**	0.496*	0.296		0.385	0.468*
	(0.029)	(0.062)	(0.244)		(0.134)	(0.086)
NewsRelease		0.603***	0.530***		0.443***	0.374***
		(0.000)	(0.000)		(0.000)	(0.000)
PreAuthor			1.477***		1.409***	0.870***
			(0.000)		(0.000)	(0.009)
Second			0.173*		0.240**	0.034
			(0.099)		(0.011)	(0.845)
Size						0.227***
						(0.001)
BtM						-1.873**
						(0.020)
PriorRet						0.811***
						(0.001)
PriorVolatility						2.435
						(0.709)
NumAnalysts						-0.261
						(0.288)
Dispersion						0.470
						(0.348)
Volume						9.935***
						(0.001)
Institutional						1.373
						(0.102)
SUE						-1.324
						(0.145)
Accrual						2.005
						(0.140)
Bundle						-0.137

						(0.610)
Year FE	YES	YES	YES	YES	YES	YES
Observations	7,983	7,983	7,983	6,838	6,838	6,838
Pseudo R-squared	0.0055	0.0176	0.0342	0.0101	0.0369	0.1127

Table 5 Clustered Campaigns and Stock Market Performance

This table presents results on clustered campaigns and stock market performance. Both the short-term market reaction to the campaign report and the long-run return are examined. All variables related to abnormal returns and abnormal short sales are shown in percentage by being multiplied by 100. Standard errors are two-way clustered by publication date and firm. P-values are in parentheses. ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.

	Absale[0]	*AR[0]*	*BHAR[1,5]*	*BHAR[1,20]*	*BHAR[1,250]*
Clustered	0.470***	-0.431	-0.871**	-1.244*	6.440*
	(0.002)	(0.369)	(0.025)	(0.052)	(0.061)
Absale[-]adj	0.643***	-0.181	-0.458*	0.417	-0.069
	(0.000)	(0.462)	(0.084)	(0.453)	(0.957)
ABSI[-1]	0.033***	-0.084*	-0.111	-0.327**	-0.666
	(0.000)	(0.096)	(0.161)	(0.043)	(0.252)
SA	-0.329***	1.643***	0.213	2.092**	7.900**
	(0.000)	(0.008)	(0.674)	(0.019)	(0.011)
NewsRelease	0.077***	-0.347**	0.125	-0.211	-2.040
	(0.003)	(0.021)	(0.500)	(0.602)	(0.324)
PreAuthor	-0.008	0.554	-0.720*	-1.458**	1.167
	(0.785)	(0.105)	(0.068)	(0.037)	(0.703)
Second	0.017	-0.262	0.255	1.205*	3.727
	(0.513)	(0.103)	(0.393)	(0.061)	(0.211)
Other Controls Included	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	6,836	6,838	6,838	6,838	6,838
R-squared	0.418	0.043	0.022	0.034	0.057

Table 6 Partition Based on the Existence of a Preceding News Release

This table presents results on two subsamples partitioned based on whether the campaign publication is triggered by an immediately preceding news release. All variables related to abnormal returns and abnormal short sales are shown in percentage by being multiplied by 100. Standard errors are two-way clustered by publication date and firm. P-values are in parentheses. ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.

Panel A	***Campaigns with a Preceding News Release***				
	Absale[0]	*AR[0]*	*BHAR[1,5]*	*BHAR[1,20]*	*BHAR[1,250]*
Clustered	0.608***	0.035	-0.897	-1.082	-1.554
	(0.006)	(0.957)	(0.125)	(0.285)	(0.818)
All controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	2,942	2,942	2,942	2,942	2,942
R-squared	0.394	0.033	0.033	0.044	0.065

Panel B	***Campaigns without a Preceding News Release***				
	Absale[0]	*AR[0]*	*BHAR[1,5]*	*BHAR[1,20]*	*BHAR[1,250]*
Clustered	0.278***	-0.883	-0.883	-1.337	16.569***
	(0.002)	(0.272)	(0.143)	(0.191)	(0.000)
All controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	3,894	3,896	3,896	3,896	3,896
R-squared	0.453	0.083	0.025	0.038	0.061

Panel C	***Trading Pattern***	
	With News	*No News*
	Clustered	
Absale[-1]adj	0.053	0.265***
	(0.587)	(0.006)
ABSI[-1]	0.053	0.008
	(0.253)	(0.824)
All controls	YES	YES
Year FE	YES	YES
Observations	2,942	3,896
Pseudo R-squared	0.0954	0.1375

Table 7 Partition Based on the Likelihood of Price Manipulation

This table presents results on the two subsamples partitioned based on whether a firms is more likely a target of price manipulation. The larger-firm sample includes firms with market capitalization greater than the median; the smaller-firm sample includes firms with market capitalization lower than the median. All variables related to abnormal returns and abnormal short sales are shown in percentage by being multiplied by 100. Standard errors are two-way clustered by publication date and firm. P-values are in parentheses. ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.

Panel A	***Larger Firms***				
	Absale[0]	*AR[0]*	*BHAR[1,5]*	*BHAR[1,20]*	*BHAR[1,250]*
Clustered	0.431*	-1.141***	-0.698***	-1.304**	1.908
	(0.055)	(0.005)	(0.010)	(0.016)	(0.654)
All controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	3,560	3,560	3,560	3,560	3,560
R-squared	0.380	0.034	0.015	0.036	0.073

Panel B	***Smaller Firms***				
	Absale[0]	*AR[0]*	*BHAR[1,5]*	*BHAR[1,20]*	*BHAR[1,250]*
Clustered	0.573***	0.181	-1.021	-1.818	16.244*
	(0.005)	(0.865)	(0.261)	(0.220)	(0.055)
All controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	3,542	3,544	3,544	3,544	3,294
R-squared	0.426	0.072	0.033	0.048	0.097

Panel C	***Trading Pattern***	
	Larger	*Smaller*
	Clustered	
Absale[-1]adj	0.173**	0.289***
	(0.039)	(0.002)
ABSI[-1]	0.053	0.002
	(0.107)	(0.969)
All controls	YES	YES
Year FE	YES	YES
Observations	3,560	3,264
Pseudo R-squared	0.1486	0.1946

Table 8 Partition Based on Author Connectedness

This table presents results on the two subsamples partitioned based on campaign authors' connectedness. Author connectedness is calculated from Page-Rank algorithm. Details are described in Appendix B. The high-connected group includes authors whose Page Rank scores rank in the top quintile; the low-connected group in the bottom quartile. All variables related to abnormal returns and abnormal short sales are shown in percentage by being multiplied by 100. Standard errors are two-way clustered by publication date and firm. P-values are in parentheses. ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.

Panel A	***High-Connected Authors***				
	Absale[0]	*AR[0]*	*BHAR[1,5]*	*BHAR[1,20]*	*BHAR[1,250]*
Clustered	0.357**	-0.402	-1.341***	-0.658	7.762**
	(0.013)	(0.132)	(0.004)	(0.484)	(0.023)
All controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	1,914	1,914	1,914	1,914	1,914
R-squared	0.414	0.055	0.030	0.063	0.097

Panel B	***Low-connected Authors***				
	Absale[0]	*AR[0]*	*BHAR[1,5]*	*BHAR[1,20]*	*BHAR[1,250]*
Clustered	0.395***	-0.368	-0.532	-2.670**	1.894
	(0.006)	(0.805)	(0.521)	(0.022)	(0.815)
All controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	1,622	1,622	1,622	1,622	1,622
R-squared	0.490	0.054	0.035	0.041	0.064

Panel C	***Trading Pattern***	
	High Connect	*Low Connect*
	Clustered	
Absale[-1]adj	0.194**	0.045
	(0.032)	(0.645)
ABSI[-1]	0.026	0.019
	0.194**	0.045
All controls	YES	YES
Year FE	YES	YES
Observations	1,914	1,622
Pseudo R-squared	0.1024	0.0912

Table 9 Reputation: Partition Based on the Transparency of Real Identities

This table presents results on SA campaigns and AI campaigns separately. Panel A shows results in the SA sample and Panel B shows results in the AI sample. Panel C presents trading patterns in both subsamples. All variables related to abnormal returns and abnormal short sales are shown in percentage by being multiplied by 100. Standard errors are two-way clustered by publication date and firm. P-values are in parentheses. ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.

Panel A	***Campaigns from Seeking Alpha***				
	Absale[0]	*AR[0]*	*BHAR[1,5]*	*BHAR[1,20]*	*BHAR[1,250]*
Clustered	0.464***	-0.611	-0.908**	-1.137*	6.797*
	(0.003)	(0.141)	(0.018)	(0.067)	(0.061)
All controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	6,498	6,500	6,500	6,500	6,500
R-squared	0.419	0.038	0.023	0.031	0.057

Panel B	***Campaigns from Activists Insights***				
	Absale[0]	*AR[0]*	*BHAR[1,5]*	*BHAR[1,20]*	*BHAR[1,250]*
Clustered	0.613	4.472	-1.181	-5.128	-9.818
	(0.111)	(0.488)	(0.623)	(0.304)	(0.339)
All controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	338	338	338	338	338
R-squared	0.417	0.161	0.043	0.059	0.109

Panel C	***Trading Pattern***	
	SA sample	*AI sample*
	Clustered	
Absale[-1]adj	0.144**	0.613***
	(0.048)	(0.009)
ABSI[-1]	0.025	-0.208*
	(0.504)	(0.092)
All controls	YES	YES
Year FE	YES	YES
Observations	6,500	338
Pseudo R-squared	0.1128	0.4040

Table 10 Robustness to Textual Features and Author Characteristics

This table examines whether the stock return pattern associated with clustered campaigns still remains after the inclusion of additional controls. Measures of textual features are defined in Appendix A. Standard errors are two-way clustered by publication date and firm. All variables related to abnormal returns and abnormal short sales are shown in percentage by being multiplied by 100. P-values are in parentheses. ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.

	Absale[0]	*AR[0]*	*BHR[1,5]*	*BHR[1,20]*	*BHAR[1,250]*
Cluster	0.263***	-1.057	-1.638***	-1.396	13.364*
	(0.001)	(0.157)	(0.001)	(0.174)	(0.082)
Specificity	-0.028	-0.168	-0.076	1.219	4.673
	(0.701)	(0.690)	(0.864)	(0.198)	(0.295)
LogFileSize	-0.011	0.349	0.221	-1.317	-7.395
	(0.916)	(0.500)	(0.716)	(0.187)	(0.248)
Negative	1.184	-11.476	19.700	95.352**	82.180
	(0.587)	(0.563)	(0.412)	(0.016)	(0.713)
Readability	0.002	-0.012	0.025*	0.032	0.071
	(0.379)	(0.260)	(0.076)	(0.313)	(0.698)
Follows	-0.000	0.106	0.068	-0.231	-0.152
	(0.989)	(0.279)	(0.515)	(0.429)	(0.899)
Record	-0.043	0.305	-0.121	0.077	0.637
	(0.434)	(0.303)	(0.762)	(0.932)	(0.923)
PositionDisclosure	-0.005	0.126	0.184	0.357	8.500*
	(0.926)	(0.697)	(0.622)	(0.674)	(0.093)
Absale[-1]adj	0.598***	-0.322	0.081	1.368	-0.242
	(0.000)	(0.326)	(0.820)	(0.263)	(0.927)
ABSI[-1]	0.035**	-0.068	-0.261**	-0.591***	-1.404
	(0.034)	(0.432)	(0.012)	(0.004)	(0.184)
All controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	1,204	1,204	1,204	1,204	1,204
R-squared	0.451	0.063	0.052	0.092	0.146

Table 11 Robustness to Author Fixed Effects

This table examines whether the results are robust to author fixed effects. All variables related to abnormal returns and abnormal short sales are shown in percentage by being multiplied by 100. P-values are in parentheses. ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.

Panel A	***Campaigns from Seeking Alpha***				
	Absale[0]	*AR[0]*	*BHAR[1,5]*	*BHAR[1,20]*	*BHAR[1,250]*
Clustered	0.494***	-0.466	-0.743	-0.530	5.068*
	(0.003)	(0.363)	(0.206)	(0.540)	(0.099)
All controls	YES	YES	YES	YES	YES
Author FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	4,872	4,874	4,874	4,874	4,874
R-squared	0.498	0.192	0.160	0.193	0.257

Panel B	*Clustered*
Absale[-1]adj	0.144**
	(0.048)
ABSI[-1]	0.025
	(0.504)
All controls	YES
Author FE	YES
Year FE	YES
Observations	4,874
Pseudo R-squared	0.215

Table 12 Position Disclosure by Authors

This table examines the likelihood of short-position disclosure by authors. In particular, it shows whether clustered campaigns are associated with a higher likelihood of short-position disclosure by authors in the subsamples where they are more likely to be opportunistic. *Position Disclosure* is equal to one if authors disclose they are shorting the target firms' stocks and zero otherwise. Standard errors are two-way clustered by publication date and firm. All variables related to abnormal returns and abnormal short sales are shown in percentage by being multiplied by 100. P-values are in parentheses. ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.

	Large Cluster	*Small Cluster*	*HighConnect Cluster*	*LowConnect Cluster*
Position Disclosure	0.176	0.440**	0.539**	0.082
	(0.210)	(0.035)	(0.024)	(0.651)
Absale[-1]adj	0.246*	0.212**	0.297***	-0.021
	(0.098)	(0.036)	(0.003)	(0.834)
ABSI[-1]	0.048	0.028	0.015	0.016
	(0.158)	(0.532)	(0.822)	(0.779)
All controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	2,442	1,647	1,192	1,044
R-squared	0.149	0.202	0.092	0.099

Table 13 Title and Text Similarity

This table examines how clustered campaigns with more similar texts or titles perform compared to clustered campaigns with less similar texts or titles. The sample includes clustered campaigns only and the similarity score is calcualted for their texts and titles using term frequency–inverse document frequency and the Gensim python library. The variable of interest, *SimTitle* (*SimText*), is an indicator that equals one if the similarity score based on title (text) is above the median. Using an indicator variable is to facilitate interpretation. Inferences do not change if I use a continuous variable. Standard errors are two-way clustered by publication date and firm. All variables related to abnormal returns and abnormal short sales are shown in percentage by being multiplied by 100. P-values are in parentheses. ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.

Panel A	***Title Similarity***				
	Absale[0]	*AR[0]*	*BHAR[1,5]*	*BHAR[1,20]*	*BHAR[1,250]*
SimTitle	0.107	-0.535	0.939	-0.912	-18.862*
	(0.442)	(0.250)	(0.337)	(0.553)	(0.082)
Text Features	YES	YES	YES	YES	YES
All controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	592	592	592	592	592
R-squared	0.543	0.264	0.081	0.202	0.216

Panel B	***Text Similarity***				
	Absale[0]	*AR[0]*	*BHAR[1,5]*	*BHAR[1,20]*	*BHAR[1,250]*
SimText	0.028	0.525	-1.634	-1.699	-6.714
	(0.820)	(0.491)	(0.207)	(0.335)	(0.640)
Text Features	YES	YES	YES	YES	YES
All controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	592	592	592	592	592
R-squared	0.542	0.264	0.088	0.204	0.202

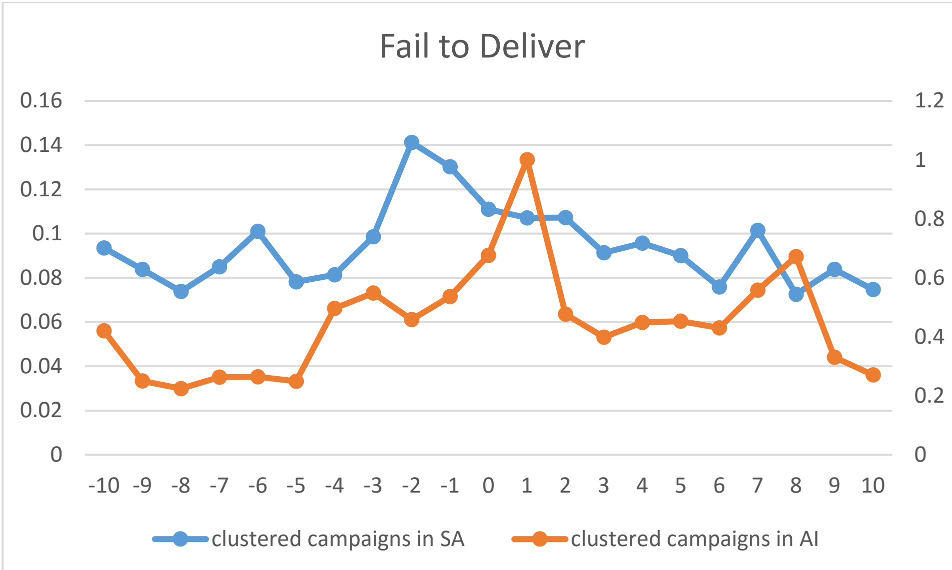
Table 14 Alternative Proxy to Measure Clustering at Month Level

This table defines *Cluster* as multiple campaigns targeting the same firm in the same *month*. "One" indicates a month with only one campaign; and "Cluster" indicates a month with multiple campaigns targeting the same firm. A target's stock-market performance in the following month, six months, and twelve months are studied. Return is adjusted benchmarking on the target's DGTW portfolio. Panel A of the table presents results based on the full sample, and Panel B the SA sample only.

Panel A		Full Sample		
DGTW adjusted return	One	Cluster	Diff (Multiple-One)	P-Value
Month1	-0.002	-0.10	-0.008	0.48
Month[1, 6]	-0.019	0.004	0.023*	0.085
Month[1,12]	-0.017	0.058	0.075***	0.001

Panel A		SA Sample		
DGTW adjusted return	One	Cluster	Diff (Multiple-One)	P-Value
Month1	-0.001	-0.014	-0.013*	0.095
Month[1, 6]	-0.014	0.010	0.024*	0.08
Month[1,12]	-0.013	0.065	0.078***	0.001

Appendix C: Fail-to-Deliver Trades around the Publication of Clustered Campaigns



This figure shows the fails-to-deliver volume for clustered campaigns in the [-10, 10] window around campaign publication. Fail-to-deliver volume is standardized by shares outstanding. The blue line indicates the pattern for clustered campaigns in SA sample, with the scale on the left; the orange line indicates the pattern for clustered campaigns in AI sample with the scale on the right. The purpose for this figure is to explore whether fails-to-deliver trades might be one possibility why the short-sale volume does not match exactly into the increase in short interest.