SSE Riga Student Research Papers
2018 : 1 (199)

ACTIVIST SHORT SELLING CAMPAIGNS: INFORMED TRADING OR MARKET MANIPULATION?

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ISSN 1691-4643
ISBN 978-9984-822-

November 2018
Riga

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Abstract

This paper examines the possibility of manipulating stock prices by the means of activist short selling campaigns and estimates the proportion of such manipulation on the 940 campaigns initiated during 2010-2017 in the US stock market. We document a strong market reaction to the disclosure of activist investor's short position. We study price patterns following the campaign initiation date and find that, on average, short sellers are informed investors who trade against temporary overvaluation. We prove that short-term abnormal returns are more pronounced if the short seller has a better reputation on the market. Since the market cannot distinguish between informed traders and manipulators in the short run, this creates incentives to profit from spreading misleading information. We show that 12% of the campaigns in our sample follow a very distinctive price pattern: the announcement generates substantial negative returns in the short term, followed by the stock rebounding back to its pre-announcement value. Using this information, we develop a back-of-the-envelope approach to estimate that around 2.3-5.4% of activist short selling campaigns show worrisome signs of price manipulation.

Keywords: activist short selling, short and distort, market manipulation.

Acknowledgements

We would like to thank our supervisor, Dr. Tālis J. Putniņš for his invaluable support and assistance throughout the thesis writing process.

1. Introduction

The classical view on trading is that an investor buys a stock hoping to profit from stock price appreciation. In contrast to that, short sellers seek to gain profits when they expect the stock price to go down. An important observation on short sellers is that their upside gains are limited (the maximum profit they earn is when the stock price reaches the value zero) while the downside is unlimited, meaning that, theoretically, they can lose an infinite amount of money. Because of such high risk, some of the short sellers can go even further and make their positions public, expecting that this will amplify the signals they are sending to the market. This type of investors is often referred to as "activist short sellers". For the purpose of our research, we define *activist short sellers* as investors entering a short position in a stock, who voluntarily disclose their position to the public and announce the reasons for short selling the stock, which can take the shape of media releases, publishing research, or other forms of expressing one's views on the company's future prospects. The information spread by the investor, in this case, is referred to as *activist campaign*.

Such campaigns seem to produce positive externalities for the financial markets and for the society in general. The media provides numerous cases of short sellers discovering frauds and serious misbehaviour in the companies they target. A good example of this is Whitney Tilson, who shorted Lumber Liquidators as he got proof that the company's great financials were due to switching towards cheaper but toxic and cancerogenic raw materials bought from Chinese factories (CBS News, 2015). Therefore, besides benefiting their own position in the stock, activist investors can contribute to a better regulatory enforcement by redirecting the public attention towards problematic companies.

However, there's another side to activist short selling. By talking down stocks publicly, the activist investors can create panic in the market and generate an overreaction to the statements they are communicating. This might be beneficial for their trading position, but it can also be perceived as market manipulation, or worse still, activist short sellers can engage in actual market manipulation by deliberately pursuing campaigns based on misleading information. The main concern is that this kind of overreaction can harm the target company's financials and future performance or even drive it towards bankruptcy. As Reuters (2016) reports, the Hong-Kong based lottery company REXLot Holdings had to undergo a fire sale to be able to satisfy the bondholders' redemption claims that arose after the Anonymous Analytics group published a fraud-uncovering report. The shares of REXLot

were suspended and they would risk default if they were not able to honor their debt obligations (Reuters, 2016). The outcome is even more outrageous if the information spread by the activist is not true, because, in this case, the price movements do not reflect price correction, but intentional harming the target company. Weiner, Weber, and Hsu (2017) provide the example of Lennar Corp., the company who managed to prove the activist short seller targeting it to be guilty of committing a securities fraud by dismissing false information about the stock. As a result, the short seller was sentenced to spend five years in prison. Another example of short-and-distort manipulation features Chromadex Inc. According to the same report, as a result of an anonymous activist short selling attack, the company lost 100 million of its market cap in a single day. After the short seller was exposed, he was forced to withdraw his report and revoke his allegation. Unfortunately, there are a few strong obstacles that firms encounter when trying to oppose the manipulators, and as a result, despite the SEC uncovering a decent number of pump-and-dump schemes, it is quite reluctant to take action vis-à-vis the short-and-distort allegations (Weiner et al., 2017).

Therefore, the question that arises is whether activist short sellers truly believe that the stocks they have shorted are overvalued, or they are manipulating the public opinion in order to profit their own position in the stock? The reason why this is important is that publishing misleading information that affects a company's share price is classified as market manipulation, which is illegal in most of the developed markets. As well, manipulation can result in inefficient resource allocation, profitable projects not being undertaken and loss in productivity for the target company. Considering the dualistic character of activist short selling, we aim to study what is the nature of activist short selling campaigns. Consequently, we state the following research question:

To what extent are activist short selling campaigns correcting the misvaluation of a stock versus using public pressure in order to manipulate stock prices?

We try to answer this question by analyzing a representative sample of activist short selling campaigns that have been running in the time period between February, 2010 and December, 2017. Our results show that activist shorts are more prone to attack liquid, volatile, and high market cap stocks, with bigger valuation multiples, and higher information asymmetry. In our sample, 48% of the campaigns initiated generate significant negative abnormal returns during the first trading days following the announcement. Over the first 60 days after announcements, the most negative CARs are associated with patent expiration and

stock promotion allegations (-51.43% and -49.68%, respectively), which cause even harsher reactions (-74.19% and -59.69%) in the longer term.

We show that the magnitude of the reaction is tightly linked to the activist's skill. Highly-skilled investors cause, on average, larger negative market responses compared to low-skilled short sellers. The main feature of our model is distinguishing informed trading from manipulation based on expected price patters. Informed trading is expected to display negative return continuation, while manipulative trades would mean-revert. Despite the earlier mentioned informational advantage, 12% of the documented campaigns result in a means reversal, which indicates the possibility of the price being subject to short-and-distort practice. However, some reversals may occur to low-skilled informed traders who placed an incorrect bet, which is why we proceed further with the analysis. We use a back-of-the-envelope approach to estimate the proportion of manipulation on the US market. Our theoretical model predicts this measure to be equal to 1-6% and the empirical analysis yields an interval of 2.3-5.4%.

Our paper contributes to the available literature on activist short sellers and market manipulation by showing that, on average, target firms experience significant negative abnormal returns following an activist short selling campaign announcement. Yet, roughly speaking, one fourth of the campaigns that generated significant negative returns in the first trading days after the announcement result in a mean reversal during the first three months after the campaign initiation, which indicates that there has been an overreaction to the activist claims that was corrected afterwards, or, there was an attempt to profit from manipulating the stock prices. The loose regulations on short selling disclosure and the market's inability to distinguish between informed traders and market manipulators in the short term provides additional incentives for manipulators to enter. As specified above, our analysis suggests that around 2.3-5.4% of such campaigns are most likely to be manipulative.

The analysis is structured as follows. Section 2 reviews the relevant literature. Section 3 describes the data used for empirical analysis. In section 4 we present a theoretical model meant to distinguish between informed trading and market manipulation, and provide guidance for the empirical tests. Section 5 describes our empirical tests.. Section 6 follows with a discussion of the main results. Section 7 acknowledges the limitation of the study and section 8 concludes. We also provide some suggestions for further research in section 9.

2. Literature review

In this section we provide the academic studies that are useful for the understanding of the topic of this study and the motivation behind the research question. We start by giving some background on activist investors and their recent performance on the market. We then proceed to a discussion on whether activist interventions improve the target company's performance or harm its long term prospects in exchange for a short-term profit. Sections 2.3 and 2.4 present empirical evidence on the main reasons for short selling and its role on the financial markets. Section 2.5 provides the overview of the recent research on activist short sellers. Finally, we guide the reader through the relevant literature on information disclosure, market manipulation and the relationship between the two.

2.1. Activist Investors

An investor acquiring 5% or above of company's equity is obliged to submit the "beneficial ownership report" with the U.S. Securities and Exchange Commission. The document includes investors who share voting or other power rights to sell the security (U.S. Securities and Exchange Commission, n.d.). Blockholders who acquire above 5% of a stock with the purpose to influence the firm or its management file 13D Schedule, while other types of investors are required to submit 13G Schedule, meaning that they are not permitted to exert any control or practice any other forms of activism over the acquired stock (U.S. Securities and Exchange Commission, 2016). By contrast, neither short activists nor short sellers in general are legally required to disclose their positions in the US (Euronews, 2018). Some progress in this area has been made via a petition to the SEC demanding short positions disclosure, which was initiated in 2015 (NASDAQ, n.d.). As well, PR Newswire (2011) reports that a study conducted by The Bank of New York Mellon in 2011 surveying 650 companies from 53 countries, which identified that 89% of US firms believe that short-selling requires additional regulatory oversight. This is due to the fact that besides activist investors revealing frauds, numerous lawsuits have been also filed against activist investors.

According to NASDAQ Glossary of Stock Market Terms (n.d.), activist investors are defined as minority shareholders whose aim is "to influence decision making at a company by voicing concerns, engaging in a dialogue with management, or lobbying other shareholders for support". Allaire and Dauphin (2015) find that hedge funds are the main initiators of such campaigns, followed by retail investors, labour unions, public pension

funds, mutual fund managers, and various other block holders. As the authors present, hedge fund activists have a wide diversity of stated objectives, most popular of which are change in payout, switch in management, demands for representation on the board, restructuration or divestitures of assets and, finally, getting the company sold off. To attain their objectives, they use a portfolio of strategies, ranging from friendly communication with management, and ending with hostile tactics such as initiation of proxy fights, threat of legal actions and public criticism on the target stocks.

Becht, Franks, Grant, and Wagner (2017) document that US is the largest market for activist shareholder interventions. Their analysis shows that the outcome of the activist intervention is the most important predictor of the success of the activist campaign, namely, the most profitable campaigns are associated with outcomes such as takeovers and changes in the corporate governance mechanisms.

According to Activist Insight (2018), the Activist Insight Index, a composite of primary-focused funds who identified their main strategy being activism, has been regularly outperforming S&P 500 and MSCI World indices since the end of the subprime mortgage crisis of 2008. This outlook is remarkable given the recent upswing in passive investing. Activists seem to be among the very few ones who using their active portfolio management strategies would generate additional value by outperforming traditional market indexes.

2.2. Activist Hedge Funds: Value-creating or Value-Destroying?

Academics continue debating whether shareholder activism improves the efficiency of the stocks they are targeting. Proponents argue that activist interventions correct corporate governance of target stocks, improve their long-term performance, or at least do not harm it (Bebchuk, Brav & Jiang, 2015; Boyson & Mooradian, 2010; Clifford, 2008). Using plant-level data, Brav, Jiang and Kim (2015) provide empirical evidence that hedge fund activism improves the productivity of assets of target companies. The authors suggest that hedge fund activism is an important value-creation channel since they can successfully identify undervalued stocks with poor capital structure and divest worst-performing assets. Similar conclusions are documented by He, Qiu and Tang (2016) who argue that activist hedge funds boosts target firm's innovation and R&D.

On the other side, opponents argue that activists act purely in their personal short-term interests and that aggressive shareholder activism can lower corporate efficiency of

target stocks. Jory, Ngo and Susnjara (2017) find robust associations between an increase in dividend payout and bond price drop following activism announcement date. This is a direct evidence that activist campaigns promote wealth transfer to shareholders at the expense of the bondholders. Cheng et al. (2012) study adversarial behavior of hedge funds against governmental bodies such as IRS by finding that stocks targeted by activist hedge funds experience greater tax avoidance, which, as they argue, is an important component for hedge funds to inflate the value of target firms.

2.3. Short Selling

One of the main reasons for going short cited in the modern academic literature is taking the advantage of temporary mispricing of securities. Lee (2016) provides evidence that increased level of short selling is associated with temporarily overpriced stocks. Diether, Lee & Werner (2009) find that short sellers trade against stocks with short-term market overreactions.

Short selling is associated with many challenges and excessive risk-bearing mainly due to its limited upside and unlimited downside when going short. Moreover, short selling constraints in the equity-loan market can increase noise trader risk and limit short sellers' ability of informational arbitrage. Constraints involve expenses of borrowing securities, risk of position being recalled, and many other types of legal restrictions. Beneish, Lee and Nichols (2015) recognize that short sellers' ability to borrow securities is limited by market supply. In their view, lendable shares are least accessible for short sellers when they seem to be most appealing to borrow. This means that lendable supply is lowest for overvalued stocks with predicted future negative returns.

2.4. The Role of Short Selling

Short selling has been always a practice of controversial views and numerous debates. Some believe short selling enhances market efficiency, while some blame short sellers for stock market declines and given their dangerous nature call for controls from regulatory bodies. Similar difference in opinions was echoed in academic literature. Proponents prove short selling is an important mechanism of informational efficiency in financial markets. Bris, Goetzmann & Zhu (2007) find that in countries where short selling is allowed, prices incorporate information much faster relative to those where short selling is restricted. They also find weak evidence to the statement that short sale constraints prevent stocks from

extreme price declines. Engelberg, Reed, and Ringgenberg (2012) prove once more that short sellers' trading advantage is a direct result of their ability to process public information and forecast future stock performance. They also show that clients, as opposed to market makers, are the most informed shorts. Lee (2016) finds that short sellers improve market quality and defends their positive role in promoting price discovery process. He argues that short selling is information-driven and traders can successfully detect and exploit temporarily mispriced securities. In his theoretical article, Miller (1977) states that in absence of short selling, overly-optimistic and poorly-informed investors (who believe that their investments will always promise higher returns than any other portfolio of stocks available), will be pushing the price upward, suggestive of informational inefficiency of stocks. Chang, Cheng & Yu (2007) provide empirical evidence of Miller's (1977) proposition by showing that when prices do not reflect all available negative information, the presence of short sale constraints results in stocks becoming overvalued. Similarly, Saffi & Sigurdsson (2010) come to the conclusion that information is incorporated into prices faster in markets with high availability of equity lending and small loan charges. In addition to their risk-bearing nature, short sellers also contribute to the markets as liquidity providers. Diether, Lee & Werner (2009) find that when there is short-term jump in buy pressure of other investors, short sellers may step in and trade. They wait till the magnitude of buying pressure diminishes so that they can recover their positions when prices mean-revert.

Atmaz (2015) develops a dynamic model to explain the changes in short interest by the means of investor beliefs. He finds that, when stocks go up, the number of short sellers increases, but the short interest does not change significantly, which is due to the fact that short interest is driven by investor disagreement, but is not directly linked with investor pessimism.

Academicians concerned about market manipulation argue that short sellers are responsible for market declines and artificially depressing prices. Brunnermeier and Pedersen (2005) study predatory trading, which they define as "trading that induces and/or exploits the need of other investors to reduce their position" (p.1825). Authors show that when large investors are forced to close their positions (for example, sell the security quickly), other market participants may learn about it and trade in the same direction as the distressed large trader, indicative of predatory trading. Attari, Mello & Ruckes (2005) support this idea by finding that other market participants will exploit large and financially-constrained traders.

They also show that predatory trading can harm market quality, since it incentivizes market manipulation and produces price deviation from fundamentals. Shkilko, Van Ness & Van Ness (2012) develop these arguments by studying predatory traders and intraday downward pressure on NYSE and NASDAQ securities during 2005-2006. They find that short sellers' trades contribute to such price declines and, moreover, it escalates the activity from non-short sellers who significantly intensify the magnitude of price declines of individual stocks. This, in fact, harms a company's fundamentals and in the nearest future, prices are expected to mean-revert back to their fundamental values. Aspects of manipulatory strategies are discussed in section 2.6.

2.5. Activist Short Sellers

Being a relatively new research area, activist short selling is barely present in the academic literature. This section is meant, therefore, to highlight the main findings that have been published so far. Zhao (2018) studies the ex-ante firm characteristic that make a company more susceptible to an activist short attack and what characteristics are useful in predicting future returns. He finds that (1) uncertainty and overvaluation features are the most powerful predictors of a firm becoming an activist short seller target, and, namely, ex-ante high level of uncertainty is strongly associated with fraud type of allegations while overvaluation features predict "bubble" allegations; (2) short seller's reputation is an important determinant of the market reaction to announcements; and (3) media coverage of the campaigns is associated with more negative returns for the target company.

Lamont (2004) documents that firms using short sale constraints tend to be overpriced. Constraints involve expenses of borrowing securities, risk of position being recalled, and many other types legal restrictions. Consequently, Ljungqvist and Qian (2016) define activist short selling as informational arbitrage meant to overcome such short selling constraints. They argue that stocks tend to be overpriced when the short sale constraints are high, and so, by publicly stating their short theses, activists convince the long investors to sell and thus, correct the misevaluation. The authors observe that on average, the market reaction is sufficiently strong to make this type of arbitrage profitable for the shorts – they document abnormal selling by longs, anomalous SEC filing views, as well as order imbalances. They also find no clear signs of manipulation in their sample as long as many firms go through delisting, changing auditors, or earnings restatement shortly after the activist campaign is initiated.

Wong and Zhao (2017) study what are the real effects of short selling campaigns on the future performance of the target companies. Their analysis shows that firms reduce their total investment, financing, and payout activities as soon as within the first quarter after the activist short selling attack is launched. By matching their sample of short selling target firms to a control sample, they also present empirical evidence on the fact that these consequences are a direct result of the activist involvement rather than the activists targeting stocks that are prone to have bad future performance. This evidence suggests that activist short sellers are indeed capable of deteriorating a firm's real decisions and future performance.

2.6. Market Manipulation

In order to assess what manipulation is and when it is considered illegal, four key concepts and the relationships among them have to be defined: *price manipulation*, *market manipulation*, *pricing accuracy*, and *market efficiency*. Kyle and Viswanathan (2008) explain that because price manipulation affects the markets directly, the terms *price manipulation* and *market manipulation* are interchangeable in most situations. On the other side, *price accuracy* is not the same as *market efficiency*. The first refers to the precision of the signals sent to the market with respect to efficient resource allocation, while the second one stands for the degree of difficulty to earn profits when incorporating all the available information. According to the authors, price manipulation should be classified as illegal when it either alters the market informativeness or when it harms market liquidity. As a result, according to the analysis performed by Kyle and Viswanathan (2008), spreading true rumors (i.e., informed trading) is generally acceptable, while spreading false rumors should be punishable.

Previous literature suggests that disclosure is profitable. Pasquariello and Wang (2017) prove that, in contrast to the common belief that information generates profits only if it is preserved private, investors can also profit in the short term by spreading privately held information, a phenomenon named "strategic disclosure". They also demonstrate that this type of disclosure improves market efficiency by increasing the market depth.

Atmaz and Basak (2017) model the investor beliefs and show that the equilibrium in the equity market is determined by two endogenous variables: the average bias and dispersion of investor beliefs. Overall, their study claims that, in good states, the stock price is more reactive to new information, and if the information is positive, the price increase is bigger in absolute terms than the decrease in the case of bad news.

On another note, Benabou and Laroque (1992) have shown that having access to private information creates incentives for manipulating stock prices, which was one of the leading arguments for establishing insider trading regulations. In their study, they also explain that the main impediment to revealing manipulators is the fact that, usually, this type of traders combine true information with misleading announcements, which creates the noise that limits the ability of other traders to learn about the manipulative patterns.

It is important to mention, however, that manipulation is not always bad. Allen and Gale (1992) contribute to this topic by illustrating that a manipulation-oriented investor can realize profits by acting as an informed trader given that the market assigns a positive probability to the manipulator being an informed trader. This is due to the fact that when the large investor enters the market other investors cannot distinguish whether it is an informed trader or a manipulator. In this setting, the manipulator can realize profits without distorting the fundamental value of the stock or spreading false information. The authors also raise the debate whether this type of manipulation is desirable or not by citing contradictory opinions.

Van Bommel (2003) explains that because small informed investors' trading capacity is usually too small to take full advantage of their private information, they may have incentives to spread this information to a larger audience in order to realize profits. The issue that arises is that given that rumors spreading can increase the rumor monger's profits by more than 50%, moral hazard can incline such investors to manipulate the price by spreading rumors when they don't have any information or even spreading false information. The research performed by Van Bommel (2003) also reveals that bluffing, or sending rumors without owning information, generates higher profits than honest rumors disclosure because in this case, the cost of information is zero. But these profits are realized only if the rumor spreader has some credibility on the market. Spreading false rumors, on the other hand, imposes an additional reputation cost for the trader as long as if the market learns about his cheating incentives, it no longer believes the disclosed information. Thus, mixing "truth" and "lies" is the most pursued strategy because it impedes the discovery of manipulation.

Finally, Goldstein and Guembel (2008) document that resource allocation role of the prices itself is a reason for manipulation. This is due to the feedback effect from the financial markets to the fundamental value of the company. A speculator can, thus, profit even if he is uninformed. He can do so by taking a short position, which will drive the price down, and as a result, this will signal that the investment project that the company plans to undertake is not

profitable and the company may choose not to undertake it. By not investing into the project, the firm's actions reduce themselves the value of stock, which benefits the speculator's position.

To sum up, the pieces of literature presented in this section claim that (i) disclosing privately-held information can be profitable, (ii) access to private information provides incentives for market manipulation, (iii) market manipulation can significantly harm the firm's fundamentals and productivity, and (iv) manipulation is possible, profitable, and hard to distinguish from informed trading, but it is also risky and punishable. By combining these findings with the earlier-stated benefits of informed activist short selling and informed short selling in general, we spot that there has been little research done on distinguishing between informed activist short sellers and manipulators, which is an important concern given the magnitude of the consequences of manipulation for the firms.

3. Data

For the empirical analysis, we use two data sources. The first one provides a total of 1031 activist short selling campaigns that took place in the US (stocks traded on NYSE, NYSE MKT and NASDAQ) in the time interval 2010-2017. The campaigns were run by 126 individual short sellers on 677 different stocks. The records report the name of the activist short seller, the year it has been founded and its headquarters location; the target company name, its symbol, headquarters location and region, the exchange venue, the sector and industry, the market capitalization and its category (large, mid, small, micro, nano); the campaign announcement date, the primary allegation, and the status of the campaign (current/ended). The information was compiled using Activist Insight Shorts database. This data was provided by our supervisor, Dr. Tālis J. Putniņš, and we have obtained the permission to use it for the purpose of our research.

We match the name of the company, the ticker and its stock exchange to Datastream database[1]. We exclude those targets classified as American Depositary Receipts, Global Depositary Receipts, Equity Units, and Warrants. We end up with 940 campaigns constituting 623 individual stocks targeted by 116 activist short sellers. A general overview in the form of a time series chart and summary statistics is presented below.

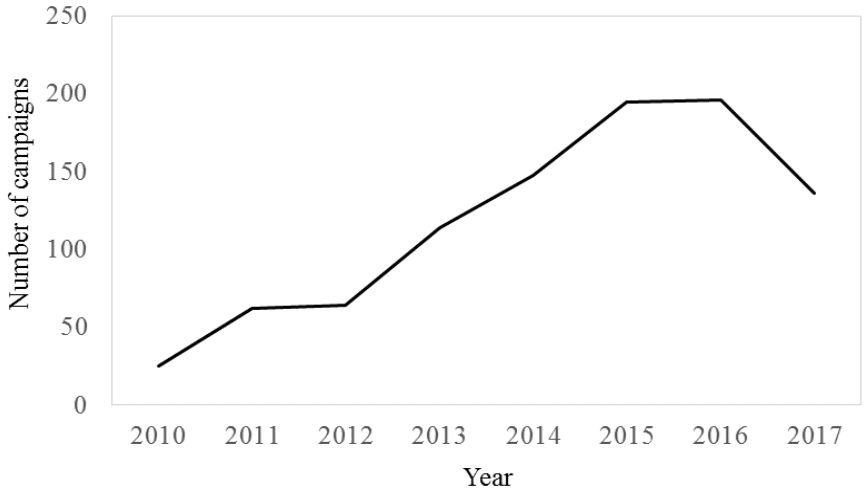

Figure 1. The number of activist short selling campaigns initiated by year.
The chart comprises only the campaigns present in our dataset. Created by the authors using data from Activist Insight Shorts.

[1] If we cannot match stocks following our list of criteria, we cross-check if companies changed their names, were involved in Mergers and Acquisitions, or changed their tickers due to being delisted or downgraded to the OTC market.

Table 1. Summary statistics of activist short selling campaigns.
This table presents numerical and percentual frequency of activist short selling campaigns by year, market cap category, primary allegation, exchange venue, and activity sector of the target company. "Freq." means the frequency in absolute numbers, which is followed by frequency expressed as percentage of the whole sample. "Cum. %" column represents the cumulative frequency. Created by the authors using data from Activist Insight.

Announcement Year	Freq.	%	Cum. %
2010	25	2,7%	2,7%
2011	62	6,6%	9,3%
2012	64	6,8%	16,1%
2013	114	12,1%	28,2%
2014	148	15,7%	43,9%
2015	195	20,7%	64,7%
2016	196	20,9%	85,5%
2017	136	14,5%	100,0%
Total	940	100%	

Market Cap Category	Freq.	%	Cum. %
Nano-Cap	129	13,7%	13,7%
Micro-Cap	168	17,9%	31,6%
Small-Cap	336	35,7%	67,3%
Mid-Cap	199	21,2%	88,5%
Large-Cap	108	11,5%	100,0%
Total	940	100%	

Primary Allegation	Freq.	%
Medical Effectiveness	105	11,2%
Other Overvaluation	99	10,5%
Industry Issues	85	9,0%
Misleading Accounting	81	8,6%
Bubble	80	8,5%
Stock Promotion	71	7,6%
Competitive Pressures	69	7,3%
Over-Levered	58	6,2%
Other Illegal	50	5,3%
Major Business Fraud	48	5,1%
Product Ineffective	48	5,1%
Ineffective Roll-Up	46	4,9%
Accounting Fraud	43	4,6%
Upcoming Earnings Miss	22	2,3%
Patent Invalid	13	1,4%
Pyramid Scheme	10	1,1%
Dividend Cut Coming	7	0,7%
Patent Expiration	5	0,5%
Total	940	100%

Exchange venue	Freq.	%
NASDAQ	611	65,0%
NYSE	318	33,8%
NYSE MKT	11	1,2%
Total	940	100%

Sector	Freq.	%
Healthcare	247	26,3%
Technology	220	23,4%
Services	146	15,5%
Consumer Goods	105	11,2%
Basic Materials	99	10,5%
Financial	59	6,3%
Industrial Goods	54	5,7%
Utilities	6	0,6%
Conglomerates	4	0,4%
Total	940	100%

As presented in Figure 1, the number of campaigns has been constantly increasing on a yearly basis except for 2017, which saw an incredibly strong bull market (Activist Insight, 2018). The summary statistics depicted in Table 1 show that healthcare, technology and services companies seem to be among the short selling activists' favorites, which constitute on aggregate more than 65% of our sample, while the most popular reasons for shorting are questionable medical effectiveness, industry issues, bubbles and other types of overvaluation, and misleading accounting.

The second data set contains financial data on all the available US stocks during 2010-2017. We retrieve from Datastream the following data: daily stock prices, book value of equity per share, market capitalization, total assets, industry classification, book value of equity, interest-bearing liabilities, payout ratio, EBITDA, revenue, insider ownership, short interest, and ROA. The number of analysts following the stock and the coefficient of variation of all the one-year analyst estimates are retrieved from I/B/E/S on Datastream. The sample includes 85,390 firm-quarter observations.

4. The Theoretical Model and Hypotheses

Our research focuses on distinguishing informed activist short selling campaigns from manipulative ones based on the differences in return patterns that these two types of campaigns generate, the average return patterns, and their determinants. In order to guide our empirical analysis we propose a probabilistic model with a few crucial assumptions. The market is composed of two types of traders: activist short sellers and other traders. There are only two types of activist short sellers: informed traders and market manipulators. With a probability m, an activist campaign is a manipulative one, and with probability $1 - m$ the campaign is an informed one. Another implicit assumption is that the informed traders consider the stock to be overvalued, meaning that the initial price P_0 is higher than the fundamental value F. Moreover, the informed trader's performance is a direct result of his skill to detect overvalued stocks, which is estimated by the performance of his past campaigns and scaled to the interval $0 \leq s \leq ½$. When $s = 0$, the investor is completely unskilled and when s approaches ½ the activist's bets are almost always correct. Therefore, the probability of the informed trader to be correct about the overvaluation is equal to $½ + s$, and, respectively, $½ - s$ is the probability of a wrong bet.

By definition, the manipulator is unaware of the true fundamental value of the stock. Therefore, in the case of manipulation, the initial price P_0 is assumed to be above or below F with equal probabilities. The market cannot distinguish between a manipulative and an informed activist short selling campaign immediately after announcement. This creates incentives for the manipulative campaigns to be initiated because the market will react as though there is some probability that the campaign is informed rather than manipulative.

There are three time points in the model:

- At $t = 0$ the activist short sellers establish their position and announce it to the market. P_0 is the stock price right before the announcement date.
- At $t = 1$ the other traders (which are assumed to be risk-neutral) react to the information announced and trade, moving the price towards $P_1 = E[F|\Omega_1]$, which is the expected value of the stock conditional on Ω_1 - the available public information at time $t = 1$ (m, s, and the knowledge that the campaign has been announced, but not knowing if the campaign is informed or manipulative).

- $t = 2$ is the point at which additional information about the stock has been released and the price P_2 has converged to its fundamental value F.

A graphical illustration of the model is presented below.

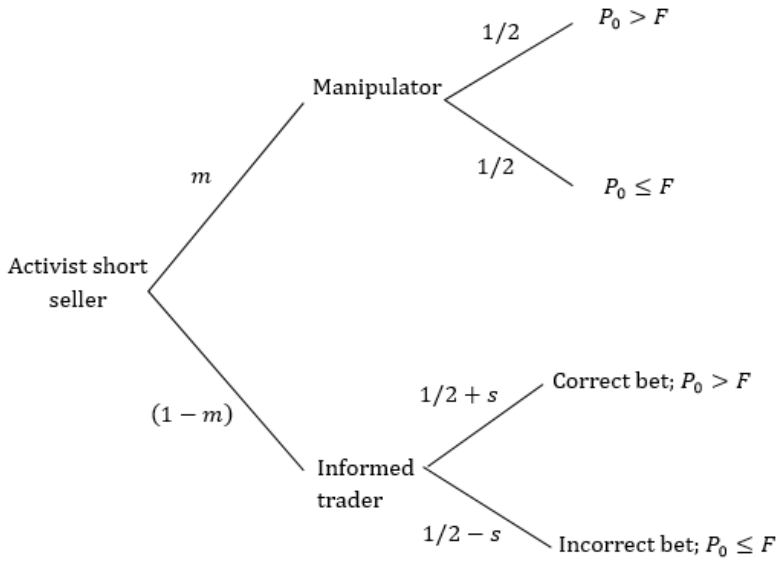

Figure 2. Graphical depiction of the probabilistic model.
m is the probability of the activist short seller being a manipulator and $m - 1$, respectively, is the probability of the activist being an informed trader. The manipulator holds no information and therefore she will target an undervalued or overvalued stock with equal probabilities $(1/2)$. The informed trader will successfully target an overvalued stock if he has some skill (s), so the probability of targeting an overvalued stock is $1/2 + s$.

The main purpose of the model is to find observable characteristics that will allow us to distinguish empirically between informed traders and manipulators. One way to look at this issue is through the returns paths perspective.

Considering the above-mentioned model, at $t = 0$ the price is equal to either $F + \varepsilon_0$ or $F - \varepsilon_0$, where ε_0 is the absolute value of the deviation of the price from its fundamental value F. Knowing all four possible cases (manipulator who targeted an overvalued stock, manipulator who targeted an undervalued stock, informed trader who targeted an overvalued stock, and informed trader who targeted an undervalued stock) expressed in Figure 2 and their occurrence (e.g. the proportion of manipulators targeting overvalued stocks would be equal to the proportion of manipulation on the market multiplied by $1/2$), we derive an equation to express F.

According to the model, the probability that the target stocks is overvalued is equal to $\frac{1}{2}m + (1 - m)\left(\frac{1}{2} + s\right)$ and the probability of undervaluation is equal to $\frac{1}{2}m + (1 - m)\left(\frac{1}{2} - s\right)$. Therefore, on average, the expected fundamental value would be equal to:

$$F = \left(\frac{1}{2}m + (1-m)\left(\frac{1}{2}+s\right)\right)(P_0 - \varepsilon_0) + \left(\frac{1}{2}m + (1-m)\left(\frac{1}{2}-s\right)\right)(P_0 + \varepsilon_0) \quad (1)$$

After opening the brackets we arrive to the following concise version:

$$F = P_0 - 2s(1-m)\varepsilon_0 \quad (2)$$

Therefore, at $t = 1$ the price P_1 (expected fundamental value) should satisfy the following condition:

$$P_1 = E[F|\Omega_1] = P_0 - 2s(1-m)\varepsilon_0 \quad (3)$$

Taking into account the specified assumptions of the model, one can infer that if market participants cannot distinguish between informed activist short selling and manipulation upon announcement, then, according to the model, P_1 will be the same both cases. Equation (3) implies that the price will decrease by $2s(1-m)\varepsilon_0$ only if the informed campaign involves some skill and m is smaller than 1. If m were equal to 1, then the market would be aware of all activist short seller campaigns being manipulative and thus, would not react to campaign announcements.

As P_0 is given and P_1 is the same irrespective of the short selling campaign being informed or manipulative, the distinction in price patterns is fully dependent on P_2 - the secondary price movement after the initial market reaction to the announcement. According to our model there are four possible outcomes:

(1) If the campaign is conducted by an informed short seller and the informed trader's bet is correct, $P_2 = F = P_0 - \varepsilon_0$, (fundamental value).

(2) If the campaign is conducted by an informed short seller and the informed trader's bet was wrong, $P_2 = F = P_0 + \varepsilon_0$.

(3) If the campaign was a manipulative one and it was perceived by the market as informed trading then the outcome is the same as in the first case: $P_2 = F = P_0 - \varepsilon_0$.

(4) If the campaign was a manipulative one but the market learned about it, then, as in the second case $P_2 = F = P_0 + \varepsilon_0$.

As a result, the intuition behind the model suggests that skilled informed short selling is expected to lower the price towards its fundamental value, resulting in negative returns

continuation until the price reaches the fundamental value. On the other hand, a manipulative short selling will generate negative returns until the market learns about the price being manipulated, which is often followed by a reversal in the form of positive returns. This crucial difference should be useful in distinguishing between informed trading and manipulation. Considering the four scenarios mentioned above, two important conclusions can be drawn. Firstly, even though informed trading can result in both return continuation and reversal, as long as the activist has some skill ($s > 0$), on average, informed campaigns will result in return continuation as long as the probability of a correct bet ($½ + s$) is bigger than the probability of a wrong bet ($½ - s$). Secondly, because in the case of manipulation we assume that the probabilities of initial overvaluation and undervaluation are equal, on average, the final price P_2 will be equal to P_0, which indicates a return reversal. These two results are graphically depicted below.

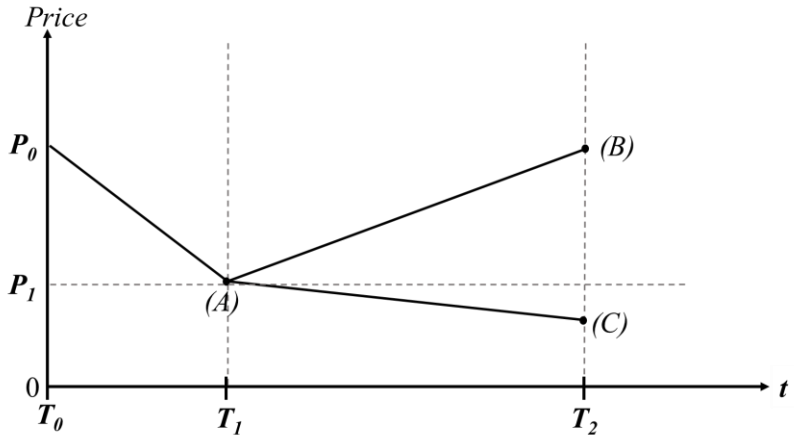

Figure 3. Expected price patterns under informed and manipulative campaigns.
The first price movement $P_0 \rightarrow P_1$ represents the drop in price after the activist short seller announces his position. The price drops irrespective of the campaign type because the market cannot distinguish between information and manipulation right after the announcement. If the campaign is information-driven, the stock is expected to continue generating negative returns until the price approaches the fundamental value (A→C). If the campaign was a manipulative one, it is expected that the market learns about it and a reversal occurs – the price is going up (A→B). Created by the authors.

Starting from the model presented in Figure 2 and taking into account the expected price patterns shown in Figure 3, we develop two more equations:

$$r = m(1 - x) + (1 - m)\left(\frac{1}{2} - s\right) \quad (4)$$

$$c = mx + (1 - m)\left(\frac{1}{2} + s\right) \quad (5)$$

where, r is the proportion of reversals, c is the proportion of continuations in the sample, and x is the proportion of manipulators who identify overvalued stocks. We assume that if

manipulators possess no material information about the fundamental prices and prices are on average correct (the proportions of overvalued and undervalued stocks on the market is the same), then $x = \frac{1}{2}$. However, for a more accurate analysis we allow this measure to slightly deviate from its theoretical mean. The probability m can be deducted using any of the above mentioned equations. For our convenience we use the reversals example and express m as:

$$m = \frac{r - 0.5 + s}{x - 0.5 + s} \tag{6}$$

The empirical results of this approach are presented and discussed in section 5.4.

Nevertheless, this approach has several drawbacks that need to be acknowledged. Firstly, the model takes into account only 2 theoretical cases, return continuation or a reversal, disregarding the magnitude of the reversals. This is important because some reversals might be a result of the volatility of the stock rather than a signal of the stock having been manipulated. Second, this model cannot give a classification to the activist campaigns that did not generate a significant market reaction (e.g. the stock continued to go up after the announcement). Third, the model is very sensitive to the empirical definition and calculation of the skill variable. Finally, the model cannot be employed when the sum of x and s is equal to 0.5 due to the mathematical setup (division by 0).

Even though return continuation and reversal do not give an exact value of m (the probability of a campaign being manipulative), this framework is useful by showing that on average, the biggest part of reversals will be associated with manipulation, while the biggest proportion of return continuation will point out to informed trading.

A potential drawback of using the price paths perspective is that across all the campaigns the average price path is flat from P_1 to P_2, and the average return is not sensitive to the manipulation probability m. The main reason for this is that knowing m, the market response to announcements is efficient such that it ensures a "fair" zero return for the risk neutral investors.

The theoretical analysis leads us to formulating four testable hypotheses:

H1: Unless the probability of manipulation is higher than 50%, on average, the activist short selling campaigns will generate significant negative abnormal returns in the first trading days after campaign announcement (i.e. the market cannot distinguish between informed

trading and manipulation in the short run, but if the probability of manipulation is lower than 50% it is inclined to believe activists' claims).

H2: The skill of the activist investor is a significant determinant of the magnitude of the short term market reaction to the activist short selling campaign announcement $(P_0 \rightarrow P_1)$.

H3: The magnitude of the initial price fall is greater when the activist's skill is higher (based on equation (3)).

H4: The magnitude of the price fall is greater when the initial perception of misvaluation is bigger (i.e., there is higher uncertainty about the fundamental value).

5. Empirical Analysis

The empirical analysis is performed in four stages. Firstly, we try to identify what are the main distinguishing characteristics of targeted firms. This will allow us to get a deeper understanding of the data we are working with and reveal what makes firms attractive for activist short sellers. Next, we look into the short-term market reaction after the campaign announcement. We quantify the reaction using Cumulative Abnormal Returns (CARs) and try to explain its magnitude by the means of target firms' and available activist investors' characteristics. Moving towards the longer term perspective, we evaluate whether there has been a cumulative abnormal return reversal during the event window, evaluate its strength and estimate the probability of manipulation.

5.1. What Companies Are More Likely to Become Targets

In order to see what factors influence the probability of becoming a target firm, we extend our sample so as to incorporate a subsample of control firms – companies that have never been targeted by short selling activists. By doing so, we are able to spot the major differences between the two subsamples. We differentiate the subsamples by the means of a binary variable – *Target*, which takes the value 1 if the stock has been targeted in a specific quarter. We start with a univariate analysis and perform a means comparison of the ex-ante firm-specific characteristics of the two subsamples. Namely, for each quarter we compare the previous quarter characteristics of the firms that have been targeted in this quarter and the rest of the companies. We then evaluate the significance of the difference between the two subgroups by the use of t-statistics tests. The results are illustrated in Table 2.

As reported in Table 2, there is a significant difference in the ex-ante measures like: total assets, profitability ratios (ROA and EBITDA margin), valuation multiples (price-to-book and Tobin's q), the level of payout, illiquidity, standard deviation of analyst forecasts, short interest, stock volatility and S&P 500 membership. Target firms seem to be smaller in terms of total assets, less profitable, have bigger valuation multiples and lower payout ratios in the quarter before getting attacked. An important observation is that even though the difference in market cap is not significant, targeted firms have the price-to-book and Tobin's q two times larger than the control firms on average. This is not very likely to happen due to extreme outliers as long as the same conclusion is relevant for the median values. Targeted stocks are also more liquid, more volatile, have higher short interest as a percentage of total

shares outstanding, and exhibit higher analyst uncertainty about their future performance before the announcement of the activist campaign. The ex-ante percentual short interest of the target firms is two times larger than the one of the control sample, showing that the market most likely expected the targeted stocks to go down. Activist short sellers also mostly target companies that do not belong to S&P 500.

Table 2. Means comparison between targeted and not targeted companies.
The table reports the mean, median, and standard deviation of firm-specific variables for two distinct subgroups present in the sample – target firms and a control sample of non-targeted firms. The last two columns report the difference between the two groups, the t-statistics and the level of significance of the difference (***** - significant at 10%, ******- significant at 5%, and ******* - significant at 1%).

	Targets			Non-targets				
	Mean	Median	Standard Deviation	Mean	Median	Standard Deviation	Difference	t-stat
Variables:								
Total Assets, (mln)	4 374,52	338,53	17106,86	11 184,69	866,43	86195,12	- 6 810,17	2.26**
Market Cap (mln)	5 733,43	715,43	22538,72	4 941,90	570,36	20444,96	791,53	(1.12)
Debt-to-Assets, %	23,38	13,05	30,24	23,83	17,44	25,42	- 0,45	0,49
ROA, %	- 11,80	1,78	34,23	- 1,97	3,03	21,57	- 9,82	12.22***
EBITDA margin, %	- 76,87	8,55	227,04	- 11,15	14,31	136,07	- 65,73	12.57***
Price-to-Book	6,36	4,35	5,39	3,12	1,87	3,57	3,24	(24.39)***
Tobin's q	3,24	2,52	2,36	1,58	1,11	1,51	- 1,67	(30,32)***
Payout ratio, %	5,08	0,00	14,50	14,08	0,00	23,09	- 9,01	10.66***
Illiquidity (10^6)	0,11	0,00	0,58	1,57	0,01	2,53	- 1,46	4.88***
Standard deviation of analyst forecasts, %	16,03	5,60	42,42	14,09	4,35	40,49	1,94	(1.91)*
Number of analysts	9,30	7,00	8,17	9,12	7,00	7,97	0,18	(0.59)
Short interest, %	9,65	7,29	8,24	4,04	2,38	4,99	5,62	(32.12)***
Volatility, %	3,64	3,18	2,21	2,79	2,25	2,04	0,86	(12.11)***
S&P membership	0,09	0,00	0,29	0,11	0,00	0,32	- 0,02	1.81*

We then proceed to estimating a model to explain the probability of becoming a target by the use of several firm-specific variables. The variables are chosen taking into consideration the primary allegation specified by the short sellers (overvaluation, over-leverage, upcoming dividend cut, ineffective roll-up, misleading accounting, upcoming earnings miss, etc.) as well as controlling for some basic stock characteristics like size, liquidity, volatility, and short interest. We, therefore, construct the following model:

$$\begin{aligned} Pr\left(Target_{i,t} = 1 \middle| X_{i,t-1}\right) = \Phi\,(&\beta_0 + \beta_1 Size_{i,t-1} + \beta_2 Misvaluation_{i,t-1} \\ &+ \beta_3 Leverage_{i,t-1} + \beta_4 Payout_{i,t-1} + \beta_5 Inf.Asymmetry_{i,t-1} \\ &+ \beta_6 Illiquidity_{i,t-1} + \beta_7 Uncertainty_{i,t-1} + \beta_8 ShortInterest_{i,t-1} \\ &+ \beta_9 Profitability_{i,t-1} + \beta_{10} Ownership_{i,t-1} + \beta_{11} S\&P\ 500_{i,t-1} + \varepsilon_{it}\ ) \end{aligned}$$

t: index for the time period (quarter)

i: subscript for individual firm

ε_{it}: error terms

β_n: estimated regression coefficients

$Size$ is estimated using the value of total assets and market cap. $Misvaluation$ is represented using price-to-book and Tobin's q valuation multiples. $Leverage$ is evaluated using the debt-to-assets ratio. The level of $Payout$ is measured using the dividend payout ratio. Brennan and Subrahmanyam (1995) argue that increased analyst coverage enhances stock's informational efficiency. Developing this idea, we expect that low analyst coverage might improve short seller's informational advantage. We use the number of analysts submitting forecasts for the stock and the standard deviation of the analyst forecasts to proxy $Information\ asymmetry$. $Illiquidity$ is calculated according to Amihud's (2002) methodology and is used to represent the level of difficulty to sell a stock without realizing a significant loss. $Uncertainty$ is expressed using stock price volatility. According to NASDAQ (n.d), investors perceive an increase in short interest of a stock as a bearish signal. Therefore, we calculate $Short\ interest$ as a percentage of total shares outstanding and use this measure to gauge the market sentiment about the anticipated price fall. $Profitability$ is expressed using ROA ratio and EBITDA margin. The $Ownership$ variable incorporates the degree of insider ownership, which, according to Bauer, Derwall & Pankratz (2016), is a good indicator of the risk of insiders extracting private benefits of control and agency problems arising. Finally, we control for the stock belonging or not to S&P 500. A more detailed description and explanation of how we construct and calculate the variables is presented in Appendix J. Beacause the data suffers from severe outliers that can bias the regression coefficients, we perform a manual check and winsorize the extreme values. The winsorization parameters applied are provided in Appendix C. Finally, a correlation matrix for the variables employed is presented in Appendix B. As it can be noticed, the most severe values of correlation are between the variables that we use interchangeably to proxy the same measure (e.g. ROA and EBITDA margin as profitability indicators). Therefore, the high level of correlation in these cases do not impact regression results.

We use opening quarterly balances for all accounting variables as long as we assume this was the last available public information for the activists, and on which the decision has been most probably made. For the variables that incorporate more frequently reported data

like price-to-book, illiquidity, and short interest, we take the average daily value for the previous quarter. For this analysis we omit the observations with negative price-to-book multiple or negative revenue as long in these cases the price-to-book and EBITDA margin do not reflect the associated proxies of misevaluation and profitability (e.g. if both revenue and EBITDA are negative, the margin will be positive, showing positive profitability). We perform a logit regression to assess the impact of the independent variables on the probability of becoming a target. We do not employ individual-fixed effects because of their main drawback: it automatically omits time-invariant dependent variables. This means that if in our sample a stock has never been shorted (each dummy $Target$ is equal to 0), panel fixed-effect logistic regression would automatically exclude these observations, which would lead to a sample-selection bias. We do, however, incorporate year-fixed effects and industry-fixed effects into the model to control for time-specific and industry-specific unobservable variables.

Appendix A displays regression results on the probability of becoming a target company. In order to evaluate the robustness of the results we use several interchangeable proxies for certain variables, thus, the eight regressions test different combinations of variables. Regressions 1-3 use the natural logarithm of total assets to proxy $Size$, while regressions 4-8 use the natural logarithm of market capitalization. Two proxies of $Information\ Asymmetry$ are tested: analyst disagreement and the number of analysts following the stock. As well, we use interchangeably ROA and EBITDA margin as a measure of $Profitability$ as well as test the price-to-book and Tobin's q as $Misvaluation$ proxies.

According to our regression results, size and valuation multiples are important determinants of becoming an activist short seller's target. Keeping other things equal, the higher the Market Cap, the higher the probability of becoming a target. The same applies for the price-to-book multiple and Tobin's q measure, which is in line with the academic literature claiming that short sellers, on average, correctly identify overpriced stocks (Lee, 2016; Ljungqvist & Qian, 2016; Zhao, 2018). When it comes to the level of debt, the higher the debt-to-assets ratio, the lower the probability of becoming a target. Despite some activist shorts initiating campaigns with overleverage allegations, a possible explanation for the significant negative relationship could be the fact that being passive investors, bondholders perform rigorous due-diligence, especially when investing in an already highly levered

company, and so, it is very unlikely that the company faces issues that are unknown to the market. Payout has a significant negative influence on the probability of being attacked, which is consistent with the view that high levels of payout indicates good performance and little disagreement between managers and shareholders. As a measure of information asymmetry, a bigger number of analysts following the stock negatively influences the probability of becoming a target, which supports the argument that the more information about the firm is available for the market, the less attractive the firm is for the activist shorts. Zhao (2018) and Ljungqvist and Qian (2016) showed that credibility is a crucial determinant of the market reaction to announcements, but only when the activist presents new, previously unknown information, rather than reiterate known information or rumors. Consistently, the more information available, the harder and more costly it is to come up with credible new facts, and so, the lower information asymmetry, the lower the probability to be targeted. As previously mentioned, the illiquidity measure is used to show the level of difficulty to sell a stock without realizing a significant loss. Our results show that the higher the illiquidity measure, the lower the probability to be targeted, meaning that short sellers do not engage in campaigns ran on illiquid stocks as there is high risk of realizing a loss when closing the position. When it comes to uncertainty, our results are consistent with Ljungqvist and Qian (2016), and Zhao (2018): higher stock price volatility, as a measure of uncertainty, increases the probability of being attacked. As a proxy for the market sentiment, short interest seems to be a good predictor of a stock being targeted by short sellers. The higher the ex-ante short interest, the higher the probability to be targeted, which speaks in favor of short sellers correctly identifying overvalued stocks. Finally, the proportion of insider ownership, as a proxy for the agency costs, is positively associated with the probability of becoming a short selling target. It can be inferred that once a short selling thesis is published, minority shareholders are more likely to act in favor of the short sellers if they fear expropriation or believe that the management acts in its own interest.

Other variables like EBITDA margin and the standard deviation of analyst forecasts show no significance in the models presented, while total assets, as a measure of size, ROA, and S&P 500 membership seem to exhibit a high level of sensitivity with respect to the selected set of variables.

5.2. Price Patterns around Campaign Announcement

In order to assess what the price pattern around the announcements of activist

campaigns looks like, we use event study methodology and follow recommendations by MacKinlay (1997) and Brown and Warner (1984). Event study is broadly used in corporate finance to investigate market reactions around various corporate events, such as announcements of mergers or acquisitions, release of earnings reports, or decisions on capital structure change. Similarly, we expect the effects of activist short selling campaigns to be reflected in stock prices of target companies, thus, yielding abnormal stock returns. Cumulative abnormal returns will help assess the average price path following the campaign initiation date, study the risk-adjusted magnitude of the market reactions to announcements, as well as understand how fast investors incorporate the information on the credibility of the activist report into prices, and whether the campaign results in price reversal or not.

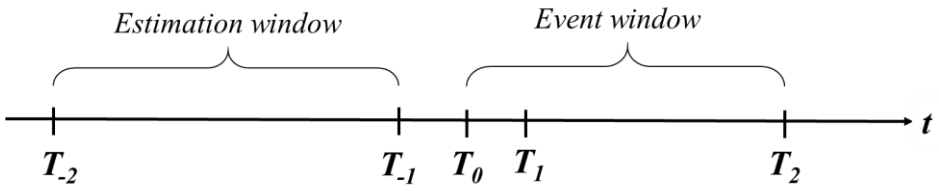

Figure 4. Estimation window and event window timeline.
Created by the authors.

Figure 4 provides illustrative explanation of the event study methodology. The timeline is split into two sections: estimation window $T_{-2} \rightarrow T_{-1}$ and event window $T_0 \rightarrow T_2$. We set the event window to start one day prior to the campaign announcement (T_0 will reflect P_0 from our theoretical model) and it will last for 60 trading days[1] (T_2 will reflect the fundamental value F when the full information about the company is revealed).

Next, we define our estimation window $T_{-2} \rightarrow T_{-1}$ to be 125 trading days (six calendar months) ending one month prior to the campaign announcement date. A six-moth estimation window will provide enough observations for reliable OLS estimates for each individual target stock. We do not include the interval $(-20;\ 0)$ because there is a risk that rumors about upcoming announcement can exercise influence on the prices even before the event date. We use the market model as described below:

[1] This will be set as our baseline event window. 60 trading days are suitable to study how target stock's fundamentals emerge following short selling campaign. We perform various sensitivity analyses with both shorter and longer event windows, including 1 day and up to 120 trading days after announcement.

$$\boldsymbol{R_{it}} = \boldsymbol{\alpha_i} + \boldsymbol{\beta_{1i}} \boldsymbol{R_{mt}} + \boldsymbol{\varepsilon_{it}} \quad (7)$$

t: index for estimation window

i: subscript for individual campaign announcement

R_{it}: continuously compounded daily returns to target company i on day t

R_{mt}: continuously compounded daily returns to the market index on day t

ε_{it}: error terms

α_i, β_i: estimated OLS regression coefficients

Using the estimated coefficients, normal expected returns $E[R_{it}]$ during the event window will show the theoretical value of the stock absent any influence from the campaign announcement event.

We use Russell 3000 index – a broad US market index which captures approximately 98% of all the U.S. investible equity securities (Bloomberg, n.d.) - as a proxy for market returns. Since we set the estimation window to be six calendar months, we drop those campaigns that had less than two months of observations during the estimation window. Similarly, we also drop the campaigns having less than two months of observations within the event window. As a result, out of 940 short selling campaigns, we are left with 917.

The remaining individual stock returns are winsorized at 0.5% from both tails to omit outliers, normalize the distribution of returns and receive unbiased coefficients. We also make sure to exclude non-trading days such as weekends and public holidays from both estimation and event windows. Finally, we set the event date equal the date the announcement took place. If it took place on a non-trading day, we adjust the event to the first available working day (e.g. if the event took place on Sunday, we set the event day on Monday).

Abnormal returns are simply the difference between actual and expected normal returns of the stock during the event window (see eq. (8)), where $E[R_{it}]$ represents the predicted/fitted values from (7).

$$\boldsymbol{AR_{it}} = \boldsymbol{R_{it}} - \boldsymbol{E}[\boldsymbol{R_{it}}] \quad (8)$$

Following equation (9), we calculate cumulative abnormal returns for each individual target stock by aggregating their abnormal continuously compounded returns over the event window. To aggregate CAR across N individual stocks, we take the mean of CAR for each

individual stock over the event window, as shown in equation (10).

$$\boldsymbol{CAR_i(T_1, T_2) = \sum_{t=T_1}^{T_2} AR_{it}} \tag{9}$$

$$\boldsymbol{\overline{CAR}(T_1, T_2) = \frac{1}{N} \sum_{i=1}^{N} CAR_i(T_1, T_2)} \tag{10}$$

Appendix D presents the development of CARs during the different time periods. As it can be noticed, markets do strongly react to the announcement of short position by activist investors. From Panel A, mean abnormal return on the announcement date is -4.79%, which is significantly different from zero. One week following the announcement, mean CAR is -8.34%, one month: -13.27%, while six months' average CAR is -35.14%. In Panel B, we show the distribution of Cumulative Abnormal Returns across various allegation announcements. As the results suggest, target stocks accused of stock promotion, patent expiration, as well as accounting and business frauds yield most negative abnormal returns during the first trading days after the announcement took place (-12.71%, -10.10%, -10.56% and -11.64%, respectively). These results are robust when studying CARs in the following 60 and 120 trading days post announcement. On average, stocks accused of accounting or business frauds have CARs equal -29.11% and -29.34% in the following three months, while targets subject to stock promotion and patent expiration have CARs of -73.95% and -59.44%, respectively. In the long-term, we see that stock promotion tends to yield the largest negative cumulative abnormal returns, which suggests that activist short sellers successfully trade against artificially inflated stock prices. We can also see that markets do not react to upcoming earnings miss or pyramid schemes –during the following trading day, average cumulative abnormal returns are -1.5% and -5.28%, respectively, which are not statistically different from zero. Similarly, those allegations do not result in significant average CARs over the following three- and six-month intervals.

Appendix E plots Cumulative Abnormal Returns starting ten trading days before and ending 120 trading days after the activist campaign announcement. In general, the results indicate that activist short sellers are, on average, informative about negative future price movements. We also study average price paths of targets split by their size. It can be observed that the lower the market capitalization category, the more extreme is the lower

boundary of CARs during the event window. As suggested by Josh Black, an Activist Insight spokesman, smaller-cap stocks are vulnerable to short selling announcements due to their nature of being "under-scrutinized and more susceptible to fraud" (Valuewalk, 2016). In the 120 days following campaign initiation date, mean (median) cumulative abnormal returns for large cap stocks is -13.79% (-9.73%), while nano cap stocks experience a -63.61% (-53.64%) risk-adjusted price drop.

5.3. The determinants of short-term stock performance

In this section, we try to estimate the main drivers behind the magnitude of abnormal returns during the first days after the campaign announcement. We run a cross-sectional regression model of CARs on stock-specific characteristics for the sample of targeted firms. The model should help us characterize and measure the variables' impact on the success of the campaign, expressed by the short term post-campaign returns (from P_o to P_1). We run the following regression:

$$CAR_i = \beta_0 + \beta_1 Size_i + \beta_2 Misvaluation_i + \beta_3 Illiquidity_i + \beta_4 Uncertainty_i + \beta_5 Information\ Asymmetry_i + \beta_6 Short\ Interest_i + \beta_7 Skill_i + \varepsilon_i$$

As presented above, we use the following potential determinants to control for the abnormal returns in our OLS regression[1]:

- $Size$ proxied by the natural logarithm of Market Capitalization twenty days prior to the campaign announcement date (not winsorized)
- $Misvaluation$ proxied by price run-up, the raw return during $t \in [-80; -20]$ prior to campaign announcement date (not winsorized)
- $Illiquidity$ proxied by the average Amihud's illiquidity measure during $t \in [-80; -20]$ (winsorized at 2.5% from right tail)
- $Uncertainty$ proxied by standard deviation of continuously compounded daily returns during $t \in [-80; -20]$ (winsorized at 1% from right tail)
- $Information\ asymmetry$ proxied by stock's average spread (%) during

[1] We do not use quarterly accounting data such as Total Assets, Leverage, or Profitability for the fact that if the same stock has been targeted by various short sellers several times during the same quarter, we would be estimating several individual equations with the same set of quarterly accounting data. To omit this problem and allow our explanatory variables to have more variation, we use daily stock characteristics.

$t \epsilon [-80; -20]$ (winsorized 2% from right tail)

- $Short\ interest$ is the average number of shares held short over shares outstanding (%) during $t \epsilon [-80; -20]$ (not winsorized)

For all daily stock data, we exclude those who have less that twenty observations during our three-month calculation window.

In addition to these variables, we use the knowledge from the theoretical model that we earlier presented to tests whether skilled activist short-sellers have higher probability of detecting overvalued stocks. Ljungqvist and Qian (2016) argue that short sellers can only affect prices (convince equity holders to sell their shares and attract new short sellers) if they have trustworthiness and outstanding track on the market. In their work, they measure short seller's credibility as the mean of three-month cumulative abnormal returns from all their previous campaigns. In our model, instead of just averaging abnormal returns to evaluate the historic performance of activist investor, we measure short seller's $Skill$ using the information ratio:

$$Skill_{j,t} = -\frac{1}{N}\sum_{i=1}^{N}\frac{CAR_i}{\sigma_{Rcc_i}} \tag{11}$$

where j is the subscript of the individual investor, t is the time subscript for each new campaign at the beginning of which the $Skill$ is calculated, CAR_i is a sixty-day Cumulative Abnormal Return from a historic activist campaign on target stock i; σ_{Rcc_i} is the standard deviation of normal daily continuously compounded returns of target stock i during $t \epsilon [-80; -20]$ before the announcement date, and N is the number of historic reports published before the current campaign[1]. The measure is similar to the one used by Comerton-Forde and Putniņš (2009) who evaluated the informativeness of short positions on the NYSE between 2006 and 2008. They argue that this measure is similar to the traditional information ratio, where CAR_{it} can be thought as alpha of the target campaign stock. In fact, this skill measure not only allows us to standardize the abnormal returns, but also captures both the skill from active portfolio management, as well as controls for most of the individual risk at the security level. Finally, we multiply the information ratio by minus one (negative CARs are good for short sellers, hence, their skill should be positive).

[1] Since we measure the historic three-month information ratio, we calculate average skill of previous campaigns initiated at least three months before the current announcement at time t.

We measure activist short seller's $Skill$ before the given campaign as a trailing average of the previous campaigns' information ratios in our sample. If this is the first campaign of the short seller in our sample, we set his $Skill$ equal to average information ratio of other short sellers' campaigns during the most recent six months. By construction, we assume that if this is the first campaign of an activist, his skill is no better that average market skill. We use also the second measure of $Skill$ calculated as one-month CAR from campaign i over standard deviation of its normal daily continuously compounded returns to perform sensitivity tests. The frequency histogram of the $Skill$ variable in our sample constructed using both methods is presented in appendix F. When looking at the charts, one can observe that the shape of the distribution does not differ essentially depending on the estimation window for measuring the skill.

In our OLS regression, we measure the depended variable CAR at different short-term time horizons: one day, one week, and two weeks. All CARs are winsorized at 0.5% from both tails. As well, we winsorized short seller's skill at 0.5% from the right tail. We present the correlation matrix for the variables employed in Appendix G. To avoid potential multicollinearity among explanatory variables, we run several regressions by separately combining market capitalization and spread with other explanatory variables. We are concerned about the possible sample selection bias, as well as capturing the unobservable characteristics that could explain negative CARs in the short-run. Firstly, to study the magnitude of short-term CARs our set of control variables benchmark the company to itself in a past period rather than analyze the differences between targeted and non-targeted stocks (e.g. CARs are risk-adjusted individually for each stock, ex-ante price run-ups and stock volatility benchmark individual past returns right before the announcement). As a result, even though there are some distinctive characteristics of targeted stocks, we control for the individual historic stock behavior before the announcement which partially eliminates the sample selection bias, controls for time-invariant unobservable firm-specific factors, and concentrates on explaining the magnitude of CARs. As for the second concern, in order to make our results more robust and capture additional unobservable factors, in our regressions we introduced allegation-fixed effects to account for the unmeasurable nature of the messages that activist short sellers communicate to the public. As argued by Ljungqvist and Qian (2016), the content of short seller's report can re-interpret the existing information, or, it can question crucial problems and reveal new facts previously unknown to investors. Introducing primary allegation fixed effects allows to control for such measures. Regression

results for the determinants of short-term abnormal returns are presented in Appendix H.

As the outcomes suggest, more negative CARs one day post announcement are driven by higher ex-ante price run-ups, lower market capitalization, as well as higher short seller's reputation (skill) on the market. Keeping all other factors constant, if price run-up increases by one percentage point (pp), CARs during the first trading day will drop by 0.05 pp (statistically different from zero). If market capitalization increases by 1% and all other factors remain unchanged, on average, CARs will decrease by 0.51 pp. Finally, when credible short sellers (those with better historic performance) step in, the magnitude of negative CARs increases. When using our first measure of skill (historic one-month information ratio), the average coefficient is -0.23. When using our second measure of skill (average three-month information ratio), the average coefficient is -0.17 pp.

One-week and two-week CAR regression outcomes suggest that the negative coefficient before price run-up increases monotonically for longer event windows. Now, the effect from an increase in raw returns is even stronger for a 5-day (-0.07) and 10-day (-0.10) intervals. This suggests that, indeed, short sellers tend to correct stocks with high valuations and drive prices towards their fundamental values (the effect of price run-up is significant at 1% benchmark in all three models). Similarly, the effect from market capitalization is stronger for a ten-day period comparing to one-day horizon (0.80 and 0.51, respectively). Even though the coefficient before skill becomes larger for one- and two-week estimation, the effect becomes statistically weaker. One explanation could be that the initial (one-day) reaction is indeed driven by short seller's prior reputation on the market, while during longer time periods the effect from company's true fundamentals emerge.

In addition to the abovementioned conclusions, we also see that market reactions are more negative for more volatile stocks, (the average coefficient is 0.93 for one-week CARs and 1.08 for two-week CARs, significant at 5% level) as well as those with low ex-ante short interest (the average coefficient is 0.16 for two-week abnormal returns, significant at 10% level). Information asymmetry and liquidity seem to be weak predictors of short-term CARs.

To sum up, we conclude that activist short sellers correctly predict bad future performance of smaller and more volatile stocks with high valuations. Finally, we show that short seller's prior reputation on the market is an important driver of short-term abnormal stock returns. This is an important conclusion which proves that more skilled short sellers are

considered more trustworthy when they initiate a new campaign, but in the long-term, short-term overreactions to short seller's skill might mean-revert since the markets learn about the true fundamental values of the stock.

5.4. Measuring the manipulativeness of activist short sellers.

From the predictions of our theoretical model, there are two possible scenarios for price development during the event window. First is the *continuation* – there were no upward rebounds after downward pressure and meaning that prices continue to fall. Continuation is an indicator of overvalued stocks – trader correctly identified the overvalued security, shorted and pushed prices back to their fundamental value. Second scenario is a *reversal*. As the pressure diminishes, prices rebound and return back to or close to their pre-announcement value. This is an indication of stock manipulation – the trader tried to persuade other market participants that the stock is overvalued, shorted it, the stock became undervalued, and prices reversed back to the fundamental value when the market got enough time to learn about the true fundamentals of the company.

Shkilko, Van Ness and Van Ness (2012) investigate significant price declines in the context of event studies. They use standard deviations of normal daily returns before the event took place as a benchmark for estimating the magnitude of the price fall. We utilize recommendations of the authors to construct our own empirical model. Our challenge is to estimate reasonable time horizon over which we will measure price patterns (following our theoretical model, this is when prices fall from P_0 to P_1). Academic literature argues that it might take up to several trading days for markets to substantially depress prices[1]. We believe that we can measure P_1 five trading days after P_0 (which is the price prior to the campaign announcement)[2].

We define a ***significant reaction*** to the announcement to be expressed as a drop in five-day CARs equal to or lower than minus two standard deviations of pre-event normal daily returns, measured at $t \in [-80; -20]$ prior to campaign announcement date. If in the following five days CARs are positive, we define the event as producing ***no reaction***. Finally, if in the following five trading days CARs are negative but above minus two standard

[1] For example, Boehmer, Jones and Zhang (2008) study daily NYSE short sale order data and find that prices incorporate the knowledge of short sellers during the first trading days.
[2] We also perform a sensitivity test and measure P_1 ten trading days after announcement.

deviations of normal daily returns, we classify such events as exhibiting ***insignificant reaction***.

From our theoretical model, after we define P_1, stocks follow either a continuation or reversal pattern from P_1 to P_2 (P_2 is when full information about the security is revealed). We continue setting our empirical model by studying long-term price patterns of those stock defined as showing a ***significant reaction***. Boehmer and Wu (2013) also perform a study on intraday short selling and price discovery mechanisms on NYSE. In their work, they define continuation as a non-positive return following the initial price drop; a rebound of less than 20% as weak reversal; a rebound larger than 20% but less than 100% as a reversal; and a rebound above 100% of the initial drop as overshooting. We develop a similar methodology and decide to split those events defined as significant reaction into three categories in the following way:

- ***Continuation***: an event when long-term negative CARs are not larger than 90% of the initial five-day negative CARs (ten-day negative CARs for robustness tests)
- ***Weak Reversal***: an event when large negative CARs are accompanied by a reversal of less than 50% of the initial five-day decline (ten-day decline for robustness tests)
- ***Reversal***: an event when large negative CARs are accompanied by a reversal of more or equal to 50% of the initial five-day decline (ten-day decline for robustness tests)

Figure 5 provides illustrative explanation of all six categories in our empirical model. As noted above, for our main (robustness test) methodology, we examine short-term price patterns in the following five (ten) trading days after the announcement, while the reversal or continuation will be measured at a three-month interval[1].

[1] Nagel (2005) can serve as an example to this time horizon. He finds that overreaction can yield excess returns in the long run, even up to six months after the portfolio formation.

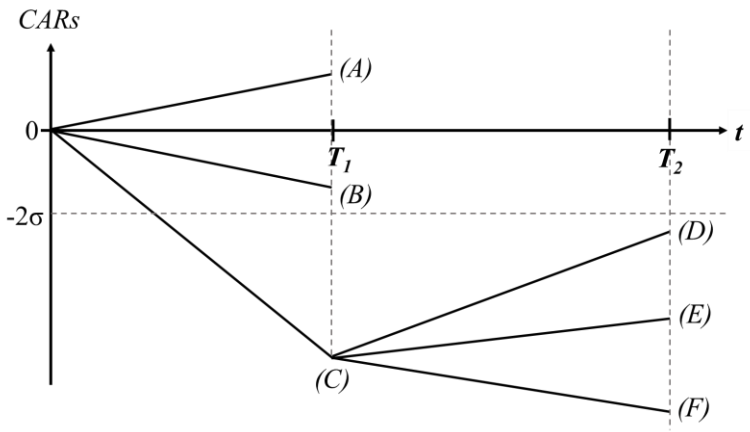

Figure 5. Price patterns following activist campaign announcement.
(A) No effect; (B) Insignificant effect; (C) Significant effect; (D) Reversal; (E) Weak reversal; (F) Continuation. T_1 equals five trading days (ten trading days for robustness checks); T_2 equals 60 trading days. Created by the authors

Appendix I introduces the summary statistics of different magnitudes of the market reaction. Around 48% (50%) of the campaigns in our sample experience a significant drop in returns during the five-day (ten-day) window after the announcement. 68.5% (70.3%) of those reveal a continuation in negative returns over the 60-day interval after the event, while 25% (19%) rebound close to their initial price levels. According to the statistics, in the interval (0;5) the mean for the whole sample CARs is -8.3%, while for the stocks that had a significant drop, the mean is -19.3%. Similarly, average sample CAR for the interval (0;10) is -9.9%, while for those classified under Significant reaction the mean is -23.4%.

5.5. Measuring the probability of manipulation.

Using the empirical values for the proportion of reversals r and the average skill of the investors - s, we perform a sensitivity analysis to see what is the theoretical probability of manipulation (m) in our sample and how sensitive it is to our assumption regarding the value of x and the measurement of skill. In order to fit the model assumptions the mean and median skill are scaled to the interval of 0-0.5 by attributing the corresponding percentile and dividing by two (e.g. the median represents the 50^{th} percentile, so the value used in the model is $\frac{0.5}{2} = 0.25$). The results are reported in Table 3. Under the assumption that the stocks targeted by manipulators are equally likely to be undervalued or overvalued ($x = 50\%$), and our skill measure is accurate, our analysis shows that theoretically, the probability of manipulation m should be in the range of 1-6% (the values calculated using the mean (0,265) and median (0,25) skill). Allowing x to deviate from the theoretical assumption and some larger boundaries for the skill measure, m should be comprised in the interval of 0-23%.

Table 3. Sensitivity analysis.
The table reports the probability of manipulation m, conditional on the level of skill of the investor, the proportion of manipulators identifying overvalued stocks, and the proportion of reversals in the sample. The skill estimates include the mean, the median, and the average of the two, as well as a 10% deviation from the calculated mean and median (first and last estimate). The percentage of reversals used in calculation is 25,23%. For this model we classify insignificant reversals as return continuations.

skill of informed traders	% of manipulators identifying overvalued stocks				
	40%	45%	50%	55%	60%
0.23	0.00	0.00	0.00	0.00	0.00
0.25	0.00	0.01	***0.01***	0.01	0.01
0.26	0.03	0.03	***0.04***	0.04	0.06
0.27	0.05	0.05	***0.06***	0.08	0.10
0.29	0.11	0.13	0.15	0.18	0.23

The model also shows that, for a given level of x, the higher the skill of informed traders, the higher the probability of manipulation, which is due to the fact that the market is more likely to react favorably for the short sellers if it knows they are sufficiently skilled, thus, creating incentives for manipulators to join. On the other end, the higher the probability of manipulators picking overvalued stocks, the higher the probability of manipulation, as there are higher incentives for a manipulator to join if the odds are in her favor.

After analyzing the results of the theoretical model, we develop a back-of-the-envelope calculation method to test the robustness of these results. As previously identified, most of the return continuations are associated with informed trading, while most reversals will refer to possible manipulation. Our goal is, thus, to separate informed trading from the sample of reversals. We start by assuming that the whole sample of campaigns that resulted in a reversal (12.10%) are manipulative. We then apply filters to eliminate informed trading based on expected observable price patterns. By doing so, we are able to approximate the upper boundary of the proportion of manipulation.

Firstly, we look at the past performance of the investors. We would expect that, because of the high risk, an activist would not engage in a manipulative campaign if he has no credibility on the market (poor past performance) as the market has no basis to believe their claims. An informed trader, however, would still make a bet if he fully trusts his estimates irrespective of the previous fails. So, we discard the campaigns that resulted in a reversal and the initiators of which were low-skilled because we assume those short sellers were informed traders. We define a low skill as having the value of skill at the moment of campaign initiation lower than the market average skill for the last 6 months. Applying this

filter, we reduce the estimate to 7.96%.

Our next filtering criterion is based on forward-looking performance. We would expect that, once a manipulative campaign has been unveiled (i.e., a reversal has occurred), the market would "punish" the investor so that his next attempted campaign will generate lower profits than his past campaigns or even a loss. However, if a reversal if followed by better than average results, it is most likely to be an unsuccessful informed campaign. Therefore, we sort out the reversals that were followed by a new campaign that managed to produce a significant drop[1] in CARs. We now shrink the estimate to the value 4.36%.

Then, we tackle some factor that may increase the stock price but do not necessarily imply that the price rebounded because of the market learning about manipulation. Ruback and Jensen (1983) present extensive evidence on the fact that merger and acquisition target firms benefit form significant positive abnormal returns after the merger or acquisition announcement. Therefore, we filter out the reversals that occurred because of a merger or acquisition announcement with reported value higher than zero. We select only mergers and acquisitions of entire share capital from Thomson Reuters M&A database. After excluding such cases we end up with 4.25%.

To check for robustness, we perform the same analysis but allow the initial reaction to be observed over a 10-day window rather than 5 days and receive a result equal to 3.49% (by relaxing this assumption the proportion of reversals in the sample is 9.49%). We then recalculate the skill measure by observing the campaign performance over the first 20 days after announcement instead of 60. Using this skill calculation we receive the estimated probability of manipulation equal to 4.03% (initial price reaction occurs during the 5-day window) and 3.49% (10-day window).

Even after all the filters have been applied, the estimate might be contaminated due to data imperfections. Also, there might be other preeminent characteristics that we were not able to control for. To increase the robustness, we add one more method of estimation. We use bootstrapping to account for the fact that the distribution of m is unknown. Using the baseline model (5-days window, 60-day skill), this technique returns the 95% confidence interval of 2.3-4.7%. Using the 10-day window we obtain the interval 2.7-5.4%.

[1] For the definition of what we consider a significant drop see p.35

6. Discussion of Results

In this section, we review our empirical analysis and relate it to the previous studies. The discussion of the results first summarizes the activist short selling market in the U.S. We then review the main ex-ante firm-specific characteristics that make stocks attractive for activist short sellers. Following, we show that markets react strongly to the release of short sellers' reports that accuse target companies of business fraud, improper corporate governance, financial irregularities, or other types of corporate misbehaviour. Third, we study the main determinants behind the magnitudes of short-term abnormal returns following the announcements of activist short campaigns. Finally, we study long-term price patterns and after campaign announcements and quantify the amount of manipulation associated with activist short selling. The last part of the discussion presents the limitations of our study.

Despite the recent drop in the number of campaigns launched, activist short sellers have been relatively active during the past seven years. Most of the reports issued by short sellers question the medical effectiveness, accuse companies of fraud, or find evidence of overvaluation and stock promotion. A sizeable number of campaigns target firms in Healthcare and Technology - industries undergoing lengthy product development processes surrounded by high uncertainty and risks of failure. In addition, short sellers mostly target small-cap stocks, accusing them of being "under-scrutinized and more susceptible to fraud" (Valuewalk, 2016).

Both univariate and logistic analyses show that short sellers target more liquid stocks with higher valuation multiples, larger information asymmetry, greater stock volatility, as well as high ex-ante short interest. This is in line with academic literature stating that short sellers correctly identify overpriced stocks (Dechow et al., 2001; Lee, 2016), and benefit from their informational advantage in stocks with high uncertainty (Zhao, 2018). Moreover, we also conclude that short sellers attack stocks with higher insider ownership, lower profitability and lower payout ratio. This leads us to conclude that activist investors not only take advantage of greater uncertainty about future stock performance but also punish companies for weak corporate governance and performance indicators. Overall, our first analysis suggests that, on average, short sellers are informed traders who correctly identify overvalued stocks that are prone to show bad performance in the future.

Using event study methodology, we conclude that activist public claims generate

significant market reactions around campaign initiation dates, which is in line with the evidence by Ljungqvist and Qian (2016). Panel A in Appendix D shows that irrespective of the definition of the short term (1, 5, 10, or 20 days), on average, the sample of campaigns generates significant negative abnormal returns immediately after the announcement. By relating this evidence to the above-mentioned conclusion that, on average, activist short sellers are informed traders, we are able to empirically confirm our first hypothesis, which states that, unless the proportion of manipulation is higher than 50%, the market will tend to trust activist claims and react in favour of short seller's position immediately after announcement.

Our model meant to explain the magnitude of the short-term price reaction shows that the information ratio, which is used to gauge short seller's skill as perceived by the market, is an important predictor of the extent to which prices decline after the announcement. This evidence confirms our second hypothesis, which states that the informed trader's skill is an important determinant of the market reaction. Namely, the higher the skill of the investor, the lower the short-term abnormal returns of the target stock, which confirms our third hypothesis.

Panel A of Appendix E shows that the average price path follows a negative trend for at least six months following the announcement date. Targets accused of stock promotion and patent expiration produce the largest negative price drops during the first six months after the release of the report, while those subject to invalid patents, pyramid schemes or upcoming earnings miss do not yield statistically significant results. We observe that large negative abnormal returns are closely related to more volatile, small stocks, with wide information asymmetry, and high valuation multiples. This evidence speaks in favour of our last hypothesis, which anticipates that stocks exhibiting higher uncertainty about future performance will experience larger price decreases right after the announcement.

Assessing the longer term stock performance, we find that in the first two weeks after campaign announcement, half of the targeted stocks experience significant risk-adjusted price declines in relation to their pre-announcement normal performance. We document that around 70% of such stocks experience the continuation of negative returns over the three-month event window. However, prices of around 10-12% of our target stocks tend to mean-revert to their initial pre-campaign values. Using a back-of-the-envelope approach based on expected market reactions under informed short selling and short and distort manipulation,

we suspect that around one third of those reversals, or 3-5% of total sample of activist campaigns, are a result of stock price manipulation.

Walker and Forbes (2013) have published an extensive discussion article on the legal prosecution of short attacks. The authors insist that the US Securities and Exchange Commission (SEC) is reluctant to take action when the targeted firms accuse short sellers of spreading misleading information, negative media coverage and public defamation. They also claim that the burden of providing proofs in this case is on the company being attacked, rather than on the activist spreading the information. Moreover, companies demanding an investigation on the short seller have to overcome burdensome beaurocratic procedures and even risk becoming the subject of the investigation themselves. The article also documents that even among the cases that succeed to be examined, very few result in actual enforcement. As far as we are concerned, our research is the first academic attempt to detect and quantify the existence of market manipulation in the context of activist short selling. Given the magnitude of market reaction to such announcements that we document, we believe that this type of activity should receive more attention from both academicians and regulators.

7. Limitations

There are several factors that might contaminate the quality of our results. First of all, we are quite limited in data. Short-and-distort as well as pump-and-dump manipulation theories are usually proved using trading orders data. By not incorporating such data we might not be able to distinguish the manipulative campaigns that happened to succeed because of a mix of information-based manipulation and trade-based manipulation rather than purely information-based manipulation. On the same line, because short sellers are not legally required to report the scale of their trades, it becomes very difficult to judge the nature of their intentions. Another issue constitutes the fact that it cannot be verified whether all campaign initiators actually enter a short position in the stock. For example, some activists claim to be fraud exposing agents and do not clearly specify whether they are trading on the stock.

Moreover, we acknowledge the limitation that a reversal could also occur because of firms responding to short seller's allegations or making operational changes in the companies. However, the primary focus of our theoretical model is to distinguish between

manipulators and unskilled activists, where we use activist's historic track record to recognize if he is skilled enough to identify overvalued stock. What is more, we believe that the possibility of positive revisions in valuations (i.e. a reversal) due to fundamentals is already factored into the model as prices can be above or below fundamentals at the announcement date. In other words, at the announcement date the markets have already priced good or bad future valuation changes. As well, our measure of skill might be flawed as it does not incorporate other types of trading done by the individual investor (successful long activism) and it also dismisses the campaigns ran on foreign stocks or before 2010. However, we should recognize that we have tested several variations of this variable, including both binary (successful campaign or not) and continuous, over various time horizons. In the unreported results, we have received robust relation between skill and negative short-term CARs, as well the amount of manipulation in the market is roughly the same. We leave the modified information ratio as a measure of skill due to the fact that it is a popular indicator capturing the skill of active portfolio managers.

8. Conclusions

Previous research suggests that short selling improves market quality and is an important source of market efficiency but it also shows that the information contained in the short theses might be misleading and even damage a company's future performance. If a short seller has enough credibility, she can create panic among long investors who start selling their positions and subsequently, depress the stock value. If the market reaction was only due to the panic and not to the informational advantage of the short activist, then, eventually, the markets absorb all the necessary information, and the prices mean-revert to their fundamental values. As a result, this is indicative of market manipulation – activist short sellers artificially drive prices down by creating panics among the investors and profit on short-term price declines.

To our knowledge, our study is the first one to quantify the manipulativeness of activist short selling on the market. Based on our analysis conducted on a sample of 926 activist short selling campaigns, we find that activist short sellers successfully target overvalued stocks with high uncertainty measures. Moreover, we see that there are significant short-term risk-adjusted reactions from market participants following the announcement of short thesis, especially to the announcements accusing target stocks of corporate fraud and stock promotion. Long-term risk-adjusted returns show that average price paths following

activist announcements indicate continuations of negative future returns. These findings suggest that, on average, short sellers are improving market quality by correcting stock prices and have material private information about poor future stock performance. We also find empirical evidence that short seller's skill is a good determinant of bad future stock performance. Answering our research question, we find that the percentage of manipulation in the case of activist short selling campaigns is rather low (2.3-5.4%), and, on average, activists are informed traders. Nevertheless, our estimates provide sufficient ground for concerns about the true trustworthiness of the activist claims and their consequences for the target companies.

This paper has several implications. First, given the recent upswing in passive trading, we show that activist investment remains one of the few sources of active portfolio management to outperform modern capital market indices. Next, we contribute to the ongoing debate of the role of activist short selling in the market by saying that even though short sellers are, on average, informed investors who correctly predict bad future stock performance, they are also involved in predatory trading when activists artificially depress target stock price which subsequently mean-revert to their fundamental values. Third, the paper could be of a particular interest of corporate managers and shareholders who could timely design defence strategies against activist short sellers.

Finally, our study can potentially benefit the policy-makers by showing that pump and dump is not the only viable type of manipulation and that, having more severe consequences for the target companies, short and distort manipulation should receive more regulatory attention than it currently does. Designing short positions disclosure requirements and simplifying the procedural barriers for the issuers (i.e. target companies) to defeat their reputation could be effective in increasing enforcement rates in cases of market manipulation and even lower the occurrence of this type of securities fraud.

9. Suggestions for future research

We consider that our research sets a rather solid foundation and thus, provides motivation for more advanced research on the topic of activist short selling and its dualistic nature. We believe that more valuable results can be obtained by capturing more filters for distinguishing informed trader from manipulation. Some of them might be related to whether the target company responded to the allegations, and in which form (press release, court case, etc); or whether there has been an investigation done by the SEC on the mentioned allegation. A more accurate value of the proportion of manipulation might be achieved by taking into account earnings restatement done by companies after the activist campaign is launched. Another factor that might affect the credibility of announcements might be the character of the activist investor (individual or hedge fund, known or anonymous).

Moreover, more attention could be devoted to those cases where a single company was targeted by multiple short sellers during a short time interval. This is a so-called wolf pack activism, where multiple investors team up to exercise the collective influence on the target company (Brav et al., 2017). Gaining more insights in this area would allow the researcher to distinguish between the manipulative actions taken by a single investor or a group of activists that combine their power to artificially drive down the stock price.

Finally, credibility might be tightly linked to the type and quality of activist statements, e.g. published research might be lore trustworthy than a blog post or a tweet. Text analysis of the activist reports might also be of good use in this case.

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11. Appendices

Appendix A. The Determinants of Becoming an Activist Short Selling Target. Logit Regression.

The numeration (1) – (8) corresponds to the number of the model. The models differ by the set of variables included. P-values are shown in parentheses (* p<0.10; ** p<0.05; *** p<0.01). *N* is the number of observations included in the regression. *chi2* is the X^2 likelihood ratio. *p* is the p-value asscoaited to the chi2 test. In this case, a *p* of 0.00 shows there are significant differences between the two observed groups (targets and non-targets).

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
ln(Total Assets)	0.04	*(0.38)*	0.07	*(0.14)*	0.09*	*(0.05)*										
ln(Market Cap)							0.40***	*(0.00)*	0.26***	*(0.00)*	0.31***	*(0.00)*	0.18***	*(0.00)*	0.33***	*(0.00)*
Price-to-Book	0.10***	*(0.00)*	0.10***	*(0.00)*			0.08***	*(0.00)*	0.08***	*(0.00)*						
Tobin's q					0.36***	*(0.00)*					0.30***	*(0.00)*	0.31***	*(0.00)*	0.31***	*(0.00)*
Debt-to-Assets	-0.01***	*(0.00)*	-0.01***	*(0.00)*	-0.003*	*(0.07)*	-0.01***	*(0.00)*	-0.01***	*(0.00)*	-0.004**	*(0.03)*	-0.00	*(0.11)*	-0.004**	*(0.02)*
Payout ratio	-0.02***	*(0.00)*	-0.02***	*(0.00)*	-0.02***	*(0.00)*	-0.02***	*(0.00)*	-0.02***	*(0.00)*	-0.02***	*(0.00)*	-0.02***	*(0.00)*	-0.02***	*(0.00)*
ln(No. of analysts)	-0.28***	*(0.00)*	-0.33***	*(0.00)*			-0.63***	*(0.00)*			-0.58***	*(0.00)*			-0.63***	*(0.00)*
St. dev. of Forecasts					-0.00	*(0.86)*			-0.00	*(1.00)*			-0.00	*(0.92)*		
Illiquidity	-1.34**	*(0.01)*	-1.58**	*(0.01)*	-1.05	*(0.22)*	-0.61*	*(0.09)*	-0.63	*(0.37)*	-0.72**	*(0.05)*	-0.60	*(0.38)*	-0.84*	*(0.05)*
Volatility	0.07**	*(0.01)*	0.11***	*(0.00)*	0.13***	*(0.00)*	0.13***	*(0.00)*	0.12***	*(0.00)*	0.13***	*(0.00)*	0.15***	*(0.00)*	0.18***	*(0.00)*
Short Interest	0.10***	*(0.00)*	0.10***	*(0.00)*	0.09***	*(0.00)*	0.10***	*(0.00)*	0.10***	*(0.00)*	0.10***	*(0.00)*	0.09***	*(0.00)*	0.10***	*(0.00)*
ROA	-0.00	*(0.22)*					-0.01***	*(0.00)*	-0.01***	*(0.00)*	-0.00	*(0.17)*				
Insider Ownership	0.02***	*(0.00)*	0.02***	*(0.00)*	0.02***	*(0.00)*	0.02***	*(0.00)*	0.02***	*(0.00)*	0.02***	*(0.00)*	0.02***	*(0.00)*	0.01***	*(0.00)*
S&P 500 Member	0.70***	*(0.00)*	0.77***	*(0.00)*	0.33*	*(0.07)*	0.18	*(0.36)*	-0.04	*(0.84)*	0.27	*(0.16)*	0.11	*(0.55)*	0.36*	*(0.06)*
EBITDA margin			-0.00	*(0.72)*	0.00	*(0.79)*							0.00	*(0.97)*	0.00	*(0.65)*
Year fixed effects	*Yes*		*Yes*		*Yes*		*Yes*		*Yes*		*Yes*		*Yes*		*Yes*	
Industry fixed effects	*Yes*		*Yes*		*Yes*		*Yes*		*Yes*		*Yes*		*Yes*		*Yes*	
N	71869		69417		64505		71869		63646		75142		64505		72694	
chi2	844.8		819.8		827.1		902.3		768.2		1010.1		838.3		980.6	
p	*0.00*		*0.00*		*0.00*		*0.00*		*0.00*		*0.00*		*0.00*		*0.00*	

Appendix B. Correlation matrix of variables used in identifying ex-ante determinants of becoming a target.

	TA	Mcap	D/A	ROA	EBITDA	PB	Tobin's q	Payout	Illiq.	St.dev. Forec.	No. of an.	Short int.	Volat.	S&P
Total Assets, (mln)	1,00													
Market Cap (mln)	0,45	1,00												
Debt-to-Assets, %	0,01	0,04	1,00											
ROA, %	0,02	0,12	0,03	1,00										
EBITDA margin, %	0,04	0,07	0,09	0,66	1,00									
Price-to-Book	-0,06	0,08	0,17	-0,08	-0,13	1,00								
Tobin's q	-0,10	0,04	-0,10	-0,10	-0,24	0,70	1,00							
Payout ratio, %	0,08	0,17	0,10	0,20	0,18	-0,06	-0,15	1,00						
Illiquidity	-0,02	-0,03	-0,02	-0,10	-0,06	-0,03	-0,03	-0,06	1,00					
Standard deviation of analyst forecasts, %	-0,03	-0,07	0,02	-0,15	-0,06	-0,02	-0,02	-0,17	0,08	1,00				
Number of analysts	0,19	0,45	0,10	0,19	0,13	0,13	0,11	0,10	-0,11	-0,10	1,00			
Short interest, %	-0,09	-0,15	0,05	-0,10	-0,12	0,12	0,17	-0,17	-0,09	0,07	0,04	1,00		
Volatility, %	-0,09	-0,19	-0,04	-0,41	-0,36	0,04	0,10	-0,38	0,13	0,22	-0,21	0,26	1,00	
S&P membership	0,21	0,44	0,08	0,18	0,11	0,07	0,02	0,26	-0,05	-0,12	0,62	-0,15	-0,27	1,00

Appendix C. Winsorization parameters for the variables used in determining the probability of becoming a target.

Variable	***Left tail***	***Right tail***
Volatility	0%	0.5%
Short Interest	0%	0.5%
Debt-to-Assets	0%	0.5%
Insider Ownership	0%	0.5%
Standard deviation of analyst forecasts	0%	1.0%
Price-to-Book	0%	2.5%
Tobin’s q	0%	2.5%
Illiquidity	0%	2.5%
ROA	2.5%	0.5%
EBITDA margin	2.5%	0.5%

Appendix D. Summary Statistics of Event Studies Analysis.

The table reports summary statistics of abnormal returns following the activist campaign announcement date. **N** refers to number of observations, **Mean** is the average abnormal return, **25%**, **Median** and **75%** refer to the quartiles of observations, **T stat.** and **P-Value** refer to T-statistics outcomes (H_o: $\overline{CAR}(T_1, T_2) = 0$). Panel A is a summary statistic for the whole sample, while Panel B is a summary statistic split by Primary Allegation.

Panel A: Summary Statistics for the Whole Sample

	N	Mean	25%	Median	75%	T stat.	P-Value
AR [0]	917	-4.79	-7.60	-2.62	0.27	*-13.28*	*0.00****
CAR [0;1]	917	-6.04	-9.98	-3.63	0.42	*-14.39*	*0.00****
CAR [0;5]	917	-8.34	-13.76	-5.28	0.33	*-14.55*	*0.00****
CAR [0;10]	917	-9.92	-17.16	-5.58	1.14	*-13.51*	*0.00****
CAR [0;20]	917	-13.27	-22.19	-8.24	2.23	*-13.47*	*0.00****
CAR [0;60]	917	-22.41	-42.50	-16.21	3.53	*-14.49*	*0.00****
CAR [0;120]	892	-35.14	-65.62	-23.66	5.92	*-14.72*	*0.00****

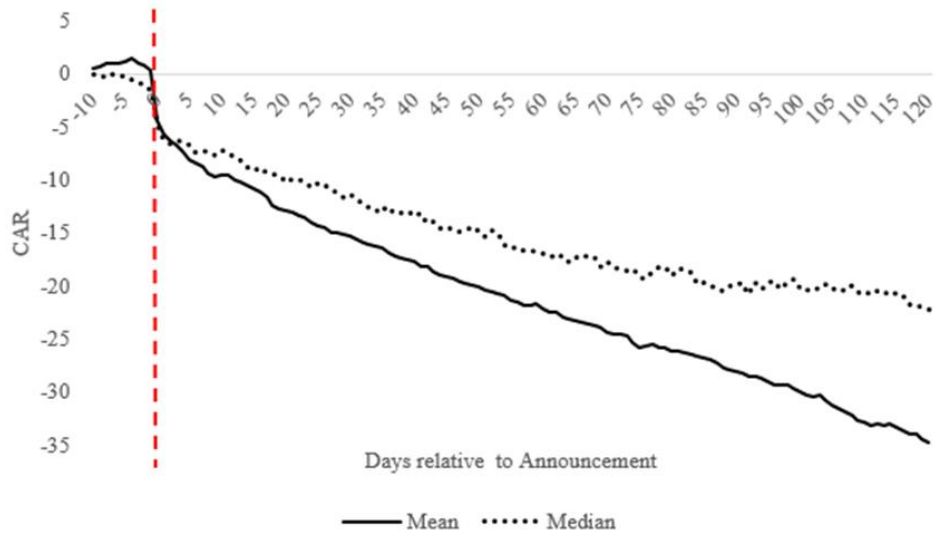
Panel B: Summary Statistics by Primary Allegation

	CAR [0;1]				CAR [0;60]				CAR [0;120]			
	N	Mean	*T Stat.*	*P-Value*	N	Mean	*T Stat.*	*P-Value*	N	Mean	*T Stat.*	*P-Value*
Accounting Fraud	43	-10.56	*-6.02*	*0.00****	43	-29.11	*-4.36*	*0.00****	42	-45.18	*-4.08*	*0.00****
Bubble	77	-4.63	*-3.12*	*0.00****	77	-26.77	*-4.78*	*0.00****	75	-43.58	*-4.86*	*0.00****
Competitive Pressure	66	-4.16	*-4.75*	*0.00****	66	-16.81	*-4.07*	*0.00****	65	-26.53	*-3.45*	*0.00****
Dividend Cut Coming	7	-7.11	*-2.61*	*0.04***	7	0.80	*0.12*	*0.91*	7	3.25	*0.36*	*0.73*
Industry Issues	85	-3.02	*-3.44*	*0.00****	85	-7.29	*-2.13*	*0.04***	84	-11.30	*-2.01*	*0.05***
Ineffective Roll-Up	45	-6.19	*-5.19*	*0.00****	45	-17.19	*-3.20*	*0.00****	44	-30.42	*-3.89*	*0.00****
Major Business Fraud	44	-11.64	*-4.01*	*0.00****	44	-29.34	*-4.00*	*0.00****	42	-45.68	*-3.92*	*0.00****
Medical Effectiveness	103	-4.99	*-4.13*	*0.00****	103	-21.04	*-3.87*	*0.00****	97	-35.66	*-4.49*	*0.00****
Misleading Accounting	81	-4.88	*-4.27*	*0.00****	81	-14.65	*-4.19*	*0.00****	79	-21.35	*-4.33*	*0.00****
Other Illegal	49	-7.53	*-3.98*	*0.00****	49	-22.09	*-5.79*	*0.00****	48	-32.24	*-5.80*	*0.00****
Other Overvaluation	96	-4.05	*-3.29*	*0.00****	96	-21.87	*-4.86*	*0.00****	95	-35.09	*-4.73*	*0.00****
Over-Levered	55	-6.22	*-3.57*	*0.00****	55	-23.12	*-3.22*	*0.00****	53	-34.48	*-2.71*	*0.01****
Patent Expiration	5	-10.10	*-2.31*	*0.08**	5	-51.30	*-3.78*	*0.02***	5	-59.44	*-2.32*	*0.08**
Patent Invalid	12	1.41	*1.20*	*0.26*	12	-19.63	*-2.25*	*0.05***	12	-48.88	*-3.03*	*0.01***
Product Ineffective	47	-7.16	*-3.71*	*0.00****	47	-26.54	*-5.21*	*0.00****	44	-41.98	*-5.22*	*0.00****
Pyramid Scheme	10	-5.28	*-1.40*	*0.19*	10	-26.81	*-1.56*	*0.15*	9	-23.25	*-0.94*	*0.38*
Stock Promotion	70	-12.71	*-5.36*	*0.00****	70	-49.55	*-5.26*	*0.00****	69	-73.95	*-5.75*	*0.00****
Upcoming Earnings Miss	22	-1.50	*-1.07*	*0.30*	22	-7.36	*-0.78*	*0.44*	22	-17.12	*-1.15*	*0.26*

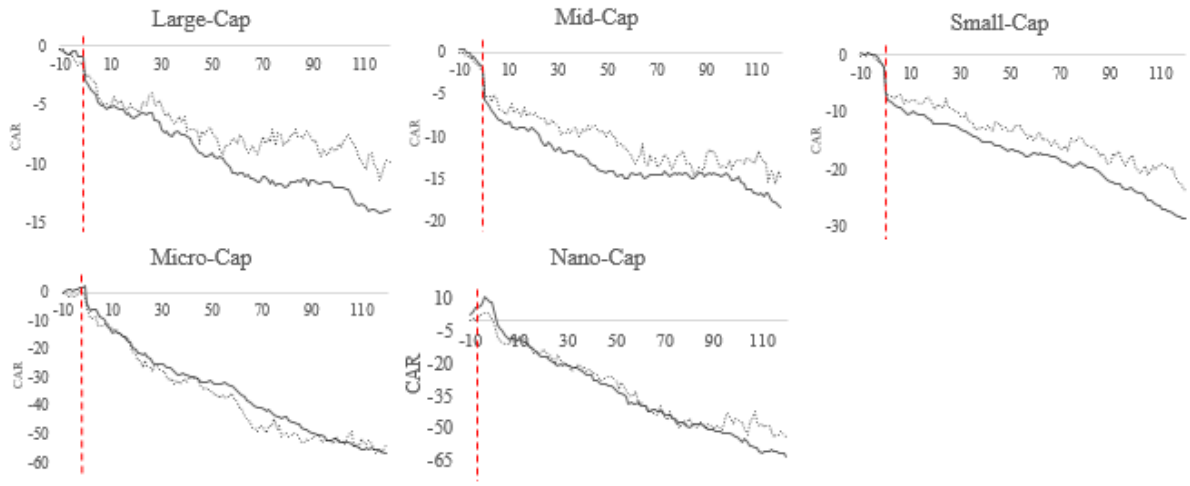
Appendix E. The Development of the Cumulative Abnormal Returns over the event window (-10, 120).

Panel A provides the average CARs patterns for the whole sample. Panel B depicts the same graph by different market cap categories. The continuous line shows the mean and the dotted line shows the median.

Panel A: Average CARs Path for the Whole Sample of Activist Campaigns.



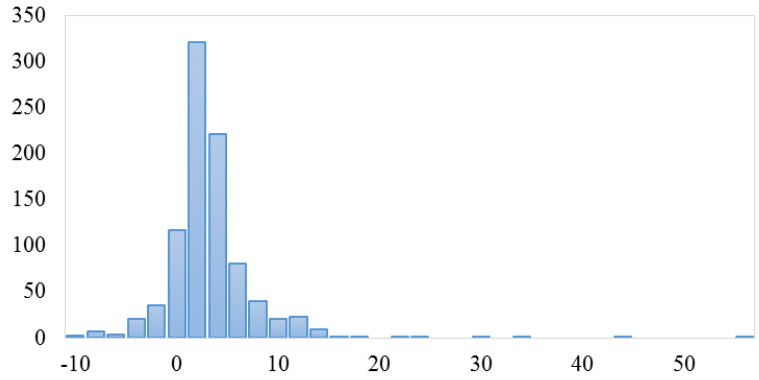
Panel B: Average CARs Path the Activist Campaigns by Market Cap Category.



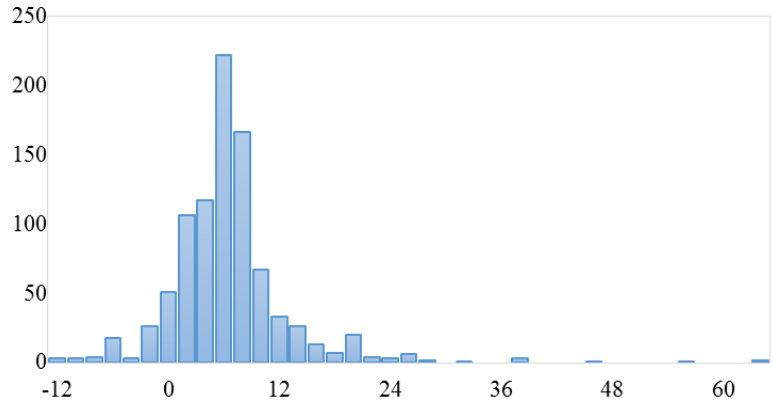
Appendix F. Frequency Histogram of the Skill variable.

The figures below show the frequency histogram of the *Skill* variable in our sample. **Panel A** shows the histogram for the *Skill* calculated using the information ratio during the first 60 days of each past campaign of the same investor. At the beginning of each new campaign initiated by an investor the *Skill* is equal to the average information ratio of all his past campaigns encountered in the sample. **Panel B** shows the same measure calculated during the first 20 days of the campaign.

Panel A: Skill Calculated during the First 60 Trading Days



Panel B: Skill Calculated during the First 20 Trading Days (robustness check)



Appendix G. Correlation Matrix for the Variables Used to Explain the Cumulative Abnormal Returns after Campaign Announcements.

	CAR[0;1]	CAR[0;5]	CAR[0;20]	Mcap	Volatility	Short Interest	Spread	Price Runup	Illiquidity	Skill 1	Skill 2
CAR[0;1]	1.00										
CAR[0;5]	0.75	1.00									
CAR[0;20]	0.63	0.80	1.00								
Mcap	0.15	0.15	0.13	1.00							
Volatility	-0.10	-0.18	-0.16	-0.48	1.00						
Short Interest	0.07	0.07	0.08	0.12	-0.01	1.00					
Spread	-0.09	-0.12	-0.11	-0.54	0.38	-0.28	1.00				
Price Runup	-0.15	-0.16	-0.16	0.01	0.13	-0.08	0.07	1.00			
Illiquidity	-0.09	-0.10	-0.08	-0.49	0.30	-0.27	0.71	0.07	1.00		
Skill 1	-0.11	-0.11	-0.10	-0.15	0.09	-0.06	0.02	-0.08	0.01	1.00	
Skill 2	-0.11	-0.12	-0.09	-0.20	0.12	-0.05	0.03	-0.08	0.03	0.69	1.00

Appendix H. Determinants of Short Term Market Reaction to Announcements. Regression Results.

Our dependent variable is short term CARs (1, 5, and 10 trading days). We use different sets of variables to check for robustness. P-values are shown in parentheses (* p<0.10; ** p<0.05; *** p<0.01). *N* is the number of observations included in the regression. R2 is the coefficient of determination – the proportion of variance of the dependent variable (CAR) explained by the regression model.

	CAR [0;1]						**CAR [0;5]**						**CAR [0;10]**					
Short Interest	0.04	0.04	0.04	0.04	0.06	0.06	0.07	0.08	0.08	0.09	0.09	0.10	0.18*	0.18*	0.19*	0.19*	0.23**	0.23**
	(0.501)	(0.472)	(0.446)	(0.433)	(0.286)	(0.297)	(0.324)	(0.260)	(0.270)	(0.234)	(0.196)	(0.167)	(0.072)	(0.063)	(0.070)	(0.065)	(0.029)	(0.031)
Price Run-up	-0.05***	-0.05***	-0.05***	-0.05***			-0.07***	-0.07***	-0.07***	-0.06***			-0.21***	-0.20***	-0.19***	-0.19***		
	(0.000)	(0.000)	(0.000)	(0.000)			(0.000)	(0.000)	(0.001)	(0.001)			(0.000)	(0.000)	(0.000)	(0.000)		
Volatility			-0.23	-0.19	-0.29	-0.26			-0.93**	-0.86**	-1.00**	-0.92**			-1.70***	-1.65***	-1.86***	-1.82***
			(0.373)	(0.449)	(0.301)	(0.353)			(0.022)	(0.033)	(0.023)	(0.029)			(0.003)	(0.004)	(0.005)	(0.006)
Illiquidity			-1.63	-1.70	-2.19	-2.17			-0.84	-1.05	0.03	0.52			1.57	1.35	18.13	17.68
			(0.705)	(0.691)	(0.632)	(0.637)			(0.904)	(0.880)	(0.997)	(0.945)			(0.884)	(0.900)	(0.134)	(0.146)
Spread					-0.03	-0.08					-0.68	-0.87					-4.19**	-4.21**
					(0.966)	(0.909)					(0.502)	(0.375)					(0.029)	(0.029)
Market Capitalization	0.54**	0.48**					0.84***	0.72**					1.43***	1.35***				
	(0.023)	(0.040)					(0.009)	(0.024)					(0.006)	(0.010)				
Skill (1)	-0.24*		-0.25*		-0.20		-0.29		-0.30		-0.22		-0.30		-0.32		-0.14	
	(0.093)		(0.079)		(0.179)		(0.130)		(0.119)		(0.274)		(0.138)		(0.122)		(0.565)	
Skill (2)		-0.18*		-0.19**		-0.15		-0.26**		-0.26**		-0.22*		-0.19		-0.18		-0.06
		(0.065)		(0.046)		(0.127)		(0.038)		(0.036)		(0.080)		(0.208)		(0.225)		(0.740)
Constant	-16.94***	-14.74**	-5.10	-4.14	-6.01	-4.49	-27.82***	-19.74***	-7.26	-1.93	-8.19	-3.51*	-50.49***	-48.71***	-15.26***	-15.20***	-16.76***	-14.37**
	(0.006)	(0.020)	(0.162)	(0.316)	(0.117)	(0.294)	(0.002)	(0.009)	(0.167)	(0.642)	(0.139)	(0.077)	(0.000)	(0.000)	(0.007)	(0.010)	(0.009)	(0.024)
Primary Allegation FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	*898*	*893*	*901*	*896*	*888*	*883*	*898*	*893*	*901*	*896*	*888*	*883*	*898*	*893*	*901*	*896*	*888*	*883*
R2	*0.11*	*0.11*	*0.11*	*0.11*	*0.08*	*0.08*	*0.10*	*0.10*	*0.11*	*0.10*	*0.08*	*0.08*	*0.15*	*0.14*	*0.16*	*0.15*	*0.09*	*0.09*
P-Value	*0.00*	*0.00*	*0.01*	*0.01*	*0.20*	*0.22*	*0.00*	*0.00*	*0.00*	*0.00*	*0.14*	*0.04*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*

Appendix I. Market Reaction to Activist Announcements. Summary Statistics.

We define a significant drop if the CARs dropped below two standard deviations; insignificant drop – a drop in CARs smaller than two pre-campaign standard deviations. Panel A reports the percentual frequency summary statistics associated with the three distinct short term market reactions to announcements and the three long term outcome possibilities: continuation, reversal, and insignificant reversal. We look at the initial reaction during two time windows: 5 days and 10 days after the announcement took place. The secondary price movement is observed starting from the 5th day after announcement (or the 10th) and till the 60th day of the campaign. Panel B reports the mean CARs in all the above-mentioned situations.

Panel A: Market Reaction Types and Their Percentual Frequencies in the Sample.

	5-day window	10-day window
Initial price movement	**Freq.**	**Freq.**
Significant drop	48.09%	49.95%
Insignificant drop	26.72%	29.77%
Price increases after announcement	25.19%	20.28%
	100.00%	100.00%
Secondary price movement (only for the stocks that exhibited a significant drop initially)		
Continuation	32.93%	35.11%
Reversal	12.10%	9.49%
Insignificant reversal	3.05%	5.34%
	48.09%	49.95%

Panel B: Average Short Term CARs for Every Defined Type of Market Reaction.

	5-day window	10-day window
Initial price movement	**Mean 5-day CARs**	**Mean 10-day CAR**
Significant drop	-19.34	-23.42
Insignificant drop	-3.57	-3.37
Price increases after announcement	6.94	8.27

Secondary price movement	**Mean 60-day CARs**	
Continuation	-55.53	-55.83
Reversal	12.39	10.75
Insignificant reversal	-15.85	-22.77

Appendix J. Variables definition.

$Target_{i,t}$	Binary variable equal to 1 if the company has been targeted in quarter t, and 0 otherwise.
$Misvaluation$	Estimated using Price-to-Book or Tobin's q ratios. Price-to-Book is calculated as a three-month average ratio starting four months and ending one month before the campaign announcement. Tobin's q is calculated using opening quarterly Assets, Debt, and Market Capitalization before the event date and according to the formula: $\frac{Market\ Value\ of\ Equity + Book\ value\ of\ Short\ term\ and\ Long\ term\ Liabilities}{Total\ Assets}$
$Size$	The natural logarithm of quarterly Total Assets or the natural logarithm of the Market Cap.
$Leverage$	Expressed as quarterly Debt-to-Assets ratio.
$Payout$	Expressed as the quarterly payout ratio.
$Information\ asymmetry$	Is quantified with measures like quarterly standard deviation of analyst forecasts and the number of analysts following the stock in a specific quarter.
$Illiquidity$	The measure is calculated according to the formula: $ILLIQ_i = \frac{1}{D}\sum_{t=1}^{D}\frac{\lvert r_{it}\rvert}{V_{it}}$, where $\lvert r_{it}\rvert$ is the absolute daily stock return at time t, V_{it} is the dollar volume traded at time t, D stands for the number of trading days in a given quarter.
$Uncertainty$	Expressed by stock price volatility calculated as the standard deviation of daily continuously-compounded returns during the same window as price-to-book.
$Short\ interest$	We calculate short interest as average number of shares held short divided by total shares outstanding during a three-month window starting four months and ending one month before the campaign.
$Profitability$	Expressed using quarterly ROA ratio or EBITDA margin.
$Insider\ Ownership$	Expressed as quarterly proportion of shares held by insiders (managers, directors, etc.)
$S\&P\ 500\ Member$	Control binary variable.