Essays in Finance

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St.Gallen, December 2019 Nicolas Kube

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Summary

This thesis contains three essays in the area of finance. The first essay investigates the impact of banks on corporate borrowers' operating performance. The second essay analyzes the effect of short selling constraints of stocks on fund managers' trading decisions. The last essay studies the monitoring intensity on target firms around hedge fund activism.

The first essay finds that firms which violate debt contracts and are overinvested in net working capital compared to other industry peers reduce unnecessary portions of net working capital. Firms that are underinvested in net working capital invest into net working capital instead. These underinvested firms extend trade credits to their customers and suppliers provide them with more trade credits.

The second essay shows that the exemption of short sale price tests of some stocks also affects not exempted, untreated stocks. Groups with locally bounded interference are important to identify such interference between treated and untreated stocks. Mutual funds can be used such that interference effects in the stock market become visible. Mutual funds buy more (less) untreated stocks when funds' proportion of treated stocks is high (low). Under the assumption of no interference, no such pattern should be observable. If interference effects are not taken into account, the analysis would yield the false result that fund managers are indifferent towards treated and untreated firms. Hence, this paper demonstrates the importance to account for interference effects in finance research.

The third chapter investigates information free riding around hedge fund activism. Market participants download activist announcement of hedge funds about 23% more often than filings of other types of activist investors. They also review other target firms' filings around hedge fund activism. Results indicate that hedge fund activism is studied more carefully at the beginning of a campaign. In the longer run, attention to large target firms' filings increases, whereas small firms experience a drop in attention. This result emphasizes that information free riding takes place in firms which are expensive to monitor and in which benefits from monitoring are relatively small.

Zusammenfassung

Die vorliegende Dissertation umfasst drei Papiere im Bereich Finance. Das erste Papier untersucht den Einfluss von Banken auf die operative Performance von Unternehmen. Das zweite Papier analysiert das Entscheidungsverhalten von Fondsmanagern im Bezug auf Leerverkaufsrestriktionen von Aktien. Das dritte Papier betrachtet das Monitoring von Unternehmen durch Marktteilnehmer, nachdem ein Hedgefond in ein Unternehmen investiert hat.

Das ersten Papier untersucht Brüche von Kreditverträgen, um den Einfluss von Banken auf das Investitionsverhalten von Managern in das Umlaufvermögen von Unternehmen zu analysieren. Unternehmen, die im Vergleich zu ihren Konkurrenten zu viel Umlaufvermögen besitzen, reduzieren Teile des dort investierten Kapitals. Im Gegensatz dazu investieren Unternehmen mit zu geringem Umlaufvermögen vor allem in ihre Kredite an ihre Kunden.

Das zweite Papier untersucht Interaktionseffekte im Bereich des Aktienhandels von Fondsmanagern. Durch die Regulation SHO in den USA waren Fondsmanager möglichen Leerverkäufen von gehaltenen Aktien unterschiedlich stark ausgesetzt. Fondsmanager, die ein hohes Risiko gegenüber potentiellen Leerverkäufen hatten, substituierten daraufhin Teile ihrer Aktien mit Aktien, bei denen Leerverkäufe restriktiver reguliert waren. Im Gegensatz dazu kauften Fondsmanager, die ein geringes Risiko hatten, Aktien, die unreguliert leer verkauft werden konnten, um an den Verleihgebühren zu partizipieren. Dieses Verhalten kann nur durch die Einbeziehung von Interaktionseffekte gezeigt werden.

Das letzte Papier betrachtet Veränderungen im Monitoring von Unternehmen, in die ein Hedgefond investiert. Offizielle Ankündigungen von Hedgefonds, dass sie in ein Unternehmen investiert haben, werden rund 23% häufiger angeschaut als Ankündigungen von anderen Typen von aktivistischen Investoren. In der längeren Frist verstärkt sich das Monitoring bei grossen und verringte sich bei kleinen Firmen. Dies ist Evidenz dafür, dass Marktteilnehmer vom Monitoring des Hedgefonds aufwandslos profitieren können, da kleine Unternehmen teurer zu analysieren sind und weniger Ertrag durch das Monitoring bieten.

1 Debt Covenant Violation and Excess Net Working Capital

Nicolas Kube [1]

Abstract

I investigate whether covenant violations induce firms to adjust investments into their operating processes. In line with the release of unproductive capital, violating firms which are overinvested in net working capital compared to other industry peers reduce unnecessary portions of net working capital. I additionally show that firms that are underinvested in net working capital invest into net working capital instead. This finding is in contrast to most findings on covenant violations which basically indicate that violating firms reduce investments. These underinvested firms extend trade credits to their customers and are able to maintain higher capital expenditures than overinvested violating firms. Suppliers provide more trade credits to underinvested firms to finance these investments.

Keywords: Bargaining power, Covenant violations, Working capital, Investments
JEL Classification Numbers: G32, M11

[1] I am grateful for comments by Markus Schmid, Manuel Ammann, Xavier Giroud, Joël Peress, Norman Schürhoff, Bo Becker, Angelo Ranaldo, Marc Arnold, Felix von Meyerinck and participants at the PhD Seminar at the University of St. Gallen and research seminar in Davos. All errors are my own.

1.1 Introduction

Prior literature shows that creditors heavily impact corporate borrowers in the case of covenant violations. Bargaining power shifts immediately towards lenders which induce firms, for example, to reduce leverage (Roberts & Sufi, 2009a), to cut investments (Chava & Roberts, 2008), or to even lay-off employees (Falato & Liang, 2016). DeAngelo, DeAngelo, and Wruck (2002) show in a case study that managers might sell-off parts of their working capital to service debt and to prevent (further) covenant violations. Such literature emphasizes that creditors protect their claims by refocussing lending firms and extracting some wealth.

Another channel to protect creditors' claims and the focus of this study is to induce lenders to run their business more efficiently. Aktas, Croci, and Petmezas (2015) show that operating performance can be improved in two different ways depending on firms' current level of net working capital. Firms with excess net working capital enhance their performance by reducing some of their unproductive capital employed in their operating processes. In contrast, firms being underinvested in net working capital profit by investments into their net working capital. Assets employed in operations can mainly be altered through inventories and accounts receivable. Reasons to invest into inventories are the prevention of losing sales through stock-outs (Corsten & Gruen, 2004), lower supply costs (Blinder & Maccini, 1991), and less fluctuations of input prices (Fazzari & Petersen, 1993). Providing longer trade credits to customers can be profitable because firms can discriminate customers (Brennan, Maksimovic, & Zechner, 1988), signal product quality (Long, Malitz, & Ravid, 1993), and establish long-term relationships (Summers & Wilson, 2002).

In line with the notion of Aktas et al. (2015) that the level of net working capital requires different strategies to improve operations, I analyze whether firms are differently affected by covenant violations depending on their current level of net working capital. I find that the probability to violate covenants increases in higher levels of excess NWC. I then assess whether firms change their operating policies differently by estimating a «quasi» regression discontinuity design suggested by Nini, Smith, and Sufi (2012). I find that violating firms alter their operating policy faster towards their optimal level than non-violating firms. Violating firms reduce their net working capital in the case of positive excess NWC, whereas firms with negative excess NWC invest into their net working capital. On average, violating firms with positive excess NWC convert a dollar spent into a dollar collected by 2.5 days faster. Violating firms with negative excess NWC extend their conversion cycle by 2.5 days. This change is about 19% larger than that of firms in compliance with their debt contracts.

I then explore different sources of this change. The separation of net working capital into its components shows that violating firms adjust their accounts receivable and payable but do not change their inventories. Firms with negative excess NWC grant longer payment terms to their customers which are partially funded by longer trade credits of their suppliers. In contrast, firms with positive excess NWC ask their customers for earlier repayments and reduce their trade credits provided by suppliers. Lastly, I investigate the effect of debt covenant violations on other firm characteristics such as sales growth or leverage. I find that banks reduce their credits to firms with negative excess NWC more, such that suppliers step in as funding partner. These firms do not have to cut investments as much as violating firms with positive excess NWC. A common positive effect of debt covenant violations is that both types of firms, those under- and those overinvested in net working capital, improve their operating performance in the following year. Although violating firms grow slower in terms of sales and assets, results indicate that investing and divesting net working capital can both be profitable after covenant violations.

I use covenant violations to explore the different impact of creditors on lenders depending on whether excess NWC is positive or negative as this setup provides three advantages. First, debt covenant violations occur frequently because covenants are set tight (e.g., Chava & Roberts, 2008). Since the private debt market is the primary source of corporate debt financing (Bradley & Roberts, 2015), many firms have to deal with the consequences of violations. Secondly, firms have been shown to alter their main corporate policies (e.g., leverage, investments) in response to covenant violations although many violations are not perceived to be serious (Gopalakrishnan & Parkash, 1995). Through their additional bargaining power, creditors can enforce such changes. Thirdly, the quasi regression discontinuity design proposed by Nini et al. (2012) allows to compare firms close to and already in violation. This view is further supported by the regression discontinuity designs applied by Chava and Roberts (2008), Roberts and Sufi (2009a), or Falato and Liang (2016).

I first contribute to the literature on operating efficiency (e.g., Aktas et al., 2015; Kieschnick, Laplante, & Moussawi, 2013) by showing that the deviation from the optimal operating policy of firms predicts covenant violations. While both states, under- or overinvestment in net working capital, characterize deviations from the optimal policy, positive excess NWC predicts more covenant violations than negative excess NWC. Hence, lean operating processes mitigate potential covenant violations. I further contribute by showing that violating firms can benefit from investing into their operating processes in response to covenant violations. However, only firms with negative excess NWC invest into their net working capital to improve their operating performance. This finding is in line with findings by Aktas et

al. (2015) that firms with negative excess NWC lower their firm risk by higher investments into their NWC. The literature on covenant violations shows that firms typically do the opposite. They reduce investments (e.g., Chava & Roberts, 2008), cut employees (Falato & Liang, 2016), or sell-off inventories (DeAngelo et al., 2002). In contrast to findings in DeAngelo et al. (2002), I do not find any systematic differences in the inventory policy between violating and non-violating firms. I further contribute to the literature on the role of suppliers and their provision of trade credits. Zhang (2018) finds that suppliers reduce trade credits after covenant violations and that the effect is lower for suppliers which highly depend on the violating customers. I add to this literature by showing that trade credits are reduced if excess NWC is positive, whereas suppliers extend them if excess NWC is negative. Suppliers provide more trade credits for underinvested firms because such firms have typically higher growth opportunities and are more leveraged than firms with positive excess NWC. Hence, I find that banks are more reluctant to extend loans for firms with negative excess NWC. This result complements findings in Wilner (2000) and Cuñat (2006) that suppliers hold an implicit equity stake in their customers.
The paper is organized as follows. Section 1.2 reviews related literature. The description of data and the empirical strategy are discussed in Section 1.3. Section 1.4 assesses the role of excess NWC to predict covenant violations. Section 1.5 presents main empirical findings of the change of excess NWC. Section 1.6 discusses sources of the change in excess NWC. Section 1.7 investigates the impact on other real determinants of firms. Section 1.8 provides robustness checks. Section 1.9 concludes.

1.2 Related Literature

1.2.1 Debt Covenants

A large body of literature suggests that creditors actively monitor and influence borrowing firms through covenants, covenant violations, and the renegotiation of debt contracts. Violations and renegotiations occur quite frequently since financial covenants are typically set very tight (e.g., Bradley & Roberts, 2015; Chava & Roberts, 2008; Dichev & Skinner, 2002; Gopalakrishnan & Parkash, 1995). Nini et al. (2012) show that more than 40% of firms violate at least one covenant during the years 1997 and 2008. Chava and Roberts (2008) find similar results as more than 30% of the loan contracts are violated at least once and do so in the mid-way through the loan. Roberts and Sufi (2009b) find that nearly all private credit agreements are renegotiated at least once. Specifically, loans are typically renegoti-

ated about every nine months on average and only few of them belong to financial distress (Roberts, 2015). Due to the tightness of covenants, Gopalakrishnan and Parkash (1995) find that over 90% of covenant violations are not perceived as serious and are waived. Similarly, Roberts (2015) show that approximately 75% of all covenant violations are renegotiated.
Asymmetric information between creditors and firms is a major reason to set covenants tight (Gârleanu & Zwiebel, 2009). Creditors use covenants as an instrument to intervene in situations when they would be otherwise negatively affected (e.g., wealth transfer). Gârleanu and Zwiebel (2009) further argue that covenants will typically be renegotiated when new profitable investment projects emerge and more reliable information can be used to assess such projections. Although many violations are not perceived as serious and are renegotiated, lenders often have to reduce their capital expenditures and investments (Chava & Roberts, 2008). They also lower their leverage and reduce their debt issuing activities (e.g., Nini et al., 2012; Roberts & Sufi, 2009a). Nini, Smith, and Sufi (2009) show that lenders impose tighter limits on capital expenditures after firm's credit risk has increased. Zhang (2018) finds that firms experience a sharp decline of trade credits from their suppliers after covenant violations. Despite changes on financing and investment policies, Falato and Liang (2016) show that firms also cut employment after covenant violations.
These findings emphasize, on the one hand side, that creditors intervene early and not only in financial distress. On the other hand, they ask for significant changes in situations when firms' performance deteriorates. Their bargaining power results from the threat to declare a loan in violation due such that they can induce such changes. Additionally, many firms rely heavily on the access to the private debt market which is their primary source of corporate debt financing (Bradley & Roberts, 2015). They have to maintain their access to the market through successful renegotiations in and out of covenant violations.

1.2.2 Working Capital

The operating process of a firm comprises the core activities of a firm to manufacture products or to offer services and hence, to generate cash flows. This process can be separated into three main sub-processes: sales, warehousing and production, and purchasing. Any larger problems or inefficiencies along these sub-processes reduce operating cash flows. Kieschnick et al. (2013) find that the marginal returns of investments into net working capital is decreasing. Aktas et al. (2015) present a more differentiated picture. Both situations, being under- or overinvested in net working capital, require different strategies to avoid negative future returns. Divesting net working capital improves firms' performance if they mainly reduce unproductively employed capital. On the contrary, investing into net working capital can also be beneficial if the level to run a firm's business efficiently is too low.

The investment into firms' customers can be profitable because they can be tied closely to the firm (e.g., Aktas et al., 2015; Long et al., 1993). Trade credits are further important to establish long-term relationships with customers (Summers & Wilson, 2002), in particular if relationships involve specific assets or investments. Moreover, trade credits are an effective way to discriminate customers by subsidizing low profit customers (Brennan et al., 1988).

Insufficient inventories are another factor to loose money. Corsten and Gruen (2004) show that stock-outs can have dramatic effects on firms' sales. Retail stores with products stocked-out face heavy losses as many customers, i.e., between 7% and 25%, do not buy any substitutes for these products in the store. Additionally, between 21% and 43% of costumers choose another store to buy these products. Corsten and Gruen (2004) estimate that retailers might lose up to 50% of the intended purchase volume. Such a situation represents an inefficient level of inventories which directly lowers operating cash flows.

1.2.3 Working Capital and Financing

Gârleanu and Zwiebel (2009) provide evidence that creditors are aware of the importance of reliable operating processes. They often implement covenants on net working capital such that firms must maintain certain levels of net working capital. For example, RSP Permian, Inc. faced a working capital ratio of 1.0 such that its current assets have to exceed its current liabilities.[2] DeFond and Jiambalvo (1994) find that managers alter their reporting of working capital to manipulate firms' income. By doing this, they try to avoid covenant violations and improve their bargaining position in the case of a potential renegotiation. DeAngelo et al. (2002) document that the level of net working capital can impact the reaction of firms on covenant violations. They show for the case of L.A. Gear that managers sell liquid inventories with discount to service debt.

The notion that net working capital is important for creditors is further supported by Aktas et al. (2015). Firms which deviate from their optimal level of net working capital show higher firm risk. They benefit from investing into their net working capital if they have negative excess net working capital. Firms with high levels of net working capital reduce their risk by the release of cash tied unproductively in the operating processes. In both situations, they are able to improve their operating performance. In line with these arguments, Bradley and Roberts (2015) show that working capital and financing are often closely related as financing working capital is one of the four most popular purposes listed in private debt contracts.

Many firms frequently use trade credits offered by their suppliers to partially finance their

[2] https://www.sec.gov/Archives/edgar/data/1588216/000119312516800524/d474132d8k.htm

business (Petersen & Rajan, 1997). Trade creditors play a distinct role when customers become financially constrained. Wilner (2000) and Cuñat (2006) argue that suppliers hold an implicit equity stake of their customers. Hence, they have incentives to provide liquidity when banks are more reluctant to do so to protect the value of their stake. Expected gains of maintaining their relationship have to outweigh costs and risks of financing trade credits in such situations. Biais and Gollier (1997) and Burkart and Ellingsen (2004) stress that suppliers have advantages in monitoring firms and less severe moral hazard problems such that suppliers still provide liquidity if banks rationalize credit. Garcia-Appendini and Montoriol-Garriga (2013) show that cash-rich suppliers substituted missing bank financing of their customers by trade credit during the financial crisis. Nini et al. (2012) show that firms in violation have to reduce their leverage and cash holdings have evaporated prior to the violation. Interest rates on bank loans increase after violations such that refinancing costs of trade credits increase. In line with the model of Cuñat (2006), increasing funding costs lower the willingness to provide trade credits since they become more expensive. In addition to the theoretical prediction, Petersen and Rajan (1997) find that firms with limited access to external credit offer less trade credit to their customers. Zhang (2018) finds that trade creditors basically reduce trade credits after covenant violations. However, trade creditors which rely mainly on the particular firm in violation reduce their trade credit less.

1.3 Data

1.3.1 Sample Construction

I combine data from two different sources. The first data set comprises covenant violations collected by Greg Nini, David C. Smith and Amir Sufi.[3] Debt contracts typically include covenants from three main categories. *Affirmative* covenants stipulate certain obligations which the borrower has to fulfill. Typical obligations are maintaining tangible assets, being in compliance with accounting principles and regulatory requirements or paying taxes. *Negative* covenants prohibit borrowers to undertake certain transactions like mergers and acquisitions, selling large fractions of the firm, or other material changes. *Financial* covenants are typically defined as accounting ratios like leverage or interest coverage which must not be exceeded or deceeded. Basically, firms have to be in compliance with their financial covenants at the end of each fiscal quarter (Sansone & Taylor, 2006). In contrast, a firm must not violate any affirmative or negative covenant at any point in time. In the case of

[3] http://faculty.chicagobooth.edu/amir.sufi/chronology.html

a violation, firms have to publish the violation and report most of them in their annual or quarterly reports. Nini et al. (2012) collected violations of financial covenants between the second quarter of 1996 and the second quarter of 2008 by parsing financial reports filed with the SEC in its Edgar database. They apply a two-stage text search algorithm. In the first step, this algorithm searches for the word "covenant" within a report. Given a match, it prints out the closest lines above and below the finding. In the next step, the algorithm looks for words related to violations (e.g. "viol", "waiv", etc.) within the printed lines around the word "covenant". If this search algorithm yields a match, the respective quarter is labelled as a quarter in violation. Lastly, they correct this data manually. They link the reports to the quarterly Compustat data. The data set of covenant violations contains the Compustat identifier, the date of the end of the fiscal quarter, and a dummy which is one if a violation is reported and zero otherwise.

The second data set is obtained from the Compustat quarterly database which can be merged with the sample of covenant violations. To construct the (unbalanced) panel of firm and violation data, I follow a similar approach as Nini et al. (2012) and merge violation and accounting data. I remove all remaining firms which belong to the financial industry (SIC 6000-6999), firms with missing values for total assets or calendar quarter (datacqtr), as well as firms with average total assets below USD 10 million in year 2000 dollars. Inflation data is obtained from the website of the Bureau of Labor Statistics. Some covenant violations are likely related to mergers and acquisitions and are thus not the result of financial distress. Hence, I exclude the four quarters prior and after a quarter with asset or sales growth of more than 100% and the respective quarter with such large growth rates (Garcia-Appendini & Montoriol-Garriga, 2013). Lastly, there is a sharp decline of observations in 2008 such that I limit the sample between the second quarter of 1996 and the fourth quarter of 2007.

1.3.2 Main Variables

Following Nini et al. (2012), I focus only on new covenant violations (*New Violation*) which are required to have four preceding quarters without any violation.[4] I exclude observations with any violations in the preceding three quarters since they are confounded by a violation. I also exclude quarters in violation which I cannot classify as new due to missing observations in the previous quarters. The second variable of main interest is excess net working capital (excess NWC) as defined by Aktas et al. (2015). Excess NWC is the sum of accounts receivable and inventories less accounts payable scaled by total sales. As common in the

[4] Firms are typically in violation for several quarters such that the initial violation captures the main effect of creditors.

literature, I multiply net working capital by 90 which refers to the days of a quarter such that the variable can be interpreted as days. It is then adjusted by its industry year-quarter median of the respective Fama-French 49 industry classification.
Main dependent variable is the change in excess NWC over four quarters. This four-quarter change, which is also applied by Nini et al. (2012), has the advantage to remove year cycles. In order to gather insights into the sources of the change, net working capital is split into its three components: accounts receivable, inventories, and accounts payable. I follow Raddatz (2006) and scale inventories and accounts payable by cost of goods sold (COGS) because margins, already accounted for in sales, are not considered. All three components are multiplied by 90 days and industry-adjusted as the main explanatory variable.
Net working capital and its components proxy for operational efficiency (Aktas et al., 2015). Receivables characterize how much trade credits a firm provides to its customers, whereas accounts payable refer to the trade credits suppliers provide to the firm. Both ratios capture how much of sales and cost of goods sold are financed and not already converted into cash. Inventories capture the capital employed in the production process.
I include various proxies for common covenant ratios as controls like the operating cash flow, leverage, interest expenses, net worth, and current ratio (Nini et al., 2012). Operating cash flow (oibdpq) and interest expenses (xintq) are scaled by the average total assets of the respective quarter. Leverage is the sum of short- and long-term debt scaled by total assets. Net worth is defined as the ratio of stockholders' equity divided by total assets. The current ratio refers to the ratio of current assets to current liabilities. The market-to-book ratio accounts for future growth opportunities. I also include the logarithm of total assets and the ratio of property, plant, and equipment scaled by total assets as well as the first difference of both variables as firm size and tangibility are main determinants of leverage. Missing values of interest expenses (xintq) and deferred taxes and investment tax credit (txditcq) are set to zero. All data are winsorized at the 1% and 99% level to mitigate the effect of outliers.

1.3.3 Empirical Strategy

I first run probit regressions to evaluate the impact of excess NWC on the probability to violate a certain covenant. Dependent variable is the indicator variable *New Violation*. *Excess NWC* refers to the industry-adjusted abnormal net working capital (Aktas et al., 2015). *Covenant Controls* include operating cash flow, leverage, interest expenses, net worth, current ratio, and market-to-book ratio. Additionally, I include polynomials to the second and third power of control variables ($HigherOrderCovenantControls$) to capture nonlinear effects around violations. To account for firm changes in the course of the previous year, *Covenant Controls*, lagged by four quarters, are added as *LaggedCovenantControls*. Instead of the four-quarter lagged excess NWC, I include the four-quarter change to avoid high correlation between the lagged and actual excess NWC. Lastly, the logarithm of total assets, firms' tangibility, as well as the first difference and the four-quarter lagged value of both variables are used as controls. δ are year-quarter and γ fiscal-quarter fixed effects. Standard errors are clustered by year-quarter and industry to account for serial correlation.

$$\begin{aligned} Pr(NewViolation_{i,t}) &= \alpha + \beta ExcessNWC_{i,t} \\ &+ \theta_1 CovenantControls_{i,t} \\ &+ \theta_2 \left(HigherOrderCovenantControl_{i,t}\right) \\ &+ \theta_3 \left(LaggedCovenantControls_{i,t-4}\right) \\ &+ \delta_t + \gamma_{i,l} + \varepsilon_{i,t} \end{aligned} \tag{1.1}$$

The second empirical strategy exploits the shift in bargaining power around financial covenant violations to estimate the impact of creditors on firms. This setup was introduced by Chava and Roberts (2008) and also applied by Roberts and Sufi (2009a) and Nini et al. (2012). One advantage to use covenant violations is that they occur quite frequently in both financially distressed and non-distressed firms. A violation immediately shifts large control rights towards creditors. Affected creditors have the right to terminate their debt contracts and declare the credits immediately due and payable. Hence, non-compliant firms have to renegotiate with their debt holders. Nini et al. (2012) apply a «quasi» regression discontinuity approach to estimate the impact of creditors. The underlying idea is that two similar firms should have similar covenants. If only one of the two comparable firms has just broken a covenant and the other is still in compliance with its covenants, firms should be similar in their main characteristics except for the characteristics creditors force to change. Nini et al. (2012) exploit firms' distance to covenant thresholds by controlling for typical ratios implemented as covenant ratios instead of actually measuring the distance. The violation dummy then captures the impact of creditors on policy changes of violating firms.

I follow the regression design of Nini et al. (2012) based on all firms in the Compustat universe to explore whether creditors require improvements of net working capital. I refine their design by interacting a new covenant violation with the current state of excess net working capital of a given firm. The interaction allows to investigate whether the current status of firms of being under- or overinvested in net working capital affects them differently upon a covenant violation:

$$
\begin{aligned}
y_{i,t+4} - y_{i,t} = {} & \beta NewViolation_{i,t} \times ExcessNWC_{i,t} \\
& + \theta_1 NewViolation_{i,t} + \theta_2 ExcessNWC_{i,t} \\
& + \theta_3 CovenantControls_{i,t} \\
& + \theta_4 \left(HigherOrderCovenantControl_{i,t}\right) \\
& + \theta_5 \left(LaggedCovenantControls_{i,t-4}\right) \\
& + \delta_t + \gamma_{i,l} + \varepsilon_{i,t},
\end{aligned} \tag{1.2}
$$

New Violation is a dummy variable which equals one if there is a new covenant violation in quarter *t*. *New Violation* × *Excess NWC* covers the the reaction of violating firms depending on their current level of excess NWC. All other control variables are defined above.

There might be a concern that this «quasi» regression discontinuity design is not appropriate since this approach is not a classic regression discontinuity design. This approach is closely related to Chava and Roberts (2008) and Roberts and Sufi (2009a). Chava and Roberts (2008) construct an ordinary regression discontinuity design around the threshold of debt covenants. They show that debt holders do impact firms and that there is a sharp decline in investments after the breach of a covenant. Roberts and Sufi (2009a) provide evidence that «quasi» and ordinary regression discontinuity designs yield both similar and reasonable results in the case of covenant violations.

Another concern is that large suppliers might ask for early payments before they deliver their products to prevent a wealth transfer towards banks. This might cause a violation. The selection criteria reduce this concern because none of the firms defaulted immediately after a violation. In addition, suppliers have superior monitoring abilities and their implicit equity stake incentivize them to support their customers (e.g., Biais & Gollier, 1997; Burkart & Ellingsen, 2004). It is, therefore, less likely that they widely cause covenant violations. Instead, Garcia-Appendini and Montoriol-Garriga (2013) show that suppliers provide financing if creditors are not willing to do so.

1.3.4 Summary Statistics

To first explore whether covenants are frequent across firms, time, and industries, Table 1.1 presents frequency distributions of covenant violations. 27.1% of all firms in the sample had to deal with at least one new covenant violation. The fraction equals 36.4% if I consider any covenant violations. The fractions are slightly lower compared to the sample of Nini et al. (2012) because firms with missing values of net working capital are not part of the sample. These firms are typically smaller and have fewer operations which are both determinants of

Table 1.1: Distribution of Covenant Violations

This table presents distributions of covenant violations. *Violation* refers to any covenant violation reported in a fiscal quarter. *New Violation* is defined as a covenant violation with four consecutively preceding fiscal quarters in compliance with covenants. In the upper part, it is first presented how many firms violated any covenant at least once in the sample. Secondly, it is reported how many fiscal quarters are in violation. The middle part presents the yearly distribution of fiscal quarters facing any *Violation* or a *New Violation*. The bottom part shows the distribution of *Violation* and *New Violation* across the ten largest Fama-French 49 industries in the sample starting with the largest industry.

Firm Level		
Violation		36.40%
New Violation		27.11%
Fiscal Quarter		
Violation		7.36%
New Violation		2.00%
Year	Violation	New Violation
1997	5.32%	1.29%
1998	6.89%	2.32%
1999	7.72%	2.12%
2000	9.09%	2.53%
2001	10.37%	2.88%
2002	9.34%	2.44%
2003	8.23%	1.85%
2004	6.25%	1.71%
2005	6.20%	1.69%
2006	5.48%	1.54%
2007	5.37%	1.48%
Largest Industries	Violation	New Violation
Computer Software	5.75%	1.52%
Electronic Equipment	8.46%	2.19%
Retail	5.67%	1.77%
Business Services	8.30%	2.28%
Wholesale	9.37%	2.82%
Medical Equipment	5.78%	1.59%
Machinery	6.81%	1.98%
Petroleum & Natural Gas	5.88%	1.60%
Communication	9.21%	2.09%
Pharmaceutical Products	4.16%	1.09%

covenant violations. Even so, many firms have to deal with the consequences of covenant violations. On average, firms report new covenant violations in 2% of all quarters and firms are in any violation in 7.4% of all quarters. There is a clear time pattern of violations in the sample. There are few covenant violations at the beginning in 1997. This value raises from 1.3% to 2.9% in 2001, the peak of the dotcom bubble. The number of violations more than doubled compared to the initial value in 1997. In the years afterwards, the value returns back to 1.5% in 2007. The bottom of Table 1.1 presents the distribution of quarterly violations across the ten most frequent Fama-French 49 Industry Classification industries in the sample. There is no clear pattern that certain types of industries are affected systematically differently. In most industries, between 1.5% and 2.3% of quarters show new violations. *Wholesale* peaks with a mean of 2.8%, whereas *Pharmaceutical Products* has the lowest value of 1.1%.

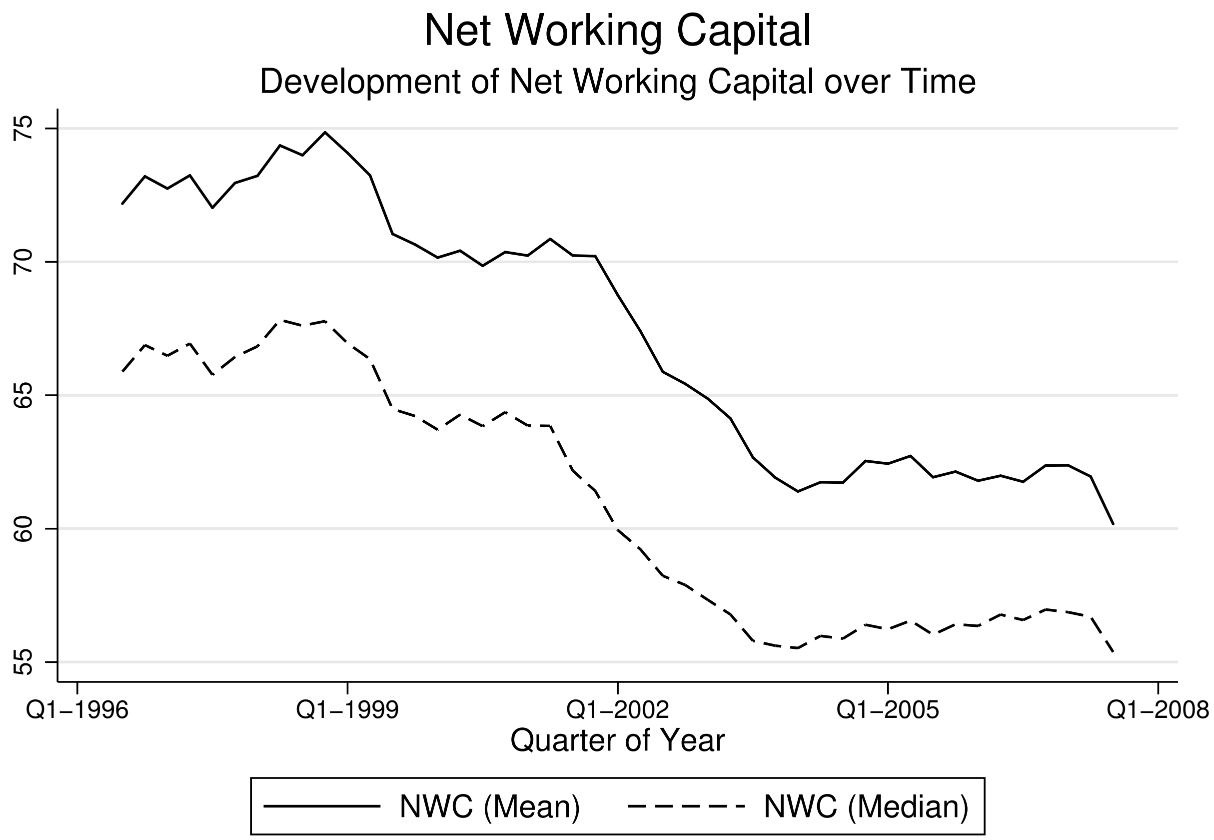

Figure 1.1: This figure presents the time trend of net working capital (NWC) between 1996 and 2007 for the sample. The solid line represents the mean value, whereas the dashed line refers to the median value. The values are calculated as the moving average over three quarters with the current quarter centered to remove seasonality.

Figure 1.1 shows that managers reduced net working capital over the sample period between 1997 and 2007. This figure plots the moving average of net working capital over a rolling window of three quarters centered around the current quarter. In the late 1990s and prior to the dotcom bubble, the level of net working capital was rather flat. Firms needed about 74 days to convert one dollar spent into one dollar received. The median value is 68 days. Beginning with the dotcom bubble, managers reduced their capital employed in operations. They accelerated their cash conversion by about 10 days until 2004. Firms converted their money within 64 days since the beginning of 2004. This is a reduction by more than 13% and reasonable as focusing on operating performance and efficiency is more important in times of crisis. More efficient operating processes release money and reduce external financing needs. The level of net working capital remains flat again after 2003. The median value of net working capital shows a parallel trend such that results are robust against outliers. In untabulated test, the pattern and the levels are similar considering only firms which remain in the sample for at least eight years. Therefore, the pattern is not driven by inefficient firms which defaulted during the crisis and selection bias is less of a concern.

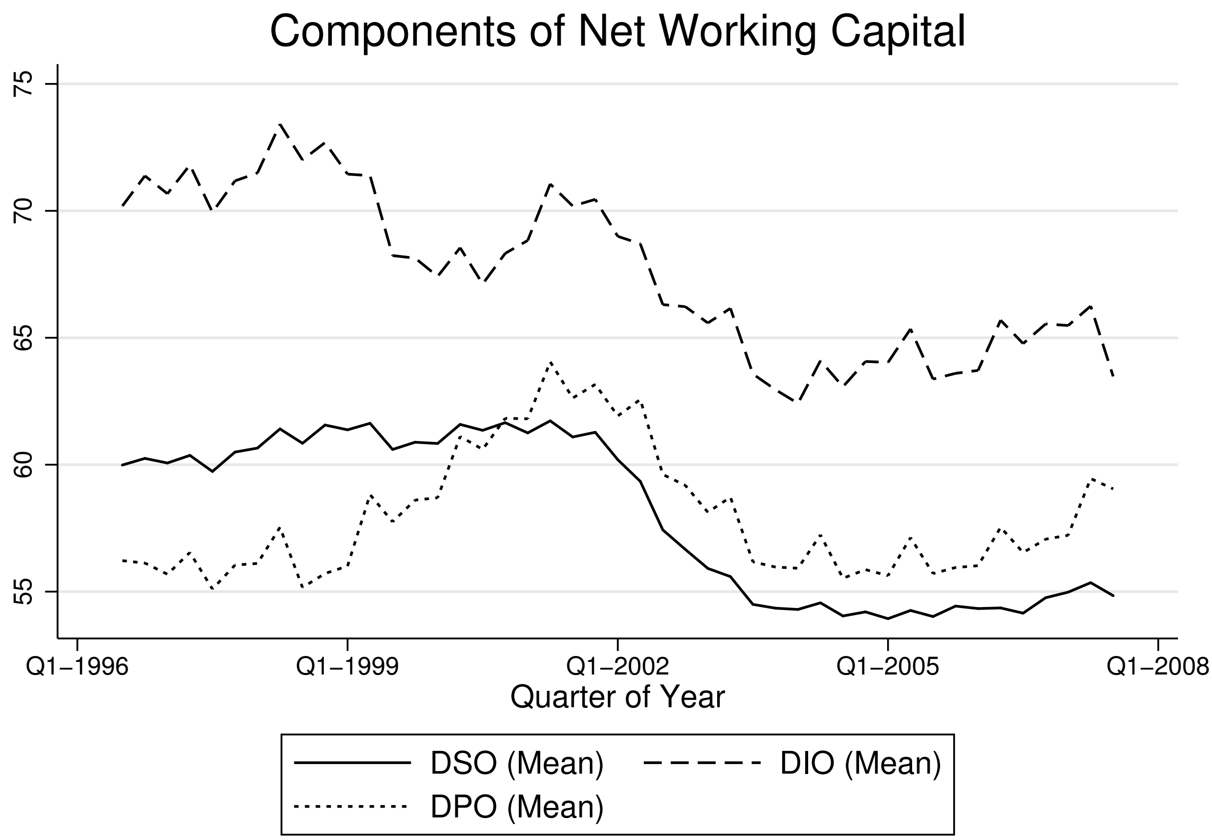

Figure 1.2: This figure presents the different components of net working capital between 1996 and 2007 for the sample. The solid line represents the three quarter moving average of days sales outstanding (DSO). The dashed line shows the development of days inventories outstanding (DIO). The dotted line shows the time trend of days payable outstanding (DPO).

Figure 1.2 refines the picture on how firms changed their net working capital. It presents levels of net working capital's individual components. There is a persistent decline of inventories over the whole time period. Inventories were hold for about 73 days in the 1990s. This holding period reduces towards 65 days. During the crisis, inventories peaked again due to the economic downturn. Firms started to alter their receivable management during the crisis in 2001. During the 1990s, they were fairly constant at 60 days. They forces customers to pay on average five days earlier such that days of sales outstanding equal about 55 days since 2004. Suppliers provided trade credits in the 1990s which lasted about 56 days and were five days shorter than days sales outstanding. In line with findings of Garcia-Appendini and Montoriol-Garriga (2013), suppliers provided more trade credits during the crisis. Days payable outstanding (DPO) increased up to 60 days. The level shifted back towards the initial level of 56 days after the crisis and moved in parallel with days sales outstanding (DSO) afterwards. These patterns provide insight that firms actively altered their operating processes towards faster production, less inventories (DIO), and earlier payments of customers (DSO). It further supports the notion that firms realized significant improvements in their working capital management.

Table 1.2 provides summary statistics on firms' quarterly financial characteristics. It presents characteristics for violating and non-violating firms separately and further distinguishes between positive and negative excess NWC. The first four variables characterize the operating processes of the firms. Following Aktas et al. (2015), they are industry-adjusted by the median of the respective industry and quarter. All other variables refer to the main control variables used in Nini et al. (2012). The third column reports tests for the equality of means of the different variables between the negative and positive excess NWC sub-samples. By construction, there are large differences in excess NWC and its components between firms with negative and positive excess NWC. Firms with negative excess NWC collect money faster from their customers, have lower inventories, and their suppliers provide more trade credit. Comparing violating and non-violating firms with negative excess NWC shows that their levels of excess NWC is fairly similar. Firms with positive excess NWC show a larger discrepancy of eight days emphasizing that violating firms face more operational difficulties. It is noteworthy to mention that excess DPO, i.e., trade credits provided by suppliers, is positive in each case. Firms with abnormally low levels of DPO are, therefore, spread across all four cases. Further, excess DPO of firms with positive excess NWC is larger for violating than for non-violating firms indicating that suppliers already provide more trade credit to those firms. This is not the case for firms with negative excess NWC.

Other control variables present a coherent picture. Violating firms have lower operating cash flows and are smaller than their non-violating counterparts. They face higher leverage and pay more interest expenses. Additionally, stockholders' equity and the current ratio are lower. The comparison of violating firms and their current state of excess NWC shows that violating firms with negative excess NWC are larger and have higher operating cash flows. On the other hand, they rely more on debt financing and less on equity because they take on

Table 1.2: Summary Statistics

This table presents summary statistics of excess net working capital (*excess NWC*) and its components as well as the main other explanatory variables. The summary statistic is divided into violating and non-violating fiscal quarters and further distinguishes between firms showing negative and positive excess NWC. *Excess NWC* is the Fama-French 49 industry-adjusted net working capital scaled by total sales per quarter (Aktas et al., 2015) and multiplied by 90 days. *Excess DSO* is defined as the ratio of accounts receivable to total sales times 90 days. *Excess DIO* and *Excess DPO* are inventories and accounts payable scaled by cost of goods sold instead. The other explanatory variables refer to Nini et al. (2012) and are formally defined at the end of this table. T-statistics refers to t-tests of equal means between the variables and are applied row-wise. All variables are winsorized at the 1% and 99% level.

		Negative Excess NWC	(t-statistics)	Positive Excess NWC
Violation	Excess NWC	-27.08	(45.05)	43.32
	Excess DSP	-5.95	(21.70)	19.02
	Excess DIO	-11.46	(23.76)	44.22
	Excess DPO	20.28	(-5.32)	8.51
	Operating CF	0.42	(-3.48)	-0.25
	Leverage	32.97	(-2.11)	30.93
	Interest Exp.	0.73	(-3.74)	0.63
	Net Worth	32.81	(9.02)	43.15
	Current Ratio	1.52	(11.54)	2.22
	Tobin's Q	1.55	(-4.47)	1.37
	Ln(total assets)	5.17	(-3.60)	4.93
	Tangibility	33.98	(-9.78)	25.29
No Violation	Excess NWC	-27.47	(323.71)	35.30
	Excess DSP	-7.34	(149.57)	15.97
	Excess DIO	-10.16	(157.04)	38.14
	Excess DPO	24.52	(-53.94)	5.21
	Operating CF	2.53	(-3.14)	2.45
	Leverage	22.82	(-4.35)	22.26
	Interest Exp.	0.46	(-14.19)	0.42
	Net Worth	46.53	(35.73)	52.28
	Current Ratio	2.43	(41.02)	3.01
	Tobin's Q	2.09	(-32.20)	1.82
	Ln(total assets)	5.65	(-10.99)	5.52
	Tangibility	29.97	(-32.49)	25.75

Variables:
Excess NWC=(rectq+invtq-apq)/saleq×90 *Excess DSO*=rectq/saleq *Excess DIO*=invtq/cogsq×90 *Excess DPO*=apq/cogsq×90
Operating CF=$oibdpq_t/((atq_t+atq_{t-1})/2)$ *Leverage*=(dlcq+dlttq)/atq *Interest Exp*=xintq/$((atq_t + atq_{t-1})/2)$ *Net Worth*=seqq/atq
Current Ratio=actq/lctq *Tobin's Q*=(cshoq*prccq-(atq-ltq+txditcq)+atq)/atq *Ln(Assets)*=ln(atq) *Tangibility*=ppentq/atq

more leverage, pay more interest expenses, and have lower net worth. Although they own more tangible assets, their growth opportunities are better than those of violating firms with positive excess NWC. Lastly, firms with negative excess NWC have more balanced ratios of short-term assets and liabilities which partly reflects more trade credit.

1.4 Does Excess NWC Predict Covenant Violations?

Table 1.3 presents results of probit regressions which test whether higher *Excess NWC* increases the probability to violate debt covenants. Dependent variable is *New Violation* as defined in Section 1.3.2. *Excess NWC* is the independent variable of main interest. All specifications include covenant controls as defined by Nini et al. (2012). Specifications in columns (4) and (5) further include covenant controls lagged by four quarters to account for firm changes in the course of the previous year. Column (5) shows results from the estimation of the full specification which further includes the second and third moment of covenant controls (*HighOrderControls*) to control for non-linear effects around covenant violations.

Coefficients of *Excess NWC* are positive and highly significant in all specifications. Firms with higher net working capital violate financial covenants much more frequently than firms with low or even negative net working capital. The economic magnitude of this relationship is large. Starting at the lowest 5^{th} percentile of excess NWC, the probability to violate a covenant is 1.9%, increases up to 2.3% at the median, and raises towards 2.7% at the 95^{th} percentile. The relative increase amounts to approximately 40%. This comparison includes the more extreme values at the 5^{th} and 95^{th} percentile. The probability increases relatively by 10% from 2.1% to 2.3% between the 25^{th} and 75^{th} percentile which is economically still large.

It can be expected to find an increasing frequency of covenant violations since higher abnormal net working capital indicates that more capital is tied unproductively in the operating processes. This points towards inefficiencies in these processes. Deficiencies in the accounts receivable management are immediately observable in higher levels of net working capital. Similarly, interruptions in the production process increase inventories. One concern is that large, bankrupt customers cause violations. In this case, firms have to write-off their claims such that net working capital would be lower. The findings thus point in the direction that inefficiencies are the main driver. The inclusion of lagged variables in columns (4) and (5) partly controls for the possibility that customers might be in difficulties to pay their invoices in a timely manner. They account for changes in excess net working capital in the course of the year. However, they do not alter results as coefficients are still positive and highly significant.

Coefficients of the other control variables yield intuitive results. Higher operating cash flows decrease the probability to breach covenants. Higher leverage is positively, whereas more net worth is negatively related with covenant violations. These results are similar to the

Table 1.3: Probability of Covenant Violation

This table presents coefficient estimates of the probit regression on new covenant violations. The dependent variable equals one if a covenant violation occurs which is preceded by four consecutive non-violating quarters (Nini et al., 2012) and zero otherwise. Excess NWC is the Fama-French 49 industry-adjusted net working capital scaled by total sales per quarter (Aktas et al., 2015) multiplied by 90 days. Covenant controls are operating cash flow, leverage ratio, interest expenses, net worth, current ratio, and Tobin's Q. Further, the natural logarithms of total assets and tangibility as well as the first differences of both variables between the current and previous quarter are included. Higher Order Moments include the second and third power of covenant controls. Lagged variables refer to covenant controls lagged by four quarters and the four-quarter change of excess NWC. Fiscal and calendar quarters are included as Time FE. Standard errors are clustered at industry and calendar quarter. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively and t-statistics is presented in parentheses.

	(1)	(2)	(3)	(4)	(5)
Excess NWC	0.002***	0.002***	0.002***	0.001***	0.001***
	(10.09)	(10.44)	(8.79)	(7.01)	(5.38)
Operating CF	-3.779***	-3.688***	-6.624***	-6.829***	-10.659***
	(-16.09)	(-16.21)	(-17.78)	(-19.65)	(-21.95)
Leverage	0.638***	0.652***	2.452***	0.315**	1.744***
	(7.71)	(7.89)	(8.38)	(2.31)	(5.25)
Interest Exp.	0.287	-0.431	-5.021	4.325	7.860
	(0.14)	(-0.21)	(-0.50)	(1.49)	(0.67)
Net Worth	0.167**	0.156**	0.124	-0.416***	-0.735***
	(2.46)	(2.31)	(1.21)	(-3.54)	(-5.07)
Current Ratio	-0.102***	-0.105***	-0.142***	-0.109***	-0.174***
	(-10.33)	(-10.55)	(-5.49)	(-7.68)	(-6.00)
Tobin's Q	-0.137***	-0.132***	-0.355***	-0.129***	-0.470***
	(-10.65)	(-10.39)	(-6.76)	(-6.66)	(-7.79)
Constant	-1.453***	-1.929***	-1.727***	-1.707***	-1.379***
	(-26.65)	(-19.82)	(-15.53)	(-16.35)	(-11.23)
Observations	121,790	121,790	121,790	97,432	97,432
Controls	YES	YES	YES	YES	YES
Lagged Controls	NO	NO	NO	YES	YES
Higher Order Moments	NO	NO	YES	NO	YES
Year Quarter FE	NO	YES	YES	YES	YES
Fiscal Quarter	NO	YES	YES	YES	YES

findings of Roberts and Sufi (2009a) and Nini et al. (2012). They also find fewer covenant violations with increasing current ratios because firms are more liquid and have fewer short-term liabilities. This first analysis shows that excess NWC is a strong predictor of covenant violations. It proxies for inefficiencies and difficulties in the operating process which result in lower earnings and cash flows such that violations become more likely.

1.5 Changes in Excess Net Working Capital

This section provides evidence on how firms change their excess NWC upon covenant violations. I apply the «quasi» regression discontinuity design presented in equation 1.2. The variable of main interest is the interaction term between *New Violation* and *Excess NWC*. This coefficient captures the potential effect of firms reacting differently depending on their current level of net working capital. According to the rationale in Aktas et al. (2015), I exclude the constant from all regression specifications. Firms should not alter their net working capital if they have already reached their optimal level. Still, my results are robust to the inclusion of the constant.

Table 1.4 presents coefficients from estimating regressions of the change in excess NWC on the interaction of *New Viol* $\times$ *Excess NWC*. The dependent variable is the four-quarter change in excess NWC. The coefficient of *Excess NWC* equals -0.313 and is highly significant. Firms with positive excess NWC reduce their net working capital over the next four quarters, whereas firms being underinvested in NWC will increase their net working capital instead. This finding is line with the results presented in Aktas et al. (2015). Violating firms change their net working capital stronger as the coefficient of *Excess NWC* $\times$ *New Viol* equals -0.057 and is highly significant. This coefficient indicates that violating firms with positive excess NWC lower their abnormal level more than non-violating firms. In contrast, firms facing excessively low levels of net working capital invest more into their net working capital than similar firms in compliance with their debt contracts. The coefficient of *New Viol* is insignificant. Firms in violation do not reduce their excess NWC in general which is further evidence that firms alter their level of net working capital towards their optimal level.

The economic magnitude of these effects is large. Changes in excess NWC can be interpreted as days, since excess NWC is scaled by 90 days to account for the quarterly nature of the data. Net working capital measures now the time between the payment of suppliers and the collection of money from customers. Firms basically reduce their excess NWC by 13.4 days for a one standard deviation increase of excess NWC. Violating firms, however, reduce their levels by 2.5 more days. This difference equals 18.7% and is economically large. Another approach is to compare this change with the median change of excess NWC of the whole sample. In absolute terms, the unconditional change of excess NWC is 9.5 days such that the reduction of 15.9 days seems to be large.

These findings are new, but complement results in previous literature. Lowering unnecessary portions of net working capital releases cash which is unproductively employed in

Table 1.4: Change in Excess Net Working Capital

This table presents regressions of the four quarter change in Excess NWC on *New Viol* and the current state of *Excess NWC*. *New Viol* is a violation preceded by four consecutive non-violating quarters (Nini et al., 2012). Excess NWC is the Fama-French 49 industry-adjusted net working capital scaled by total sales per quarter (Aktas et al., 2015) multiplied by 90 days. Control variables are the same as in Table 1.2. Standard errors are clustered at industry and calendar quarter. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively and t-statistics is presented in parentheses.

	(1)	(2)	(3)
New Viol	-0.281	-0.134	0.108
	(-0.42)	(-0.20)	(0.15)
New Viol × Excess NWC	-0.074***	-0.071***	-0.076***
	(-2.98)	(-2.88)	(-2.88)
Excess NWC	-0.189***	-0.193***	-0.178***
	(-39.13)	(-39.49)	(-32.62)
Operating CF	73.499***	103.681***	113.316***
	(20.87)	(18.09)	(14.73)
Leverage	4.884***	-1.143	-4.240
	(4.29)	(-0.35)	(-1.10)
Interest Exp.	61.724	754.908***	635.381***
	(1.40)	(5.99)	(4.27)
Net Worth	6.226***	3.932***	1.798
	(9.27)	(3.07)	(0.98)
Current Ratio	0.199***	1.883***	1.999***
	(2.84)	(6.32)	(5.89)
Tobin's Q	-0.343***	-0.478	-0.453
	(-4.22)	(-0.98)	(-0.89)
Observations	104,313	104,313	77,270
R^2	0.108	0.111	0.108
Controls	YES	YES	YES
Lagged Controls	NO	NO	YES
Higher Order Moments	NO	YES	YES
Year Quarter FE	YES	YES	YES
Fiscal Quarter FE	YES	YES	YES

the operating process and might improve firms' operating performance. Both motives are supported by findings in Kieschnick et al. (2013) and Aktas et al. (2015) that high levels of net working capital are value-decreasing. Such reductions in net working capital are further presented in DeAngelo et al. (2002) who show the massive sell-off of inventories to service debt. According to results in Chava and Roberts (2008) that firms have to cut investments and reduce leverage after covenant violations, releasing cash from operations partially offset missing debt financing.

The results also point towards higher efficiency as firms with positive excess NWC focus on faster cash conversion cycles, i.e., they reduce the time between paying their suppliers and collecting money from their customers. This motive is indirectly supported by the findings that firms undertake fewer acquisitions in the aftermath of covenant violations (Nini et al., 2012) and that they even lay off employees (Falato & Liang, 2016). The evidence on excess NWC is thus in line with the argument that creditors force firms to reduce growth and to postpone expansion strategies.

The result that violating firms with negative excess NWC invest into their net working capital is new to the literature. According to previous findings in the literature on creditors' bargaining power (e.g., Chava & Roberts, 2008; DeAngelo et al., 2002), creditors might force firms to sell-off parts of their net working capital even if firms have negative excess NWC. Such an enforcement by creditors, however, would exacerbate the financial situation of violating firms. The literature also suggests that many violations occur out of financial distress and are renegotiated or waived (e.g., Gopalakrishnan & Parkash, 1995; Roberts, 2015) because creditors are interested in lower risk of the borrower. This rationale is supported by Aktas et al. (2015) who show that firm risk reduces after investments into negative excess NWC. Further reductions of negative excess NWC can have serious consequences for the firms instead. Customers might regard shorter payment terms as a signal of increasing default risk and hence, declining attractiveness of firms' products. Long et al. (1993) argue that longer payment terms often indicate higher product quality. Since accounts receivable typically tie firms and customers, they often form long-term relationships (Summers & Wilson, 2002). Profitable long-term relationships are especially important after covenant violations to maintain cash flows. Additionally, firms have to spend less advertising and acquisition costs to attract new customers if they can maintain their long-term relationships. Raising low levels of excess NWC can thus be a profitable strategy for creditors to stabilize the financial situation of violating firms. In line with these arguments, the negative coefficient on the interaction term emphasizes that underinvested firms indeed invest into their net working capital.

1.6 Components of Net Working Capital

Net working capital can be separated into working capital, accounts receivable and payable, as well as inventories. This separation of net working capital into its individual components allows to investigate the sources of the total change of excess NWC by estimating the regression in equation 1.2 for each component separately. Each component is again adjusted by the industry median in the respective quarter.

1.6.1 Working Capital

This first subsection investigates the change of excess working capital and focuses on the production and sales process. Columns (1) and (2) of Table 1.5 refer to the four quarter change of excess working capital. Results are similar to the main analysis in Table 1.4. *Excess NWC* has a highly significant coefficient of -0.164. Firms with negative excess NWC invest into their working capital in the subsequent four quarters by either providing more trade credit or building up inventories. The coefficient on the interaction term *New Viol* $\times$ *Excess NWC* is significantly negative and equals -0.055. Violating firms with negative excess NWC increase their working capital, whereas firms with positive excess NWC reduce it. The effect is robust to the inclusion of lagged and high order controls in column (2). The economic magnitude is large as a one standard deviation increase in excess NWC reduces excess working capital by 6.62 days. In violation, there is an additional reduction of 2.32 days which is similar to the main analysis. Findings on excess working capital emphasize that firms alter their aggregated short-term assets employed in their sales and production processes to adjust their net working capital towards a more efficient level.

1.6.2 Accounts Receivable

I separate working capital and focus only on accounts receivable. Accounts receivable are important to form long-term relationships to customers (e.g., Long et al., 1993; Summers & Wilson, 2002). However, providing trade credits is costly and will be typically reduced in financial distress (e.g., Cuñat, 2006; Petersen & Rajan, 1997). Columns (3) and (4) of Table 1.5 present the effect of covenant violations on the four-quarter change of excess days sales outstanding (DSO). Results are similar to those presented for excess working capital. There is a negative relationship between *Excess NWC* and the change of excess DSO. The coefficient is highly significant and equals -0.071 in the full specification presented in column (4). Firms reduce their excess DSO in the following four quarters by 3.06 days for a one standard deviation increase of *Excess NWC*. They grant shorter payment terms for their customers to reduce superfluous NWC. This is consistent with findings in Kieschnick et al. (2013) or Aktas et al. (2015). Results are also in line with the prediction of longer payment terms (e.g., Long et al. (1993); Summers and Wilson (2002)) if net working capital is abnormally low. The coefficient of the interaction term *New Viol* $\times$ *Excess NWC* is significantly negative and equals -0.035. Firms in violation alter their receivable management much more than firms in compliance with their debt contracts. Firms with positive excess NWC shorten their time for payment allowed, whereas firms with negative excess NWC do

Table 1.5: Change in Excess Components of Net Working Capital

This table presents regressions of the different excess components of Excess NWC on *New Viol* and the current state of *Excess NWC*. Excess components are working capital, days sales outstanding (DSO), days inventories outstanding (DIO), and days payable outstanding (DPO). All components are adjusted by the industry-median of the respective quarter. Working Capital is the defined as receivables and inventories scaled by sales times 90 days. All other components are defined in Table 1.2. *New Viol* is a violation preceded by four consecutive non-violating quarters (Nini et al., 2012). Excess NWC is the Fama-French 49 industry-adjusted net working capital scaled by total sales per quarter (Aktas et al., 2015) multiplied by 90 days. Control variables are the same as in Table 1.2. Standard errors are clustered at industry and calendar quarter. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively and t-statistics is presented in parentheses.

	Working Capital		DSO		DIO		DPO	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
New Viol	-1.029	-0.434	-0.535	-0.473	0.107	0.418	1.125	0.631
	(-1.52)	(-0.62)	(-1.24)	(-1.08)	(0.16)	(0.60)	(1.08)	(0.57)
New Viol × Excess NWC	-0.055**	-0.053**	-0.026*	-0.035**	-0.006	-0.006	-0.057**	-0.061**
	(-2.22)	(-2.07)	(-1.88)	(-2.37)	(-0.21)	(-0.20)	(-2.13)	(-2.04)
Excess NWC	-0.164***	-0.154***	-0.080***	-0.071***	-0.118***	-0.120***	0.021***	0.020***
	(-36.26)	(-30.07)	(-31.02)	(-25.73)	(-25.20)	(-20.71)	(4.12)	(3.59)
Observations	104,362	77,295	104,651	77,475	104,270	77,200	104,512	77,357
R^2	0.091	0.091	0.055	0.051	0.037	0.040	0.005	0.012
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Lagged Controls	NO	YES	NO	YES	NO	YES	NO	YES
Higher Order Moments	NO	YES	NO	YES	NO	YES	NO	YES
Year Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Fiscal Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES

the opposite. Violating firms reduce their time for payment allowed by 1.49 additional days for a one standard deviation increase of excess NWC. This magnitude accounts for the main portion of the change in excess working capital which equals 2.3 days.

1.6.3 Inventories

In this subsection, I investigate whether firms alter their inventories after covenant violations. DeAngelo et al. (2002) provide evidence that firms might liquidate inventories to service debt and to avoid covenant violations. In contrast, Corsten and Gruen (2004) find that stock-outs are typically associated with unexpectedly high losses due to switching customers. Blinder and Maccini (1991) add that inventories can be used to reduce supply costs such that maintaining inventories can be necessary and profitable. Columns (5) and (6) of Table 1.5 present the effect of covenant violations on the four-quarter change of excess days inventories outstanding (excess DIO). Coefficients of *Excess NWC* are highly significant and negative with a point estimate of -0.12. This indicates that firms with negative excess NWC increase inventories, whereas firms with positive levels reduce them. The economic magnitude of the effect is large as firms reduce their excess DIO by 5.17 days for a one standard deviation increase of *Excess NWC*. However, the coefficients of the interaction term *New Viol* × *Excess NWC* and *New Viol* are insignificant. Both indicate that violating firms do not change inventories differently compared to non-violating firms. Selling inventories after a violation is, therefore, not the primary source to release capital employed.

1.6.4 Accounts Payable

This last subsection focuses on the reaction of suppliers and their willingness to provide trade credits after covenant violations. Columns (7) and (8) of Table 1.5 report coefficients of the four-quarter change in excess days payable outstanding (excess DPO). Coefficients of *Excess NWC* equal 0.02 and are highly significant in both specifications. A one standard deviation increase of *Excess NWC* increases excess DPO by 0.86 days. Hence, firms with positive excess NWC were granted more trade credits in the next four quarters. Longer trade credits are one source of financing firms' working capital and thus lower their net working capital. The coefficients on the interaction term *New Viol* × *Excess NWC* are significantly negative and equal -0.06. This indicates that suppliers shorten their time for payment allowed for firms with positive excess NWC. In contrast, they extend the time for payment allowed for firms with negative excess NWC. The economic magnitude is large as a one standard deviation increase of *Excess NWC* shortens excess DPO by 2.62 days. This result is in line with the findings by Zhang (2018) that there is a sharp decline of trade credits after covenant violations. Since covenant violations are more frequent in the case of positive excess NWC, the aggregated effect should indicate a reduction in trade credits. However, the finding that suppliers extend trade credits to firms with negative excess NWC is consistent with findings in Wilner (2000) and Cuñat (2006). Suppliers provide more trade credits if firms become financially constraint and banks are reluctant to provide financing as they hold an implicit equity stake. Zhang (2018) also finds that suppliers which rely heavily on a particular violating firm hardly reduce their trade credits. As shown in the summary statistic in Table 1.2, violating firms with negative excess NWC have the highest leverage and interest expenses as well as the lowest net worth. However, their growth opportunities are higher than those of violating firms with positive excess NWC. Therefore, suppliers' equity stake in violating firms with negative excess NWC should be higher than their equity stake in violating firms with positive excess NWC.

This section provides a more differentiated picture on how firms alter excess net working capital. They adjust both sites of the balance sheet as the changes in working capital and trade credits are significant. The effect on the asset site is mainly driven by the change in accounts receivable.

1.7 Impact on Other Real Determinants

The last section presented evidence on the sources of the change in excess NWC. This section explores whether the level of excess NWC has also an impact on other real determinants of violating firms. I investigate the effect on leverage and capital expenditures, followed by the impact on growth in size and in sales, as well as on improvements in operating cash flow. Table 1.6 presents coefficient estimates of the regression of these different firm characteristics on the interaction of covenant violations and excess NWC.

Column (1) refers to the change in leverage in the course of the subsequent year, whereas column (2) presents coefficient estimates on the level of leverage four quarters later. The coefficients of *Excess NWC* equal -0.003 and -0.002, respectively and are significant in both regressions on leverage. Firms which increase their excess NWC typically take on more debt. This finding is supported by Bradley and Roberts (2015) that financing working capital is one of the most frequent purposes stated in debt contracts. Coefficients of *New Viol* $\times$ *Excess NWC* equal 0.011 and 0.016, respectively and are significant at the 10% and 5% level. The effect on leverage is reversed for violating firms with negative excess NWC. These firms reduce their leverage. The summary statistic indicates that violating

Table 1.6: Impact on Other Real Determinants

This table presents the regressions of the four-quarter changes in leverage (Δ *Lev*) and the leverage (*Lev*), investments (*Capex*), sales growth (*Sales*), assets growth (*Size*), and operating cash flow (*Cash Flow*) on new covenant violations and excess NWC. Investment is capital expenditures over the next four quarters scaled by average assets. Sales and assets growth are the log differences between the quarter in one year and the current one. Operating cash flow is earnings before depreciation scaled by average assets. *New violation* is a covenant violation preceded by four consecutive non-violating quarters (Nini et al., 2012). *Excess NWC* is the Fama-French 49 industry-adjusted net working capital scaled by total sales per quarter (Aktas et al., 2015). Control variables are the same as in Table 1.3. Standard errors are clustered at industry and calendar quarter. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively and t-statistics is presented in parentheses.

	(1) Δ Lev.	(2) Lev.	(3) Capex	(4) Size	(5) Sales	(6) Cash Flow
New Viol	-0.057	-0.510	-0.142	-2.435***	-3.207***	0.178**
	(-0.19)	(-1.39)	(-1.05)	(-3.83)	(-4.70)	(2.16)
New Viol $\times$ Excess NWC	0.011*	0.016**	-0.006**	-0.012	0.013	0.000
	(1.80)	(2.25)	(-2.11)	(-0.93)	(0.74)	(0.09)
Excess NWC	-0.003***	-0.002**	-0.001*	-0.004	0.024***	0.000
	(-3.16)	(-2.38)	(-1.65)	(-1.55)	(7.50)	(0.83)
Observations	77,306	77,306	76,055	77,763	77,620	74,843
R^2	0.059	0.911	0.683	0.303	0.145	0.168
Controls	YES	YES	YES	YES	YES	YES
Lagged Controls	YES	YES	YES	YES	YES	YES
Higher Order Moments	YES	YES	YES	YES	YES	YES
Year Quarter FE	YES	YES	YES	YES	YES	YES
Fiscal Quarter FE	YES	YES	YES	YES	YES	YES

firms with negative excess NWC have already the highest leverage. It is thus reasonable to expect that creditors try to reduce the leverage most for this group. The reduction of *Excess NWC* by one standard deviation is associated with a reduction in leverage by 0.5%. This change equals about 2.3% of the mean value of leverage which is 22.5%. Violating firms with positive excess NWC have more liquid assets on their balance sheet and might be able to pledge some of their net working capital as collateral. Further, their leverage is lower and book equity is larger (see Table 1.2) which allows more flexibility in renegotiating with creditors. In contrast, firms with negative NWC have no such option. Comparing the reduction in leverage with the increase in trade credits shows a coherent picture which is in line with the predictions of Wilner (2000) and Cuñat (2006). Suppliers provide trade credits to constrained violating firms for which banks ration credit most. This notion is further supported by firms' growth opportunities. Tobin's Q is higher for violating firms with negative excess NWC than for violating firms with positive excess NWC. Suppliers' equity stake is, therefore, worth more in violating firms with negative excess NWC.

In line with the previous findings and predictions from the literature, violating firms with negative excess NWC are able to invest more than their violating counterparts with positive excess NWC. Column (3) of Table 1.6 shows a significant coefficient of *New Viol* $\times$ *Excess NWC* of -0.006. A reduction of excess NWC by one standard deviation increases capital expenditures by 0.25%. The effect is also large in economic terms as firms invest on average about 6% of total assets such that the effect equals 4.2%. Hence, more underinvested, violating firms are able to invest after covenant violations, whereas violating firms with positive excess NWC have to cut investments.

Columns (4) to (6) present coefficient estimates on operating performance. Column (4) shows a significant coefficient of *New Viol* of -2.435. This indicates that the growth rates of total assets of violating firms are about 2.4 percentage points lower over the next four quarters than those of non-violating firms. The effect is similar for the growth in sales which is presented in column (5). Firms' growth rate of sales drops by about 3.2 percentage points. Both results are similar to findings in Nini et al. (2012). The insignificant interaction term indicates that both types of firms, being under- or overinvested in net working capital, are harmed by covenant violations. In contrast, column (6) shows that firms in violation improve their operating cash flow by 17.8 basis points. Firms focus more on improvements in their operations and thus on better performance. Although the coefficient on the interaction term is insignificant, the result on violation is important. Firms change their operations differently depending on their current level of excess NWC by investing or divesting into NWC. These opposite reactions lead both to improved performance. The results emphasize that investing into net working capital can also be a profitable strategy to react to covenant violations. However, this only holds for firms which are inefficiently underinvested in net working capital.

1.8 Robustness Checks

This section presents robustness checks to support the relationship between covenant violations and excess NWC. First, I use an indicator variable instead of the continuous variable *Excess NWC*. This indicator variable *Excess NWC (Dummy)* equals one if excess NWC is negative and zero otherwise. Such an implementation mitigates the impact of extreme values which might drive results. Table 1.7 presents coefficient estimates of three specifications based on equation 1.2, where I replace *Excess NWC* by the *Excess NWC (Dummy)*. The coefficient of *New Viol* in column (1) is highly significant and negative with a point estimate of -3.55. Firms in violation accelerate their period to convert money by 4.7 days. The coefficient of *Negative Excess NWC (Dummy)* equals 8.3 and is highly significant indicating that firms with negative excess NWC invest into their net working capital. The coefficient

Table 1.7: Robustness: Change in Excess NWC applying Dummies

This table presents regressions of the four quarter change in Excess NWC on *New Viol* and an indicator variable *Neg. Excess NWC* which equals one if Excess NWC is negative and zero otherwise. *New Viol* is a violation preceded by four consecutive non-violating quarters (Nini et al., 2012). Excess NWC is the Fama-French 49 industry-adjusted net working capital scaled by total sales per quarter (Aktas et al., 2015) multiplied by 90 days. Control variables are the same as in Table 1.2. Standard errors are clustered at industry and calendar quarter. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively and t-statistics is presented in parentheses.

	(1)	(2)	(3)
New Viol	-4.705***	-4.270***	-3.726***
	(-4.30)	(-3.93)	(-3.22)
New Viol × Neg. Excess NWC (Dummy)	5.488***	5.096***	5.273***
	(3.84)	(3.58)	(3.53)
Neg. Excess NWC (Dummy)	8.286***	8.381***	7.358***
	(33.82)	(33.64)	(29.56)
Observations	104,313	104,313	77,270
R^2	0.041	0.044	0.047
Controls	YES	YES	YES
Lagged Controls	NO	NO	YES
Higher Order Moments	NO	YES	YES
Year Quarter FE	YES	YES	YES
Fiscal Quarter FE	YES	YES	YES

of the interaction term *New Viol* × *Negative Excess NWC (Dummy)* equals 5.3 and is highly significant. Violating firms facing negative excess NWC do enlarge their net working capital by 5.3 more days. The coefficient of the interaction term is larger than the coefficient of the indicator variable *New Viol* such that violating firms with negative excess NWC invest into their excess NWC. Significance and economic magnitude are both robust to the inclusion of higher order (column (2)) and lagged control variables (column (3)). These results support findings of the main analysis presented in Table 1.1.

Table 1.8 addresses potential problems with extreme values in a different way. In columns (1) to (3), I reestimate equation 1.2 again but I exclude the middle third of the distribution of *Excess NWC*. This sample contains only observations with extreme values in the lower and upper third of the sample. The coefficient of the interaction term *New Viol* × *Excess NWC* is still highly significant which supports the findings that violating firms change their excess NWC much more than non-violating firms. The coefficient of *Excess NWC* remains significant and negative. The inclusion of further control variables in columns (2) and (3) does not change results as the coefficients on the interaction terms are all close to -0.07 and significant. Columns (4) to (6) represent the complementary analysis when extreme values of *Excess NWC* are excluded. In order to exclude one-third of the observations, I remove observations which belong to the lowest and highest sixth of the distribution of *Excess NWC*. The coefficient of the interaction term *New Viol* × *Excess NWC* is highly significant and equals -0.092. Similar to the other specifications, the coefficient of *Excess NWC* remains negative and highly significant. The inclusion of further control variables in columns (5) and (6) do not alter results supporting the stability of these estimators.

These regressions support the previous results that firms in violation reduce their excess NWC if unnecessary capital is employed in the operating processes. Violating firms with negative levels of excess NWC invest instead in order to reduce inefficiently low levels of net working capital.

In the next test presented in Table 1.9, I split the sample along the median value of *Excess NWC* into one sample consisting of observations with negative excess NWC and a second sample which contains only observations with excess NWC equal or larger than zero. Columns (1) to (3) refer to specifications which belong to the sample with negative excess NWC. The coefficient of *New Viol* is highly significant and negative in all three specifications. After a new covenant violation, firms lower their excess NWC on average. However, the coefficients on the interaction term *Pilot* × *Excess NWC* and *Excess NWC* are both negative and significant. The partial effect of *New Viol* is offset by the combination of *Excess NWC* and the interaction term. A one standard deviation decrease of NWC leads

Table 1.8: Robustness: Change in Excess NWC addressing Extreme Values

This table presents regressions of the four quarter change in Excess NWC on *New Viol* and the current state of *Excess NWC*. Columns (1) to (3) exclude observations of the middle third of the distribution of Excess NWC. Columns (4) to (6) exclude the one-third most extreme values of Excess NWC by neglecting the lowest and highest sextile. *New Viol* is a violation preceded by four consecutive non-violating quarters (Nini et al., 2012). Excess NWC is the Fama-French 49 industry-adjusted net working capital scaled by total sales per quarter (Aktas et al., 2015) multiplied by 90 days. Control variables are the same as in Table 1.2. Standard errors are clustered at industry and calendar quarter. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively and t-statistics is presented in parentheses.

	No Middle Tercile			No Extreme Sextiles		
	(1)	(2)	(3)	(4)	(5)	(6)
New Viol	-1.033	-0.775	-0.776	-0.635	-0.592	-0.027
	(-1.19)	(-0.89)	(-0.82)	(-1.03)	(-0.96)	(-0.04)
New Viol × Excess NWC	-0.070***	-0.066***	-0.069***	-0.092***	-0.088**	-0.089**
	(-2.76)	(-2.65)	(-2.59)	(-2.67)	(-2.57)	(-2.38)
Excess NWC	-0.191***	-0.197***	-0.182***	-0.109***	-0.113***	-0.107***
	(-39.28)	(-39.51)	(-32.38)	(-19.90)	(-20.47)	(-18.12)
Observations	69,542	69,542	51,102	69,542	69,542	52,327
R^2	0.125	0.129	0.126	0.032	0.034	0.040
Controls	YES	YES	YES	YES	YES	YES
Lagged Controls	NO	NO	YES	NO	NO	YES
Higher Order Moments	NO	YES	YES	NO	YES	YES
Year Quarter FE	YES	YES	YES	YES	YES	YES
Fiscal Quarter FE	YES	YES	YES	YES	YES	YES

Table 1.9: Robustness: Sample Split of Excess NWC

This table presents regressions of the four quarter change in Excess NWC on *New Viol* and the current state of *Excess NWC*. Columns (1) to (3) refer to observations with negative Excess NWC only. Columns (4) to (6) include only observations with positive Excess NWC. *New Viol* is a violation preceded by four consecutive non-violating quarters (Nini et al., 2012). Excess NWC is the Fama-French 49 industry-adjusted net working capital scaled by total sales per quarter (Aktas et al., 2015) multiplied by 90 days. Control variables are the same as in Table 1.2. Standard errors are clustered at industry and calendar quarter. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively and t-statistics is presented in parentheses.

	Negative Excess NWC			Positive Excess NWC		
	(1)	(2)	(3)	(4)	(5)	(6)
New Viol	-4.096***	-4.085***	-3.679**	2.139	2.140	2.468*
	(-2.62)	(-2.61)	(-2.25)	(1.53)	(1.55)	(1.68)
New Viol × Excess NWC	-0.140**	-0.142**	-0.136*	-0.071*	-0.067*	-0.075*
	(-2.02)	(-2.04)	(-1.82)	(-1.85)	(-1.77)	(-1.82)
Excess NWC	-0.189***	-0.192***	-0.190***	-0.213***	-0.215***	-0.196***
	(-19.59)	(-19.88)	(-17.37)	(-28.92)	(-29.02)	(-23.41)
Observations	52,061	52,061	38,148	52,252	52,252	39,122
R^2	0.090	0.091	0.104	0.139	0.145	0.132
Controls	YES	YES	YES	YES	YES	YES
Lagged Controls	NO	NO	YES	NO	NO	YES
Higher Order Moments	NO	YES	YES	NO	YES	YES
Year Quarter FE	YES	YES	YES	YES	YES	YES
Fiscal Quarter FE	YES	YES	YES	YES	YES	YES

to an increase of excess NWC by 3.2 days. This effect is robust to the inclusion of further control variables as the coefficients remain constant. Similarly, columns (4) to (6) report significantly negative coefficients of the interaction term for the sample comprised of observations with positive excess NWC. For a one standard deviation increase of excess NWC, firms will divest excess NWC by 7.85 days. From an economic perspective, it is reasonable to find that firms with positive excess NWC are able to reduce net working capital more than firms with negative excess NWC can increase net working capital. Firms with negative excess NWC are still financially constrained such that their refinancing sources and their flexibility to invest are limited.

Table 1.10: Robustness: Change in Excess NWC scaled by total assets

This table presents regressions of the four quarter change in Excess NWC on *New Viol* and the current state of *Excess NWC (Assets)*. *New Viol* is a violation preceded by four consecutive non-violating quarters (Nini et al., 2012). *Excess NWC (Assets)* is the Fama-French 49 industry-adjusted net working capital scaled by total assets per quarter. Control variables are the same as in Table 1.2. Standard errors are clustered at industry and calendar quarter. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively and t-statistics is presented in parentheses.

	(1)	(2)	(3)
New Viol	0.001	0.001	0.000
	(0.51)	(0.41)	(0.06)
New Viol × Excess NWC (Assets)	-0.034***	-0.033***	-0.042***
	(-2.77)	(-2.76)	(-3.39)
Excess NWC (Assets)	-0.107***	-0.111***	-0.103***
	(-45.73)	(-45.37)	(-39.07)
Observations	105,537	105,537	77,976
R^2	0.065	0.068	0.067
Controls	YES	YES	YES
Lagged Controls	NO	NO	YES
Higher Order Moments	NO	YES	YES
Year Quarter FE	YES	YES	YES
Fiscal Quarter FE	YES	YES	YES

Table 1.10 presents regression coefficients of an alternative calculation of excess NWC. Instead of using quarterly sales as denominator (Aktas et al., 2015), I use total assets to scale net working capital. This variable focuses more on firms' actual capital and asset structure and shows how much of firms' assets have to be financed externally. The coefficients support the picture already presented above when applying the measure of excess NWC as suggested in Aktas et al. (2015). *Excess NWC (Assets)* is highly significant and equals -0.11 indicating that firms with positive excess NWC will reduce their superfluous position. Contrary, firms underinvested in NWC will increase their level. The interaction term is negative and highly

significant. The coefficient estimates remain fairly constant and highly significant including further control variables. These results support the notion that firms in violation react even stronger to reach more optimal levels of net working capital. In summary, the alternative measure of excess NWC supports the results using the variable definition in Aktas et al. (2015).

1.9 Conclusion

Covenant violations have typically significant impacts on firms. Creditors induce violating firms to refocus on their core business and to lower expansion activities. Firms have to reduce leverage (e.g., Roberts & Sufi, 2009a), cut investments (e.g., Chava & Roberts, 2008), or lay-off employees (Falato & Liang, 2016). In contrast to these findings and in line with findings in Aktas et al. (2015), I find that firms being highly underinvested in their operations employ strategies to invest into their net working capital after violations. This strategy is more value-enhancing than additional reductions. These firms also get access to more trade credit of their suppliers which they use to finance longer payment terms for their own customers. Firms facing superfluous net working capital employ a complementary strategy to reduce excess NWC by asking their customers for earlier repayments. Further, they reduce trade credits which they receive from their suppliers. Both strategies are profitable in terms of improving operating cash flows but do not protect firms from lower asset and sales growth. However, there are differences in leverage and investments. Firms being underinvested have to reduce leverage stronger but are able to invest more than overinvested violating firms. Suppliers step in as funding partner. Such a pattern is in line with the implicit equity stake of suppliers (e.g., Cuñat, 2006; Wilner, 2000) and the empirical findings of Zhang (2018).

2 Mutual fund trading and interference effects through the implementation of Reg SHO

Nicolas Kube [1]

Abstract

I show that the Reg SHO experiment conducted by the SEC, which randomly exempted about one third of the U.S. stocks in the Russell 3000 index from short sale price tests, also affected not exempted, untreated stocks. Groups with locally bounded interference are important to identify interference. I use mutual funds to implement a within-group estimation of interference effects so that I can identify mutual funds as one potential channel for the occurrence of interference effects. The random proportion of treated stocks in mutual funds' portfolios set asymmetric incentives to trade treated and untreated stocks. Mutual funds buy more (less) nonpilot stocks when the fund's proportion of pilot stocks is high (low). Under the assumption of no interference, no such pattern should be observable. Importantly, analysis yields the false result that fund managers are indifferent towards pilot and nonpilot firms if interference effects are not considered. Hence, this paper demonstrates the importance to account for interference effects in finance research.

Keywords: Interference effects, SUTVA, Short Sales, Reg SHO, Mutual Funds.
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2.1 Introduction

The implementation of Regulation SHO in July 2004, which randomly exempted about one-third of listed U.S. stocks included in the Russell 3000 index from short sale restrictions, increased short selling activities in these stocks. However, it also raises the question whether this program leads to interference between treated and untreated stocks. Interference means that untreated stocks are indirectly affected through the presence of treated stocks. The presence of interference would question the validity of empirical estimators which use the comparison of the treatment and control group.

The empirical estimation of interference effects relies on within-group interference such that interference is locally bounded within distinct groups. Interference can then be identified by comparing group members' outcome when these members belong to groups which are differently affected by the treatment (treatment intensity). However, such groups are often hard to find, especially in the deeply integrated financial market. I propose that mutual funds can be seen as such groups. They show asymmetric trading incentives to trade certain stocks depending on how strongly they are affected by the new regulation. Additionally, they could not anticipate the future treatment status of stocks such that they are randomly affected and their treatment intensity varies considerably. From an economic perspective, they have incentives to balance the potential underperformance of heavily shorted stocks with the incentive to earn higher lending fees on those stocks.

Under the assumption of no interference, the outcome of untreated stocks should be independent of the fraction of treated stocks (e.g., Crépon, Duflo, Gurgand, Rathelot, & Zamora, 2013; Ferracci, Jolivet, & van den Berg, 2014). I find that mutual funds with only few affected stocks buy treated and sell untreated stocks, whereas funds which are highly affected do the opposite. Such a pattern is evidence for interference effects. I, therefore, reject the null hypothesis of no interference effects and identify mutual fund managers' trading behavior as one potential channel how interference effects can occur in financial markets. I also demonstrate the estimation bias when interference effects are neglected. The coefficient of the treatment dummy in the multivariate regressions analyzing whether mutual fund managers will buy or sell treated stocks are insignificant. Thus, based on such an analysis, false conclusions on mutual fund managers' preference on short selling would be drawn because the biased estimators suggest that managers are indifferent towards treated and untreated stocks.

Interference effects have an economic effect and empirical consequences. First, they can be an unintended and unexpected byproduct of a new policy or regulation which harm or benefit unaffected firms. Identifying interference effects helps to evaluate the policy's indirect effects. Secondly, they can be a severe source for biased estimators because treatment and control group are compared. Parts of the estimated effect refer to changes in the control group. Being able to demonstrate the absence of interference effects in certain settings also improves the credibility of estimators and that the effect comes truly from the change in the treatment group.

The main challenge to identify interference effects empirically is the construction of the control group. By definition, parts of the control group are affected through the treatment group if interference effects are expected. Hence, the estimation of the impact of the treatment on the control group requires another control group. To overcome the problem of confounded counterfactuals, I apply a within-group estimation which is designed to identify interference effects. This idea follows the experimental setup of a two-step randomization in which untreated participants react differently to a higher or lower presence of treated participants (e.g., Crépon et al., 2013; Hudgens & Halloran, 2008; Manski, 2013). Two-step randomization experiments are designed to identify direct and indirect effects explicitly by randomizing the treatment intensity of groups first and then the actual treatment of the group members. Such an approach is always important when interaction effects are likely and their impact is important to be understood. In contrast, the SEC applied a classic experimental design with a random assignment procedure across all stocks in the Russell 3000 index. The analysis shows that the random treatment assignment of such an experiment is not sufficient to evaluate the full impact of short sale price tests. Experiments are designed to remove the impact of other potential explanatory factors because the treatment and control group have similar characteristics through the randomization procedure. However, such experiments also rely on the requirement that there are no interference effects between the treatment and the control group. This requirement is known as Stable Unit Treatment Value Assumption (SUTVA). From an economic perspective, the presence of treated (pilot) stocks changes the relative attractiveness of control stocks to be shorted because untreated stocks are still restricted by short sale constraints. Indeed, there are some concerns that this program may cause interference effects. At the Roundtable on the Regulation SHO Pilot[2] at the mid of the program, Prof. Larry Harris argued that "there are people who employ short selling strategies that aren't specific to individual stocks they will direct their order flow in the pilot period to only those stocks [...] that are unrestricted. So the effects that we see in the unrestricted stocks are liable to be overstated (p.94)." Prof. Bruce N. Lehmann added that "the good sellers [...] stay in the pilot stocks, but the evil bad short sellers will

[2] https://www.sec.gov/about/economic/shopilottrans091506.pdf

take a vacation from these stocks while the Commission is looking (p.109)." Alexander and Peterson (2008) have to explicitly assume that no interference effects were present when they assess the impact of the new short selling regime.

This paper complements the paper of Boehmer, Jones, and Zhang (2019). They show interference effects in the quotes of short sellers around the implementation and repeal of Reg SHO of the Security Exchange Commission in 2005 and 2007. In contrast, I show that long investors reacted much earlier and anticipated the change in short selling activities. Moreover, I provide evidence that mutual funds can be used as a reasonable setup to detect interference effects. First, there is strong theoretical and empirical evidence that mutual fund managers trade asymmetrically depending on the treatment intensity they have to deal with. Secondly, mutual funds can be used to implement within-group estimation because their trading was mainly based on the composition of their stock portfolios immediately prior to the announcement of the pilot stocks. Lastly, the property that different funds with different treatment intensities hold the same stock can be exploited to estimate asymmetric reactions of fund managers even on the stock level.

I also contribute to the large literature on the impact of short sellers in several ways. Alexander and Peterson (2008) and Diether, Lee, and Werner (2009a) analyze the impact of the pilot program on the stock market. They find that short sale activities increase in pilot stocks. I show that mutual fund managers reallocated their fund holdings prior to the effective implementation of the program in response to the anticipated short sale activities. They balance the trade-off between the potential negative and positive consequences. Funds which have high treatment intensities reduce their holdings in pilot stocks. That behavior is in line with findings in Asquith, Pathak, and Ritter (2005) or Cohen, Diether, and Malloy (2007) who show an underperformance of heavily shorted stocks. On the other hand, funds with low fractions of pilot stocks invest more into treated stocks which yields additional lending fees. Such a pattern is shown by H. Chen, Desai, and Krishnamurthy (2013) and Evans, Ferreira, and Porras Prado (2017).

Lastly, I contribute to the growing body of literature on interference effects in corporate finance. The experimental setup avoids many problems typically associated with the introduction of new regulations. First, it constructs a control and treatment group. Secondly, the allocation was random and both groups show similar characteristics (Fang, Huang, & Karpoff, 2016). This makes it possible to focus on the detection and estimation of interference effects because they were not considered or ruled out beforehand. I show that econometric techniques based on the experimental two-step randomization procedure help to identify interference in mutual fund trading empirically (see also Crépon et al., 2013; Ferracci et al., 2014; Huber & Steinmayr, 2017; Hudgens & Halloran, 2008; Manski, 2013; Philipson, 2000) and that this methodology yields also economically intuitive results.

This paper is organized as follows. Section 2 discusses the consequences of interference and how to estimate them. Section 3 introduces regulation REG SHO and its consequences. Further, this section motivates Reg SHO as potential source for interference effects. Section 4 shows how to estimate interference effects using mutual funds. Section 5 gives an overview of the data. Section 6 shows results on interference effects on the stock level. Section 7 confirm the results as it assesses the trading patterns on the aggregated fund level and addresses alternative explanations. Section 8 concludes.

2.2 Problem of Interference between Firms

2.2.1 Biased Estimates

The estimation of the average treatment effect (ATE) rests upon the assumption of no interference between the treatment and the control group as well as no interference between the members within each group. This assumption is called stable unit treatment value assumption (SUTVA). The estimator estimates the difference between the treatment and the control group (e.g., Rubin, 1974, 1990) as presented in equation 2.1:

$$ATE = Y_t(i) - Y_c(i) \tag{2.1}$$

Interference describes situations in which the treatment received by one individual also affects the outcome of other individuals (Tchetgen & VanderWeele, 2012). Typical sources of interference can be social interactions (Manski, 1993), learning or copying effects (Leary & Roberts, 2014)), non-cooperative games with punishment (Akerlof, 1980), creating distinguishing features between individuals like job placement assistance (Crépon et al., 2013), or changing the flow through networks or societies (Perez-Heydrich et al., 2014). The presence of interference raises concerns about the validity of empirical estimators of the average treatment effect (ATE). The average treatment effect (ATE) then consists of changes in the treatment $Y_t(i)$ and control group $Y_c(i)$. These estimators do not allow to disentangle whether the effect stems from the treatment or from the control group. Prominent examples of the impact of interference come from the field of vaccination. The probability of becoming infected in a population decreases the more people in the population are vaccinated (e.g., Perez-Heydrich et al., 2014). Neglecting the indirect effects on the control group leads to a highly underestimated effectiveness of the vaccination programs.

2.2.2 Estimating Interference Effects

According to the example of vaccination, experimental procedures with two-step randomization are designed to explicitly estimate potential interference effects (e.g., Crépon et al., 2013; Hudgens & Halloran, 2008; Manski, 2013; Philipson, 2000). These procedures rely on two key assumptions. First, interference effects occur locally between individuals. They are bounded within certain groups and do not affect other groups. Groups are thus independent from each other. The second assumption is a systematic relation between the number of treated members within a group, i.e. the group's treatment intensity, and the potential outcome of group members. In order to rule out selection biases based on group characteristics or characteristics of group member, randomization takes place at two stages. The treatment intensity is first randomized across different groups. The actual treatment status of each group member is then randomized within groups conditional on the groups' previously assigned treatment intensity. The first step addresses potential selection biases related to group characteristics explaining treatment intensities. The second step rules out systematic effects of characteristics of group members.[3] In an ideal setup, two «super» control groups can be constructed (e.g., Crépon et al., 2013). Members of super control groups, by construction, are not prone to any interference within the group. One super control group consists only of untreated members. This group represents the best possible control group for other untreated individuals which are exposed to interference effects. Another super control group includes only treated members. This second type of control group can be used to estimate interference on treated individuals in other groups.

The potential outcome $Y(z_j, d_i)$ depends not only on the (binary) treatment $D = d_i,\ D \in \{0, 1\}$ for member i but also on the treatment intensity $Z = z$ within group $J = j$ member i belongs to. The treatment intensity is a function of the number of treated members within each group $z_i = f(d)$ (e.g., equally-weighted fraction of number of individuals). The direct and the indirect effects can then be written separately (Huber & Steinmayr, 2017):

Average direct effect:

$$\delta(z) = E[Y(z, 1) - Y(z, 0)] \tag{2.2}$$

Average interference effect:

$$\begin{aligned} \theta(z', z, d) &= E[Y(z', d) - Y(z, d)] \text{ with } z' \neq z \text{ and } d \in \{0, 1\} \\ &= \underbrace{E[Y(z', 1) - Y(z, 1)]}_{Interference\ Treated} + \underbrace{E[Y(z', 0) - Y(z, 0)]}_{Interference\ Untreated} \end{aligned} \tag{2.3}$$

[3] For endogenous treatments, Ferracci et al. (2014) propose a double matching approach to construct a sample of comparable groups with treated and untreated individuals.

Equation 2.3 emphasizes two potential sources of interference. Interference can occur at the level of treated members. Treated members $\theta(z', z, 1)$ might be affected differently when treatment intensity z changes to z'. The same argument holds for the untreated members. The indirect effect on the untreated are, however, often of larger importance. This group typically represents the control group which should be unconfounded to estimate unbiased effects.

$$Y_{i,k} = \alpha + \beta_1 D_i + \beta_2 D_i \times Fraction_k + \beta_3 Fraction_k + \beta_4 X_i + \beta_5 X_k + \epsilon \tag{2.4}$$

The regression framework 2.4 shows the different effects. β_1 refers to the effect of being treated. β_2 estimates the additional interference effect on the treated. β_3 represents the interference effect on untreated individuals. Both estimates β_2 and β_3 depend on the treatment intensity across groups and can be interpreted as true interference effects when the different super control groups exist. If there are no super control groups, coefficients indicate only the existence of interference effects because they show a systematic relation of the outcome and different treatment intensities.[4] X_i and X_k include control variables of the individuals and the group characteristics, respectively.

2.3 Mutual Funds, Reg SHO and Reasons for Interference Effects

Regarding Reg SHO, Prof. Larry Harris voiced the concern that "people [...] employ short selling strategies that aren't specific to individual stocks"[5] such that they will focus on pilot stocks and neglect nonpilot stocks. The presence of interference between pilot and nonpilot stocks requires three main determinants. First, short sales had to occur frequently in the market at the time of the implementation such that short selling is a concern for mutual fund managers. Second, the design of Reg SHO must be suitable to alter short sale activities and thus increase the probability of interference. Lastly, there must be economic reasons why mutual fund managers react to Reg SHO.

This section first introduces the presence and regulation of short sales around the time of the

[4] A setup with few distinct treatment intensities shows the effect of a super control group because one can apply dummies for each treatment intensity. Using the super control group as base category allows to interpret the coefficients of dummies as true interference effects on untreated individuals which refer to different treatment intensities (Crépon et al., 2013). Having no super control group restricts this interpretation to the relative effect of higher treatment intensities such that one is able to reject the null of no interference.

[5] Roundtable on the Reg SHO (p. 94): https://www.sec.gov/about/economic/shopilottrans091506.pdf

implementation of Reg SHO. It then presents how Reg SHO was designed and summarizes evidence on the impact of the new regulation from prior literature. Lastly, it discusses how Reg SHO may lead to interference in the decision of fund managers to invest into pilot and nonpilot stocks.

2.3.1 Presence of Short Sales

Short sales played a large role in the stock market around the time Reg SHO was implemented. Boehmer, Jones, and Zhang (2008) report that short sales accounted for about 13% of the volume of NYSE SuperDOT between 2000 and 2004. In 2005, short sales represented 24% of the NYSE and 31% of the Nasdaq share volume (Diether, Lee, & Werner, 2009b). The majority of firms could be shorted cheaply and there was large supply of most lendable stocks. Very small stocks with low institutional holdings were hardly shorted. However, they only accounted for about 1% of the total market value (D'Avolio, 2002).
At this time, short sellers' activities were restricted by Rule 10a-1 under the Securities Exchange Act of 1934. This rule, also known as the Uptick Rule, required pricing tests for short sales in order to achieve three main goals: "(i) allowing relatively unrestricted short selling in an advancing market, (ii) preventing short selling at successively lower prices, thus eliminating short selling as a tool for driving the market down, and (iii) preventing short sellers from accelerating a declining market by exhausting all remaining bids at one price level, causing successively lower prices to be established by long sellers."[6] The Uptick Rule sets a lower bound for the quote of short sales which depends on the past stock prices (e.g., minus tick, uptick). In principle, quotes cannot be lower than the last trading price.[7] The Uptick Rule indeed restricted short selling in declining but also in advancing markets and more than 90% of short sell orders were delayed or canceled (Alexander & Peterson, 1999). Some types of short sales (e.g., particular arbitrage trades between different exchanges, arbitrage of stocks and convertible bonds on this stock) were exempted from this rule. However, these trades accounted only for 1.5% of all short sales (Boehmer et al., 2008).

2.3.2 Exemption of Short Sale Price Tests

In 2004, the Security Exchange Commission (SEC) launched a Pilot program to investigate the impact and effectiveness of its short sale price tests. The reason was that this regulation was established in 1938 when the market was smaller and less liquid. This program, known

[6] Securities Exchange Act Release No. 13091
[7] Alexander and Peterson (1999) and Diether et al. (2009a) provide a detailed description and numerical examples.

as Rule 202T of Regulation SHO (17 CFR 242.202T), was adopted on July 28, 2004. In order to evaluate the impact of price tests on short sales, a random assignment mechanism similar to a classic experimental design was employed. The SEC chose all stocks included in the Russell 3000 Index which were listed at the New York Stock Exchange (NYSE), NASDAQ, or the American Stock Exchange (AMEX) on July 28, 2004.[8] Stocks were ranked in decreasing order based on their average daily trading volume of the year prior to the announcement. This ranking was done for each stock exchange separately. Every third stock in each group was chosen as pilot stock, starting with the second stock in each group. Pilot stocks were then exempted from short sale price tests. The period during which the program was effective started on May 2, 2005 and lasted until July 6, 2007.[9] Since the selection of pilot firms and the program details were confidential until July 28, 2004, firms and market participants could not anticipate or react to this program in advance. Further, the assignment of being a pilot stock was binding and could not be changed afterwards.

The introduction of the Pilot program had various effects on individual firms and on the whole market. Security Exchange Commission (2007) finds that short selling activities in pilot stocks increased after the implementation of the Pilot program and that the effect was stronger for NYSE-listed stocks. Alexander and Peterson (2008) complement these findings and add that short sellers split their orders of pilot stocks more frequently. They do not find any effects on quoted or effective spreads nor evidence for higher price volatility or eroded price efficiency. Diether et al. (2009a) show similar results but find also higher short sale volumes and frequencies for Nasdaq-listed firms. Moreover, they show that the relative bid depth of NYSE-listed firms increased. Boehmer and Wu (2013) provide evidence that short sellers help to incorporate relevant information into stock prices on an intraday basis. Stocks with higher short sales show less intraday deviation of transaction prices, shorter price delays, and hardly any drift after negative earnings surprises. On average, price efficiency of pilot stocks raised by 17% after the exemption from price tests. Grullon, Michenaud, and Weston (2015) find that the smallest firms, which were part of the Pilot program, underperformed the market by nearly 9% over the subsequent two years.

Despite the effect on market and trading measures, Grullon et al. (2015) show that small firms, which are part of the Pilot program, reduced their capital expenditure and their frequency of equity issuance during the effectiveness of the program. Fang et al. (2016) report the relationship between short selling activities and earnings management. Pilot firms

[8] All firms which commenced their initial public offering or were distributed as a spin-off after April 30, 2004 were excluded from this procedure.

[9] Initially, the program was supposed to start on January 3, 2005 and last for one year. However, the start was postponed to May 2, 2005 and lasted until July 6, 2007.

reduced their discretionary accruals significantly during the effectiveness of the program.

2.3.3 Reasons for Interference Effects

Short sale activities are important determinants for mutual fund managers' investment decisions and can affect their decisions whether to trade pilot or nonpilot stocks. In principle, there are two main reasons to consider short sale activities: to earn lending fees and to avoid negative stock returns. H. Chen et al. (2013) find that mutual fund managers actively engage in short sale activities which generate abnormal returns of 1.5% per year. Evans et al. (2017) show different results. Mutual funds which lend equities underperform similar funds not engaging in lending by about 0.5% and 0.7%. The underperformance is, however, concentrated in funds which face investment restrictions set by their asset management company. Johnson and Weitzner (2019) find that fund managers retain large fractions of lending fees instead of returning them to their investors such that they rely heavily on stocks with high lending fees. D'Avolio (2002), Massa, Zhang, and Zhang (2015), and Evans et al. (2017) show that mutual funds and their custody banks are a major source of lending inventory because many funds participate in securities lending programs. Fund managers which lend shares gain cash as collateral (D'Avolio, 2002) which can be used to manage funds' outflows more efficiently and they benefit from interest payments and appreciation on this collateral (Evans et al., 2017). Duffie, Gârleanu, and Pedersen (2002) model the incentive to buy stocks for inflated prices if these stocks can be lent in the future.

Short sellers are known for improving the informational content of stock prices by incorporating negative expectations (e.g., J. Chen, Hong, & Stein, 2002; Figlewski, 1981; Harrison & Kreps, 1978; Miller, 1977; Scheinkman & Xiong, 2003). Jones and Lamont (2002) or Ofek and Richardson (2003) provide evidence that short selling constraints indeed facilitate overpricing. Desai, Ramesh, Thiagarajan, and Balachandran (2002) show an underperformance of heavily shorted stocks listed at Nasdaq. Cohen et al. (2007) support this finding as increasing short selling demand leads to an underperformance of heavily shorted stocks by about 3%. Similarly, Asquith et al. (2005) show that portfolios composed of highly shorted stocks underperform the market.

Short sellers might be a threat for mutual fund managers in stock picking. Christophe, Ferri, and Angel (2004) provide evidence that short sellers are highly informed traders which anticipate negative news and try to exploit such information. They find that short sellers anticipate unexpected negative earnings announcements very well and sell short these stocks. Such stocks indeed face stronger price drops after unexpected negative announcements. A similar argument related to funds is stressed by Brunnermeier and Pedersen (2005). They model that short sellers anticipate short falls of liquidity of mutual funds. Short sellers can exploit these situations when mutual fund managers have to fire sell assets for depressed prices. Short selling of current holdings then further depresses prices of these stocks.

The different impacts of short sellers set two opposing incentives for mutual fund managers to invest into but also to sell-off pilot stocks. Expecting that short sellers will sell short pilot stocks much more frequently compared to nonpilot stocks, mutual fund managers can earn higher lending fees by holding large positions of pilot stocks. On the other hand, fund managers have to expect lower stock returns, be exploited by better informed short sellers, and have the concern of "predatory trading" (Brunnermeier & Pedersen, 2005) if they hold more pilot firms.

There are already some concerns in the literature about potential interference caused by Reg SHO. As quoted above, Prof. Larry Harris was concerned that short sellers mainly focus on pilot stocks. Further, Boehmer et al. (2019) show interference effects of short sellers' quoting behavior around the beginning and end of the Pilot program. Moreover, Alexander and Peterson (2008) were already confronted with potential interference problems. They explicitly state in footnote 3 that they have to "assume[...] that traders do not shift their short selling from other stocks in order to focus on pilot stocks."

2.4 Using Mutual Funds for Estimating Interference Effects

2.4.1 Mutual Funds as Groups

Equations 2.2 and 2.3 point out the importance of having distinct groups with different treatment intensities to estimate interference effects. Crépon et al. (2013), for example, apply regional labor markets as separate, independent groups which have different job placement assistance. In contrast to regional labor markets, the financial market is deeply integrated. This facilitates the likelihood of interference. However, such an integration makes it difficult to find independent groups to estimate interference effects. I argue that individual mutual funds can be seen as well-separated, independent groups embedded in the financial market. Mutual fund managers' investment decisions in response to Reg SHO are mainly influenced by their asset composition of pilot stocks at the announcement and the resulting (random) treatment intensity. They have to consider short selling activities in the whole market as well as the exposure of their own holdings to such short selling activities in order to balance opposing incentives. Mutual funds also show relatively high comparability given their similar investment objectives and functionality. Although Reg SHO did not consider mutual funds as specific groups, fund characteristics are well-documented which can be used to address the lack of a two-step randomization procedure. The inclusion of fund characteristics helps to control for underlying, additional factors which might explain fund managers' trading behavior and would otherwise bias results. Moreover, no fund had to sell-off large portions of their assets immediately since the program started about a year after the announcement of the pilot stocks. It is thus unlikely that fund managers' behavior spills over heavily to the whole market and to other funds such that the key assumption of locally bounded interference seems reasonable. These features allow to compare differently affected funds and analyze potential interference induced by Reg SHO.

The SEC assignment procedure creates another difficulty to estimate interference effects since it affected the whole stock market. There are no super control groups (Crépon et al., 2013). However, the continuous treatment intensity across funds can be used to detect interference and indicates its relative effect along treated and untreated stocks.[10] Due to the random treatment assignment, funds' treatment intensity should vary heavily across similar funds. Such large variation increases the power to detect potential interference (Philipson, 2000). The property that different mutual funds trade the same stock provides a unique opportunity to analyze interference at the single stock level. Similar funds with different treatment intensities should trade the same stock differently if fund managers consider the presence of pilot stocks in their fund portfolio. Since fund managers share basically the same set of information about a certain firm, firm specific effects can be controlled for. In combination with fund characteristics, one can disentangle other factors related to the decision to invest into the stock from the effect induced through the treatment intensity itself. In order to assess interference, three different types of analyses outlined below are implemented.

2.4.2 Holding Level Analysis

The first analysis refers to Equation 2.2 and assesses the change of funds' single holding positions. Dependent variable is the quarterly change in the holding position of stock i held by fund j between the quarters t and $t+1$. I measure the holding positions in three different ways. The main holding measure is the market-value-weighted proportion of the stock position i on a fund's total holdings. As an alternative measure, I use the percentage change

[10] The lack of the super control groups makes it impossible to estimate the pure indirect effect. However, showing a significant relationship of different treatment intensities and mutual fund trading behavior can be used to reject the null hypothesis that there are no interference effects.

in the number of total shares of stock i held by fund j and the change in shares scaled by shares outstanding of the respective firm. All variables are formally defined in Appendix A, and discussed in Section 2.5.2. Using changes in stock positions is more appropriate than using the different stock positions themselves because the treatment intensity is constructed by using the particular stock positions and thus highly correlated with the next quarter's stock positions. Hence, the change of stock positions proxies better for managers' trading behavior in response to their fund's treatment intensity. Main explanatory variables are *Pilot*, *Treatment Intensity*, and *Pilot* × *Treatment Intensity*. This specification closely follows the framework in Crépon et al. (2013). However, there are two main differences. First, they apply a two-step randomization experiment with two super control groups, whereas Reg SHO did not create super control groups. Secondly, Crépon et al. (2013) have only five discrete values of treatment intensities. Therefore, they are able to estimate interference effects stepwise using dummy variables which allow for nonlinear effects. I estimate potential interference effects using the continuous treatment intensity:

$$\begin{aligned}\Delta Proportion_{i,j,t,t+1} = \alpha &+ \beta_1 Pilot_i + \beta_2 Pilot_i \times Treatment\ Intensity_{j,t} \\ &+ \beta_3 Treatment\ Intensity_{j,t} \\ &+ \beta X_{i,t} + \beta X_{j,t} + \delta_t + \gamma_j + \zeta_{i,j,t} + \epsilon\end{aligned} \tag{2.5}$$

$X_{i,t}$ and $X_{j,t}$ include a set of control variables of mutual fund and stock characteristics based on Covrig, Defond, and Hung (2007) and Cohen and Schmidt (2009). δ_t controls for time fixed effects. γ_j accounts for strategy fixed effects defined as funds' Lipper Object Code. $\zeta_{i,j,t}$ controls for the type of the specific position change whether, in particular, a position is completely sold during a quarter. All variables are discussed in Section 2.5.2 and formally defined in Appendix A. β_1 represents the average effect of being a pilot stock. β_2 measures the interference effect between treated stocks. It captures the trading behavior of fund managers on pilot stocks at different treatment intensities. β_3 measures the trading behavior in nonpilot stocks at different treatment intensities and thus indicates the presence of interference effects between pilot and nonpilot stocks.

2.4.3 Stock Level Analysis

The second type of analyses separates pilot and nonpilot stocks into two distinct groups. The main advantage of this specification is the inclusion of stock fixed effects. The impact of treatment intensity can be assessed at the single stock level. Hence, this analysis closely follows Equation 2.3. This analysis holds $X_{i,t}$ and $X_{j,t}$ constant and varies the treatment intensity only (see also z and z' of $\theta(z', z, d)$ as presented in Equation 2.3). The disadvantage of these analyses is the exclusion of the *Pilot* dummy because stock fixed effects fully absorb this dummy. The analysis, therefore, presents a robustness check on the occurrence of interference effects.

$$\begin{aligned} \Delta Proportion_{i,j,t,t+1} = {} & \alpha + \beta_1 Treatment\ Intensity_{j,t} \\ & + \beta X_{i,t} + \beta X_{j,t} + \kappa_i + \delta_t + \gamma_j + \epsilon \end{aligned} \tag{2.6}$$

All variables are the same as in Equation 2.5. κ_i refers to the stock fixed effects which control for unobserved stock characteristics and estimate the impact of the stocks' within variation of *Treatment Intensity*.

2.4.4 Fund Level Analysis

The last type of analyses assesses the overall trading pattern of mutual funds conditional on their initial treatment intensity. The rationale behind these analyses is to find evidence that mutual fund managers trade differently on the aggregated level depending on their initial treatment intensity. This is indirect evidence for interference because such patterns should reflect the analyses on the holding level. Analyses on the aggregated fund level can further be applied to rule out alternative explanations like the substitution of assets into cash or that investors withdraw money from funds with certain treatment intensities. The basic regression framework analyzes the change of treatment intensity over the next three quarters compared to the initial treatment intensity.

$$\Delta Treatment\ Intensity_{j,0,t} = \alpha + \beta_1 Treatment\ Intensity_{j,0} + \beta X_{j,t} + \gamma_j + \theta_j + \epsilon \tag{2.7}$$

where $Treatment\ Intensity_{j,0}$ is the initial value-weighted proportion of holdings of pilot firms in mutual fund j on June 30, 2004. First, I investigate the change in treatment intensity $\Delta Treatment\ Intensity_{j,0,t}$ for $t \in 1, 2, 3$ to assess whether there is any effect of *Treatment Intensity* on the aggregated fund managers' trading behavior. t refers to the following quarters. Next, I split Δ*Treatment Intensity* into its sources. Funds can change their treatment intensity by partially selling positions, completely disposing of positions, or investments into stocks which they have not held in the previous quarter. In these regressions, I calculate the value-weighted proportion of pilot firms for each type of change and fund separately. The advantage of aggregation is that diversification within new stock positions cannot affect results. In a next step, I run three different robustness checks using this setup. In order to rule out that funds shift their assets mainly into cash, Δ*Treatment*

Intensity will be replaced by change in cash holdings. Similarly, I look at the effect on total net assets to rule out the explanation that investors withdraw money systematically from funds with certain treatment intensities. Finally, I explore how fund managers alter the diversification of their funds.

2.5 Data and Summary Statistics

2.5.1 Data

I construct the intersection of mutual fund data from CRSP (Center for Research in Security Prices) and holding data provided by Thomson/CDA. Both databases can be merged using the MFLINKS Linking Table (e.g., Barras, Scaillet, & Wermers, 2010; Doshi, Elkamhi, & Simutin, 2015; Fama & French, 2010; French, 2008; Linnainmaa, 2013). I focus on funds which mainly invest into US common stocks since the new regulation was implemented in the US stock market. As Fama and French (2010), Linnainmaa (2013), or Harris, Hartzmark, and Solomon (2015), I exclude passively managed funds since I am interested in the reaction of fund managers to the introduction of Reg SHO. I include only funds which can invest broadly into the market[11] (Almazan, Brown, Carlson, & Chapman, 2004) such that fund managers are not restricted to specific industries or investment areas. Industries, for example, may face certain treatment intensities which restrict fund managers' ability to effectively change the treatment intensity in their fund towards their preferred level. I remove all funds which changed their objective or asset manager during the sample period to remove potential sources of biases. Funds with several share classes are aggregated by size. As the announcement of pilot firms took place on July 28, 2004, the sample period starts with the most recent report of each mutual fund prior to the announcement on June 30, 2004. I only include funds which report their holdings regularly at the end of a calendar-quarter. This restriction ensures that variables constructed from CRSP and Thomson holding data coincide in time and I do not have to impose further assumptions about changes in holdings between different dates. I focus on the time period until March 2005 because short sellers were still restricted by the short sale price tests. Market participants were aware of the upcoming changes on May 2, 2005 imposed by the new regulation. Mutual fund managers had therefore sufficient time to form expectations about short sellers' future activities in pilot and nonpilot firms.[12] Following to the cleaning procedure of Doshi et al. (2015), I exclude

[11] The following Lipper Objective Codes are included: "G", "GI", "MC", and "SG". I exclude actively managed funds with the objective "EI" and "MR" since there exist only few of them in the sample.

[12] Grullon et al. (2015) show that short sellers started shorting pilot stocks prior to the effectiveness of the rule. However, only small firms were affected and short sellers' activities were still restricted by

funds with a market capitalization lower than USD 15 million or less than 10 stocks. This also addresses the concern that interference effects are typically weak when groups are small (Philipson, 2000). I then use the CUSIP from Thomson to assign the respective Permno from CRSP to each holding. Holdings without any Permno are removed (e.g., Doshi et al., 2015). Lastly, I merge the most recent accounting data from Compustat using the CCM Linking Table. Accounting data must not be older than one year.[13]

2.5.2 Main Variables

There are three related main explanatory variables. The first is *Pilot*, an indicator variable which equals one if the stock was assigned as a pilot stock through Reg SHO and zero otherwise. The second variable is *Treatment Intensity* which is calculated as the market-value-weighted proportion of pilot stock holdings within each fund at report date. It measures the exposure of a given fund to unrestricted short sales. The third is the interaction of both *Pilot* $\times$ *Treatment Intensity*. This variable captures the effect of pilot stocks surrounded by many other pilot stocks.

Dependent Variables

I use three dependent variables at the fund level. All three variables refer to the quarterly change of funds' portfolio weight in a given stock i in fund j between quarter t and $t+1$. The first and most important variable is a measure related to Cohen, Frazzini, and Malloy (2008) and Cohen and Schmidt (2009). I apply the value-weighted change of the portfolio weight in a given stock (Δ%TNA). The reason to focus on the position change is that fund managers have to adjust their randomly affected stock holding positions in the aftermath of the announcement. To analyze stock positions which are newly bought into a given fund during a quarter, I use the value-weighted stock position at the report date of a fund. Using market values to calculate stock holding positions has two advantages. They consider changes in the stock prices of holdings such that fund managers must not necessarily change the numbers of shares to hold a certain position. Additionally, the value-weighted stock position is closely related to diversification because fund returns are based on the market value of each holding position.

The second measure is the percentage change of shares of a given stock i held by fund j at time t (e.g., Cohen & Schmidt, 2009; Covrig et al., 2007). $\%\Delta Shares$ is closely related to ($\Delta\%TNA$) but focuses on actual changes of stock positions. Lastly, I apply $\%\Delta Shares$

short sales price test such that short sellers basically provided liquidity.

[13] This requirement reduces the holding data by 0.03%.

Outstanding when analyzing new stock positions. It is defined as the number of shares of stock i held by fund j divided by the number shares outstanding of stock i. This variable captures the engagement of a fund in a certain firm. For the analyses on the aggregated fund level, I apply *Change in Treatment Intensity* between the initial treatment intensity and the subsequent quarters. Secondly, I calculate the same differences for cash holdings and the percentage changes of total net assets (TNA) to control for alternative explanations.

Control Variables

I include several control variables at the fund level. The logarithm of funds' total net assets (*Ln(TNA)*) controls for fund size (Cohen & Schmidt, 2009). Larger funds typically hold larger absolute stock positions which restrict fund managers' ability to alter these large holdings quickly. The concentration of stock holdings within a fund (*Ln(Holding HHI)*) accounts for the impact of few, large stock positions in a fund's portfolio and is closely related to diversification. It is calculated as the natural logarithm of the Herfindahl-Hirschman Index across stock holdings of a given fund. *Management Fee* proxies incentives for fund managers to trade and to earn high alphas. *% Ind* accounts for the weight of a particular industry in a given fund (Cohen & Schmidt, 2009). I use the Fama-French 48 Industry Classification to calculate *% Ind*. *Strategy FE* account for the different fund objectives based on the Lipper Objective Code. *Time FE* refer to the particular report date.

Covrig et al. (2007) and Cohen and Schmidt (2009) propose several firm-related control variables which explain fund holdings. I include the natural logarithm of the market capitalization of each stock at the end of the respective month (*ME*). Larger firms are typically held by more funds, are more liquid and often shorted, and important to replicate benchmark portfolios. Related to size and benchmarking, I control for the *Market Weight* of a firm in the value-weighted CRSP universe at the end of a particular month. *Past Return* accounts for the cumulative past return of the previous 11 months of a particular stock. I include the *Book-to-Market Ratio* to account for growth opportunities. *Leverage* accounts for the risk and tax benefits of a firm and is calculated as the sum of long- and short-term debt divided by total assets. *Return on Equity*, defined as the ratio of net income plus deferred taxes to the book value of equity, and *Earnings-to-Price Ratio*, the ratio of net income to the market value of equity, controls for firm's profitability. Since many fund managers prefer stocks with high and regular dividend payments, *Dividend Yield* is included. It is the ratio of cash dividends to the market value of equity. *Big Four* is an indicator variable which equals one if a firm's financial report is certified by one of the big-four accounting firms and zero otherwise. All continuous variables are winsorized at the 1% and 99% level.

2.5.3 Summary Statistics

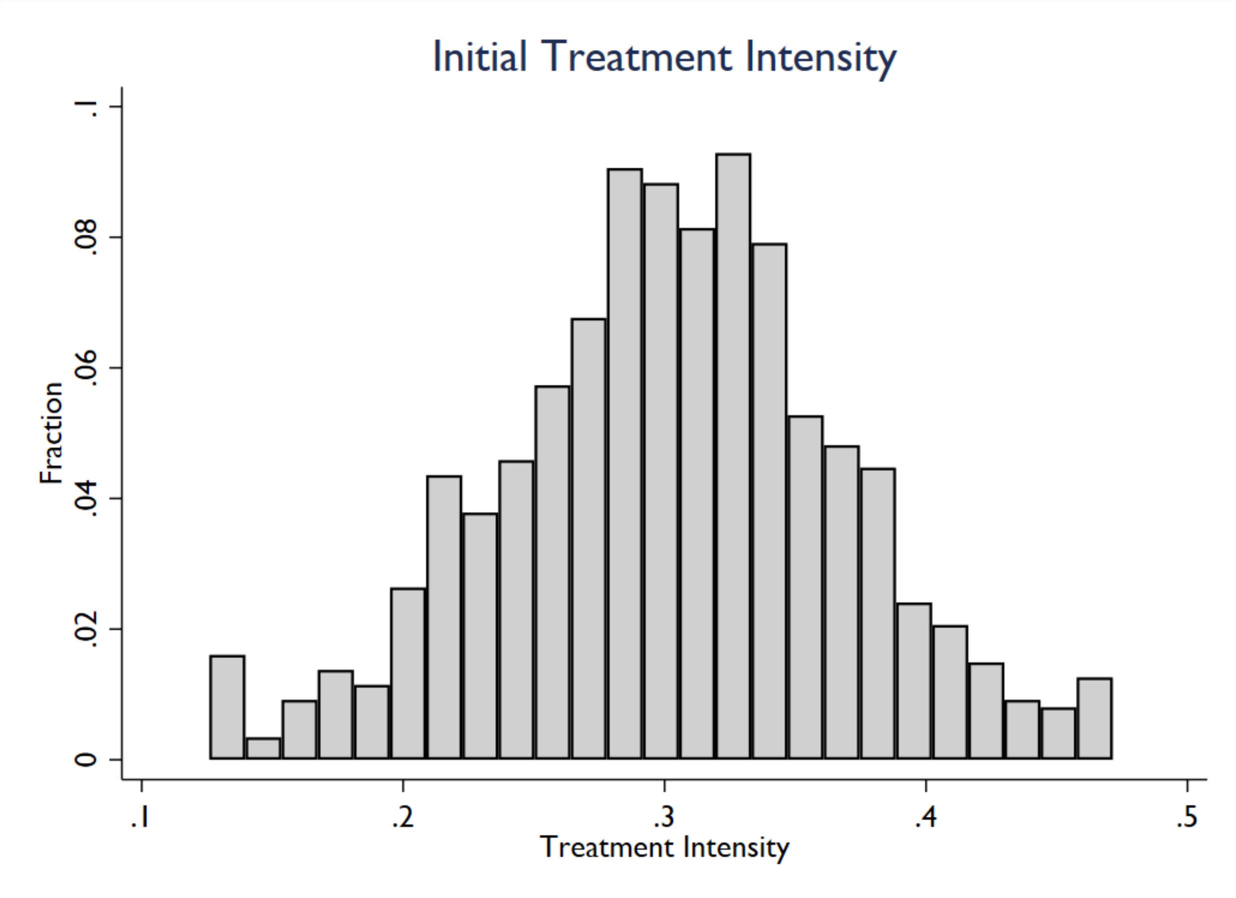

Figure 2.1: Initial Treatment Intensity of Mutual Funds on June 30, 2004

The most important variable is *Treatment Intensity* which is the value-weighted proportion of pilot assets in the funds' holdings. Figure 2.1 shows that the distribution is fairly symmetric with a mean and median of 30%. Such a distribution can be expected as Grullon et al. (2015) and Fang et al. (2016) point out that the assignment mechanism of being treated was random. It is also evidence that mutual fund managers were not able to anticipate treated stocks before the announcement. *Treatment Intensity* ranges from 13% to 47% such that fund managers are confronted with various and random treatment intensities. In order to implement a framework of within-group interference effects, groups have to share similar characteristics. Table 2.1 reports fund characteristics as of June 30, 2004, the last report date prior to the announcement of the pilot stocks. The sample includes 872 different funds. I separate these by funds' investment strategy. The biggest group comprises 377 funds which mainly invest into growth stocks. The smallest group represents mid-cap funds with only 119 different funds. Growth & Income funds and Small-Cap funds occur with a similar frequency of 174 and 202 funds, respectively. The distribution of *Treatment Intensity* across

Table 2.1: Summary Statistics of Mutual Funds

This table provides summary statistics of the main variables of mutual funds as of June 30, 2004 which is the funds' last report date prior to the announcement of the Pilot program. The table shows characteristics for each of the four different fund types in the sample separately. *Treatment Intensity* is the market-value-weighted proportion of the sum of pilot stock holdings divided by the sum of pilot and nonpilot stock holdings of each fund. *TNA* measures funds' total net assets. *Number Stocks* is the number of distinct stocks a mutual fund holds. *Concentration* is defined as the Herfindahl-Hirschman-Index applied to the market values of all stock positions held by a mutual fund. *Management Fee* is the fee a fund charges and measured in percentage points. All variables are calculated as of June 30, 2004 and winsorized at the 1% and 99% level.

	5^{th}	25^{th}	Mean	Median	75^{th}	95^{th}	N
All Funds							
Treatment Intensity	0.19	0.26	0.30	0.30	0.34	0.41	872
TNA	6	44	847	152	594	3726	872
No. Stocks	26	49	107	72	113	273	872
Holding HHI	0.01	0.01	0.02	0.02	0.03	0.05	872
Management Fee	-0.33	0.56	0.62	0.75	0.93	1.18	851
Growth Funds							
Treatment Intensity	0.20	0.27	0.31	0.31	0.35	0.42	377
TNA	4	30	873	123	567	4017	377
No. Stocks	22	40	101	63	95	312	377
Holding HHI	0.01	0.02	0.02	0.02	0.03	0.05	377
Management Fee	-0.63	0.47	0.56	0.73	0.88	1.18	366
Growth & Income Funds							
Treatment Intensity	0.18	0.24	0.28	0.28	0.32	0.38	174
TNA	13	64	1255	206	750	6328	174
No. Stocks	25	45	90	70	103	225	174
Holding HHI	0.01	0.01	0.02	0.02	0.03	0.05	174
Management Fee	0.08	0.50	0.61	0.67	0.85	1.07	174
Mid-Caps Funds							
Treatment Intensity	0.22	0.27	0.30	0.30	0.34	0.40	119
TNA	6	60	568	152	465	2902	119
No. Stocks	35	56	95	87	120	194	119
Holding HHI	0.01	0.01	0.02	0.01	0.02	0.03	119
Management Fee	-0.67	0.63	0.65	0.83	0.93	1.21	115
Small-Caps Funds							
Treatment Intensity	0.18	0.27	0.31	0.32	0.35	0.41	202
TNA	9	55	613	173	650	2160	202
No. Stocks	37	63	140	94	147	391	202
Holding HHI	0.00	0.01	0.02	0.01	0.02	0.04	202
Management Fee	-0.21	0.66	0.71	0.85	1.00	1.25	196

different types of funds is quite similar which supports the argument that funds are treated randomly and that this should lead to similar behavior across all fund types. Only funds which invest into Growth & Income Stocks have slightly lower treatment intensities of 28% compared to the expected value. The median size of funds is USD 152 million. Growth & Income funds are the largest funds with median size of USD 206 million. Mid- and Small-Cap funds hold basically more diversified stock positions than both Growth fund categories. Management fees are higher for funds which mainly invest into smaller stocks. The median is 0.83% and 0.85% for Mid- and Small-Cap funds, respectively.

Table 2.2: Summary Statistics of Firms

This table provides summary statistics of the main variables of the firms which are held by mutual funds. *Market Capitalization* is calculated as firms' stock price times shares outstanding at the end of a month (in USD million). *Leverage* is the sum of long-term and short-term debt divided by firms' total assets. *Return on Equity* is calculated as firms' net income scaled by the book value of equity. *Dividend Yield* is the ratio of cash dividends to market value of equity. *Earnings-Price-Ratio* is defined as the ratio of net income to market value of equity. *Book-to-Market-Ratio* is the ratio of the book value to the market value of equity. *Past Return* is the cumulative return over the past 11 months. *Big Four* is an indicator variable which equals one if firms' auditor is E&Y, Deloitte, KPMG, or PWC and zero otherwise. There are 17,628 firm-year observations. All continuous variables are winsorized at the 1% and 99% level.

	5^{th}	25^{th}	Mean	Median	75^{th}	95^{th}	N
ME	48	192	2,670	560	1,762	13,620	17,628
Leverage	0.00	1.62	20.94	16.40	32.26	61.17	17,127
Return on Equity	-70.39	-0.52	0.96	8.74	14.94	34.03	17,507
Dividend Yield	0.00	0.00	0.78	0.00	0.79	3.70	14,124
Earnings-Price	-0.25	-0.02	-0.02	0.03	0.05	0.10	14,399
Book-to-Market	0.08	0.25	0.49	0.42	0.67	1.16	13,801
Past Returns	-44.47	-5.37	22.23	15.23	38.76	113.86	16,590
Big Four	0.00	1.00	0.82	1.00	1.00	1.00	17,628

Table 2.2 provides summary statistics on the stock characteristics of the fund holdings. There are 17,628 different firm-year observations matched on stock holdings. The median market capitalization of firms is USD 560 million. Size (ME) is positively skewed as the mean is almost five times bigger than the median. Leverage ranges from no leverage up to more than 60% at the 95^{th} percentile. The return on equity is 8.7% at the median but can take on largely negative values at the 5^{th} percentile. For most of the firms, the dividend yield is zero because they do not pay out cash dividends. At the 75^{th} percentile, the dividend yield equals 0.8% and increases up to 3.7% at the 95^{th} percentile. The median value of book-to-market ratio equals 0.4 which indicates that the market value of equity is more than twice as high as the book value. Stocks performed positive during this time period with median cumulative returns of 15% over the past 11 months excluding the most recent month. However, returns range from -5% to 39%.

2.6 Stock Level Analysis

In this section, I analyze fund managers' trading behavior in individual stocks and focus on the effect of different treatment intensities across funds. Focusing on treatment intensities captures possible interference between treated and untreated stocks in the trading behavior. I first run regressions that do not take into account possible interference effects. The first specifications include only the indicator variable of being treated as *Pilot* stock. This indicator variable captures the effect whether mutual fund managers increase or decrease stock holdings of pilot stocks after the announcement. In the second analysis, I include the *Treatment Intensity* of a given fund at the end of the respective quarter and interact it with the *Pilot* dummy. *Treatment Intensity* captures the effect of having more pilot stocks in a fund's portfolio on the decision to invest into nonpilot stocks. *Pilot* × *Treatment Intensity* estimates such an effect on the investment into pilot stocks. Next, I run robustness checks exploiting the within-variation of *Treatment Intensity* at the single stock level. I split the sample into pilot and nonpilot firms and investigate the effect of *Treatment Intensity* separately. This analysis is closely related to Equation 2.3 when control variables are held constant and only *Treatment Intensity* varies. I further investigate new stock positions bought by fund managers. In the last step, I analyze the effect of *Treatment Intensity* on large and small stocks to analyze possible heterogeneity of interference.

2.6.1 Ignoring Interference Effects

Table 2.3 reports results of the regression of the change in investment into stock positions on the *Pilot* dummy. *Pilot* captures the effect of being exempted from any short sale price tests. The dependent variable is the change in funds' portfolio weight in a particular stock ($\Delta\%TNA$). Standard errors are clustered at the firm level (Cohen & Schmidt, 2009). A positive and significant coefficient would indicate that fund managers invest more into pilot stocks. The first specification, presented in column (1) of Table 2.3, shows an insignificant coefficient of *Pilot*. Since Reg SHO does not randomize across mutual funds controlling for fund characteristics is important. The inclusion of fund controls, as shown in column (2), does not alter the coefficient of *Pilot*. The coefficients of control variables of fund characteristics show the expected results. The coefficient of *Ln(TNA)* is positive and significant indicating that larger funds increase stock positions more than smaller funds. The coefficient on *LN(Holding HHI)* is negative and significant. More concentrated funds typically reduce individual stock positions in order to diversify their holding positions. The negative and

Table 2.3: Mutual Fund Investments into Pilot Stock

This table reports results of the regression of the change of stocks' holding size of mutual funds on being a pilot stock *Pilot*. The dependent variable is the quarterly change in the market-value-weighted holding position of stock i in fund j between t and *t+1* ($\Delta\%TNA_{i,j,t,t+1}$). *Pilot* is an indicator variable which equals one if the stock is exempted from short sales price tests and zero otherwise. Control variables of fund characteristics are *LN(TNA)*, *LN(Holding HHI)*, and *Management Fee*. *% Ind* measures the proportion of stock holdings in the respective Fama-French 48 Industry Classification. Stock controls are included but not reported for the sake of brevity. All variables are formally defined in Appendix A. *Time FE* account for the respective reporting quarters. *Strategy FE* refer to the respective Lipper Objective Code. *Change Type FE* is an indicator variable which equals one if a stock position is completely sold during a quarter and zero otherwise. All regressions include an intercept. Standard errors are clustered at firm level and t-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

VARIABLES	(1)	(2)	(3)
Pilot	-0.002	-0.003	0.004
	(-0.25)	(-0.37)	(0.57)
Ln(TNA)		0.018***	0.021***
		(27.38)	(28.40)
LN(Holding HHI)		-0.222***	-0.199***
		(-62.04)	(-60.72)
Management Fee		0.001	-0.008***
		(0.60)	(-2.78)
% Ind		-0.566***	-0.622***
		(-11.87)	(-12.38)
Observations	246,470	242,865	182,491
Adj. R^2	0.332	0.395	0.403
Fund Controls	NO	YES	YES
Stock Controls	NO	NO	YES
Time FE	YES	YES	YES
Strategy FE	NO	YES	YES
Change Type FE	YES	YES	YES

significant coefficient of *% Ind* supports the idea of diversification. Fund managers reduce stock holdings much more when they already hold higher weights in the respective industry of the particular stock position. Column (3) of Table 2.3 shows coefficient estimates from regressions that additionally include stock characteristics as control variables.[14] The coefficient of *Pilot* stays insignificant and supports previous results.

So far, results suggest that fund managers are indifferent between pilot and nonpilot stocks, a result that is supported by prior literature. Diether et al. (2009a), for example, conclude that price tests on the NYSE and Nasdaq "can safely be permanently removed". However,

[14] For the sake of brevity, I do not show the coefficients of control variables of stock characteristics. Since the assignment mechanism was independent of financial characteristics, they should not explain much in these regressions. Fang et al. (2016) also show that treated and untreated firms have similar characteristics.

there are important motives for mutual fund managers to reconsider short sale activities during the experiment. The presented setup is not able to capture the effect of pilot stocks held by a given fund on the decision to hold other pilot and nonpilot stocks. In the next steps, I show how interference can affect the treatment effect and how it yields a different picture on fund managers' investment decisions.

2.6.2 Full Specification with Interference Effects

The previous section neglects potential interference between pilot and nonpilot stocks which might bias, inter alia, the coefficient of *Pilot*. The reason to assume interference rests upon the incentives for mutual fund managers to substitute pilot and nonpilot stocks. This in turn is expected to depend on the current weight of pilot and nonpilot stocks in the funds' portfolios. The inclusion of *Treatment Intensity* accounts for the presence of other pilot stocks and their effect on investments into nonpilot stocks. The interaction between *Pilot* and *Treatment Intensity* estimates the effect of *Treatment Intensity* on the investment into pilot stocks. These regression specifications account for the effect that mutual fund managers implement different trading strategies depending on the treatment intensity in their funds' portfolio. Table 2.4 mirrors Table 2.3 but additionally includes *Treatment Intensity* and the interaction term *Pilot* × *Treatment Intensity*.

Coefficients of *Pilot* turn to be highly significant and positive in all specifications. This indicates that mutual fund managers invest more into pilot than nonpilot stocks. According to findings in H. Chen et al. (2013), Evans et al. (2017), or Johnson and Weitzner (2019), fund managers have a preference for stocks which can be easily shorted to participate from benefits of short selling (e.g., lending fees). However, the coefficient of *Pilot* × *Treatment Intensity* is negative and significant at the 1% level. The attractiveness to invest into pilot stocks decreases and becomes even negative with increasing treatment intensities in funds. Funds with low treatment intensities invest more into pilot stocks, whereas funds with high treatment intensities reduce their holdings in pilot stocks. This pattern finds support in the literature by findings in Desai et al. (2002), Asquith et al. (2005), or Cohen et al. (2007). They show that portfolios composed of highly shorted stocks underperform benchmark portfolios (e.g., the market). The coefficient of *Treatment Intensity* is positive and significant which indicates that fund managers which face higher treatment intensities buy more nonpilot firms. The opposite signs of the coefficients of *Pilot* × *Treatment Intensity* and *Treatment Intensity* indicate substitution effects between pilot and nonpilot stocks. The results are robust to the inclusion of control variables at the fund and stock level as shown in columns (2) and (3) in Table 2.4, respectively.

Table 2.4: Mutual Fund Investments into Pilot Stock **WITH** Interference

This table reports results of regressions of the change of stocks' holding size of mutual funds on the *Pilot* dummy, *Treatment Intensity*, and the interaction of both. This specification thus captures potential interference effects between pilot and nonpilot stock. The dependent variable is the quarterly change in the market-value-weighted holding position of stock i in fund j between t and *t+1* ($\Delta\%TNA_{i,j,t,t+1}$). *Pilot* is an indicator variable which equals one if the stock is exempted from short sales price tests and zero otherwise. *Treatment Intensity* is the market-value-weighted proportion of pilot stocks in a mutual fund on a report date. Control variables of fund characteristics are *LN(TNA)*, *LN(Holding HHI)*, and *Management Fee*. *% Ind* measures the proportion of stock holdings in the respective Fama-French 48 Industry Classification. Stock controls are included but not reported for the sake of brevity. All variables are formally defined in Appendix A. *Time FE* account for the respective reporting quarters. *Strategy FE* refer to the respective Lipper Objective Code. *Change Type FE* is an indicator variable which equals one if a stock position is completely sold during a quarter and zero otherwise. All regressions include an intercept. Standard errors are clustered at firm level and t-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

VARIABLES	(1)	(2)	(3)
Pilot	0.177***	0.101***	0.113***
	(9.37)	(6.10)	(6.03)
Pilot × Treatment Intensity	-0.588***	-0.338***	-0.354***
	(-8.16)	(-5.76)	(-5.35)
Treatment Intensity	0.231***	0.085**	0.131***
	(5.91)	(2.40)	(3.44)
Ln(TNA)		0.018***	0.021***
		(27.19)	(28.22)
LN(Holding HHI)		-0.221***	-0.198***
		(-61.69)	(-60.45)
Management Fee		0.002	-0.007**
		(0.62)	(-2.44)
% Ind		-0.564***	-0.620***
		(-11.81)	(-12.32)
Observations	246,470	242,865	182,491
Adj. R^2	0.333	0.395	0.403
Fund Controls	NO	YES	YES
Stock Controls	NO	NO	YES
Time FE	YES	YES	YES
Strategy FE	NO	YES	YES
Change Type FE	YES	YES	YES

Results presented above are evidence for interference between pilot and nonpilot stocks. The investment behavior of mutual fund managers crucially depends on the proportion of pilot and nonpilot stocks in a fund's portfolio. Under the assumption of no interference, such a pattern should not be observable. Interference occurs in both pilot and nonpilot stock holdings as indicated by significant coefficients of *Treatment Intensity* and *Pilot × Treatment Intensity*. The reason for interference rests upon asymmetric incentives for mutual fund managers to buy and sell pilot and nonpilot stocks. They can earn abnormal returns by lending stocks to short sellers. This explains why fund managers with few holdings of pilot stocks in their portfolio increase their holdings of pilot stocks. As shown in Grullon et al. (2015), pilot stocks were sold short more frequently than nonpilot stocks after the announcement of pilot stocks and show negative abnormal returns. Thus, mutual fund managers with many pilot stock holdings have incentives to sell parts of these holding positions to avoid underperformance in the future.

2.6.3 Treatment Intensity at the Single Stock Level

Equation 2.3 emphasizes that changing the treatment intensity can be exploited to show the impact of interference. Table 2.5 reports analyses related to Equation 2.3 by splitting the sample into pilot and nonpilot stocks. The inclusion of stock fixed effects allows the estimation of the impact of varying treatment intensities at the single stock level. One major drawback of this setup is its inability to estimate the *Pilot* dummy since stock fixed effects absorb the pilot dummy. Hence, this setup works as a robustness check for interference effects. Columns (1) to (3) refer to pilot stocks, whereas columns (4) to (6) cover nonpilot stocks. The first specifications in columns (1) and (4) include the *Treatment Intensity*, time, and stock fixed effects. Columns (2) and (5) additionally include control variables at the fund level. The full specifications in columns (3) and (6) use control variables at the fund and stock level. The dependent variable is the change of a stock's weight in a fund's portfolio ($\Delta\%TNA$).

Results in columns (1) to (3) support the findings from Table 2.4. The coefficients of *Treatment Intensity* are negative and significant in all specifications that include pilot stocks. Hence, funds with higher treatment intensities reduce their holdings in a given pilot stock. The inclusion of control variables at the fund level which is shown in column (2) does not alter the coefficient of *Treatment Intensity*. The effect remains also stable controlling for additional stock characteristics as presented in column (3). Columns (4) to (6) report the complementary results for nonpilot stocks. Coefficients on *Treatment Intensity* are positive and significant at the 1% level. Fund managers increase their holdings of a particular nonpilot stock with increasing treatment intensity. Such trading behavior is in line with the previous findings and the theoretical prediction that funds with high treatment intensities substitute nonpilot stock holdings for pilot stock holdings. Both setups, applying pilot and nonpilot stocks separately, support regression results from the full specification presented in Table 2.4. The advantage of the setup applying stock fixed effects rests upon the within-variation of treatment intensity at the single stock level which directly shows the impact of treatment intensities on stock holdings.

Table 2.5: Changes in Stock Holding Positions at the Stock Level

This table reports results of regressions of the change of stocks' holding size of mutual funds on *Treatment Intensity* for different sub-samples. Columns (1) to (3) represent the sub-sample of pilot stocks, whereas columns (4) to (6) cover the sub-sample of nonpilot stocks only. The dependent variable is the quarterly change in the market-value-weighted holding position of stock i in fund j between t and $t+1$ ($\Delta\%TNA_{i,j,t,t+1}$). The inclusion of *Stock FE* estimates the regressions at the stock level. *Treatment Intensity* is the market-value-weighted proportion of pilot stocks within a mutual fund on a report date. Control variables of fund characteristics are *LN(TNA)*, *LN(Holding HHI)*, and *Management Fee*. *% Ind* measures the proportion of stock holdings in the respective Fama-French 48 Industry Classification. Stock controls are included but not reported for the sake of brevity. All variables are formally defined in Appendix A. *Time FE* account for the respective reporting quarters. *Strategy FE* refer to the respective Lipper Objective Code. *Change Type FE* is an indicator variable which equals one if a stock position is completely sold during a quarter and zero otherwise. All regressions include an intercept. Standard errors are clustered at firm level and t-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	Pilot			Nonpilot		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.107**	-0.100**	-0.129**	0.132***	0.123***	0.119***
Intensity	(-2.43)	(-2.29)	(-2.55)	(5.00)	(4.51)	(3.62)
Ln(TNA)		-0.001	-0.001		0.000	-0.000
		(-0.66)	(-0.86)		(0.17)	(-0.19)
LN(Holding HHI)		0.005	0.006		-0.008***	-0.009***
		(1.31)	(1.47)		(-3.01)	(-3.06)
Management Fee		0.009**	0.008**		0.015***	0.015***
		(2.46)	(2.14)		(6.08)	(5.22)
% Ind		-0.537***	-0.603***		-0.495***	-0.521***
		(-5.53)	(-5.32)		(-9.43)	(-7.76)
Observations	58,597	57,995	46,076	133,200	131,896	95,993
Adj. R^2	0.029	0.031	0.053	0.029	0.033	0.055
Fund Controls	NO	YES	YES	NO	YES	YES
Stock Controls	NO	NO	YES	NO	NO	YES
Time FE	YES	YES	YES	YES	YES	YES
Strategy FE	NO	YES	YES	NO	YES	YES
Stock FE	YES	YES	YES	YES	YES	YES

2.6.4 New Stock Positions

Stock positions which are not held at the beginning of a given quarter but bought by fund managers during the quarter ("New stock positions") provide another opportunity to analyze whether fund managers react differently to various treatment intensities or whether the pattern rests upon random trading behavior. I implement the regression framework from Section 2.6.2 but use the size of new stock positions as dependent variable. The size of stock positions are measured as the natural logarithm of the market-value-weighted proportion of stock holding i on fund j at time $t+1$. Two main explanatory variables are applied. The first variable *Treatment Intensity* accounts for the weight of pilot stocks in a fund at the beginning of quarter *t*. The second variable *High Treatment* equals one if the treatment intensity belongs to the highest tercile of the distribution and zero if it belongs to the lowest tercile. The rationale of this analysis is to capture two similar funds with fairly different treatment intensities which both invest into the same new stock. Both explanatory variables are interacted with the *Pilot* dummy.

Table 2.6: Investment into New Stock Positions

This table reports results of regressions of the investment decision to invest into new stocks on the *Pilot* dummy, *Treatment Intensity*, and the interaction of both for different sub-samples. New stocks are defined as stock positions which were not held at the beginning of a quarter. Columns (1) to (3) covers the full-sample of new stock investments and estimates the effect of *Treatment Intensity*, whereas columns (3) to (6) shows results of *High Treatment*. Dependent variable is the the market-value-weighted proportion of new stock position on funds' total assets calculated at the end of a quarter. Columns (2) and (5) estimates regressions on pilot stocks only. Columns (3) and (6) include only nonpilot stocks in the regressions. *Pilot* is an indicator variable which equals one if the stock is exempted from short sales price test and zero otherwise. *Treatment Intensity* is the market-value-weighted proportion of pilot stocks in a mutual fund on a report date. Control variables of fund and stock characteristics are the same as in Table 2.3. All variables are formally defined in Appendix A. *Time FE* account for the respective reporting quarters. *Strategy FE* refer to the respective Lipper Objective Code. The inclusion of *Stock FE* estimates the regressions at the stock level. All regressions include an intercept. Standard errors are clustered at firm level and t-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	Full Sample			High vs. Low Treatment		
	Full	Pilot	Nonpilot	Full	Pilot	Nonpilot
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Treat. Intensity	-1.679***	-1.040***	-1.132***			
	(-9.78)	(-3.74)	(-5.93)			
Pilot ×	0.585**					
Treat. Intensity	(1.98)					
High Treatment				-0.298***	-0.229***	-0.211***
				(-12.12)	(-5.89)	(-7.43)
Pilot ×				0.061		
High Treatment				(1.47)		
Pilot	-0.180**			-0.014		
	(-2.00)			(-0.45)		
Observations	22,403	6,952	15,451	13,962	4,235	9,727
Adj. R^2	0.485	0.515	0.546	0.521	0.543	0.593
Fund Controls	YES	YES	YES	YES	YES	YES
Stock Controls	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Strategy FE	YES	YES	YES	YES	YES	YES
Stock FE	NO	YES	YES	NO	YES	YES

Table 2.6 presents results of the two analyses of new stock positions in funds. Columns (1) and (3) show results from the regression of the size of new stock positions on *Pilot*, *Treatment Intensity*, and their interaction *Pilot* × *Treatment Intensity*. *Treatment Intensity* has a negative and significant coefficient of -1.68 indicating that fund managers buy smaller new stock positions with increasing treatment intensity. The interaction term *Pilot* × *Treatment Intensity* is positive and significant at the 5% level. This indicates that new holdings of pilot stocks are larger than those of nonpilot stocks. However, the coefficient on *Pilot* × *Treatment Intensity* is three times smaller than the coefficient on *Treatment Intensity*. Funds with higher treatment intensities thus buy smaller stock positions of pilot stocks than funds with low treatment intensities. Such a pattern is in line with a motive to diversify holdings exposed to unrestricted short sale activities. Funds with high treatment intensities currently rely more on pilot stocks such that they have to focus more on the diversification of their portfolio holdings. Columns (2) and (3) support this finding. Column (2) presents results on pilot stocks only and applies stock fixed effects. The main explanatory variable is *Treatment Intensity*. The coefficient is negative and highly significant indicating that fund managers invest less into a certain pilot stock with increasing treatment intensity. Column (3) presents a significantly negative coefficient of *Treatment Intensity* such that the same pattern applies for nonpilot stocks.
Columns (4) to (6) specifically analyze funds with extreme values of treatment intensity. Such funds should react much stronger to their treatment intensity. Column (4) shows a negative coefficient of *High Treatment* of -0.30. New stock holdings of highly treated funds are thus about 30% smaller compared to funds with low treatment intensities. The effect is similar for pilot and nonpilot stocks. Columns (5) and (6), which report the sub-sample results for pilot and nonpilot stocks separately, support these findings. The coefficients on *High Treatment* in both the pilot and nonpilot stock samples are negative and significant. In summary, findings in Table 2.6 emphasize that fund managers which face high treatment intensities focus more on diversification to reduce the potential negative impact of short selling activities.

2.6.5 Robustness Tests

In order to support previous results on the relationship between treatment intensity and fund managers' trading behavior, I test two other dependent variables. The first variable is the quarterly percentage change of shares (Δ*%Shares*) of stock i held by fund j adjusted for stock splits (Cohen & Schmidt, 2009). The second variable is the change in the number of shares (Δ*%Shares Outstanding*) of stock i held by fund j divided by shares outstanding of

Table 2.7: Robustness: Mutual Fund Investments into Pilot Stock **WITH** Interference

This table reports robustness checks of regressions of the change of stocks' holding size of mutual funds on the *Pilot* dummy, *Treatment Intensity*, and the interaction of both. The dependent variable in columns (1) to (3) is the percentage change of shares ($Ln(Shares_{i,j,t+1}/Shares_{i,j,t})$) held by certain fund. The dependent variable in columns (4) to (6) is the quarterly change in the percentage of shares held by a given fund scaled by shares outstanding and adjusted for stock splits. *Pilot* is an indicator variable which equals one if the stock is exempted from short sales price tests and zero otherwise. *Treatment Intensity* is the market-value-weighted proportion of pilot stocks in a mutual fund on a report date. Control variables of fund and stock characteristics are the same as in Table 2.3. All variables are formally defined in Appendix A. *Time FE* account for the respective reporting quarters. *Strategy FE* refer to the respective Lipper Objective Code. *Change Type FE* is an indicator variable which equals one if a stock position is completely sold during a quarter and zero otherwise. All regressions include an intercept. Standard errors are clustered at firm level and t-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	% Shares			% Shares Outstanding		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Pilot	0.067***	0.063***	0.079***	0.046***	0.051***	0.042***
	(4.61)	(4.31)	(4.78)	(7.09)	(7.41)	(6.00)
Pilot ×	-0.207***	-0.193***	-0.234***	-0.123***	-0.142***	-0.121***
Treat. Intensity	(-4.65)	(-4.34)	(-4.56)	(-6.46)	(-6.85)	(-5.30)
Treat. Intensity	0.107***	0.053**	0.086***	0.124***	0.207***	0.174***
	(4.21)	(2.11)	(2.93)	(10.22)	(15.84)	(11.73)
Ln(TNA)		0.000	0.000		-0.031***	-0.035***
		(0.68)	(0.22)		(-37.69)	(-34.66)
LN(Holding HHI)		-0.005***	-0.005**		-0.033***	-0.049***
		(-2.78)	(-2.33)		(-33.06)	(-39.18)
Management Fee		-0.026***	-0.027***		0.006***	0.014***
		(-11.42)	(-10.48)		(9.30)	(17.53)
% Ind		-0.126***	-0.220***		-0.082***	-0.093***
		(-3.92)	(-6.75)		(-6.55)	(-7.58)
Observations	173,733	171,827	128,511	246,462	242,857	182,491
Adj. R^2	0.000	0.003	0.005	0.110	0.199	0.227
Fund Controls	NO	YES	YES	NO	YES	YES
Stock Controls	NO	NO	YES	NO	NO	YES
Time FE	YES	YES	YES	YES	YES	YES
Strategy FE	NO	YES	YES	NO	YES	YES
Change Type FE	NO	NO	NO	YES	YES	YES

stock i (Covrig et al., 2007). The first variable refers to the change in the actual position. The second variable captures the strategic engagement of a fund in a specific firm.

Table 2.7 presents coefficient estimates of the regressions which consider potential interference. Columns (1) to (3) refer to changes in shares held by a given fund ($\Delta\%Shares$). Columns (4) to (6) present results on the change of shares held by a given fund scaled by shares outstanding ($\Delta\%Shares\ Outstanding$). Results are similar to those presented in Table

2.4. The coefficients of *Pilot* are positive and significant at the 1% level in all specifications indicating that fund managers have preferences for pilot stocks and invest more in such stock positions. The negative and significant coefficients of the interaction term (*Pilot* × *Treatment Intensity*) show the declining attractiveness of pilot stocks with increasing treatment intensity. Lastly, the positive and highly significant coefficients of *Treatment Intensity* support the evidence that interference effects are existent. Fund managers invest more into nonpilot stocks when they face higher treatment intensities in their funds' portfolio. The analyses of both alternative measures of investment behavior support the findings of the main analysis on interference effects. Fund managers substitute pilot stocks into nonpilot stocks when they rely heavily on pilot stocks.

Table 2.8: Robustness: Holding Size

This table reports robustness checks of regressions of the change of stocks' holding size of mutual funds on the *Pilot* dummy, *Treatment Intensity*, and the interaction of both. The sample excludes stock positions which are completely sold during a quarter. Further, I include the size of the holding position at the beginning of the quarter instead of the other control variables of stock characteristics. The dependent variable is the quarterly change in the market-value-weighted holding position of certain stock in a certain fund. *Pilot* is an indicator variable which equals one if the stock is exempted from short sales price tests and zero otherwise. *Treatment Intensity* is the market-value-weighted proportion of pilot stocks in a mutual fund on a report date. *Ln(Proportion)* is the natural logarithm of a stock's holding position at the beginning of a quarter. Control variables of fund and stock characteristics are the same as in Table 2.3. All variables are formally defined in Appendix A. *Time FE* account for the respective reporting quarters. *Strategy FE* refer to the respective Lipper Objective Code. *Change Type FE* is an indicator variable which equals one if a stock position is completely sold during a quarter and zero otherwise. All regressions include an intercept. Standard errors are clustered at firm level and t-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	Full		Pilot	Nonpilot
VARIABLES	(1)	(2)	(3)	(4)
Pilot	0.063***	0.049***		
	(3.40)	(3.14)		
Pilot × Treatment Intensity	-0.206***	-0.155***		
	(-3.26)	(-2.96)		
Treatment Intensity	0.101***	0.058*	-0.096**	0.072**
	(2.74)	(1.88)	(-2.16)	(2.52)
Ln(Proportion)		-0.022***	-0.034***	-0.032***
		(-12.82)	(-12.46)	(-24.93)
Observations	128,545	171,866	52,513	119,353
Adj. R^2	0.004	0.009	0.041	0.040
Fund Controls	YES	YES	YES	YES
Stock Controls	YES	NO	NO	NO
Time FE	YES	YES	YES	YES
Strategy FE	YES	YES	YES	YES

Another robustness check investigates whether the size of a certain stock position at the beginning of a quarter affects results. I exclude stock holdings which are completely sold or newly bought during a quarter. Their holding position at the beginning of the quarter is either equal to the size which is sold or zero otherwise. Table 2.8 presents results of four different regressions. Column (1) shows coefficients from estimating the specification which includes control variables on the stock and fund level. The control variables on the stock levels are the main predictors of the size of the stock position. The coefficient on *Pilot* is positive, whereas *Pilot* × *Treatment Intensity* is negative. The coefficient of *Treatment Intensity* is again positive. All three coefficients are significant at the 1% level such that the results support the findings of the main Table 2.4. Column (2) shows results from regressions in which the natural logarithm of the relative holding size of the respective stock position on the fund's portfolio is included instead of the control variables on the stock level. Coefficient estimates are again in line with previous results. Coefficients of *Pilot* and *Treatment Intensity* are positive and significant. *Pilot* × *Treatment Intensity* is negative and significant. Columns (3) and (4) show results on the sample which is split into pilot and nonpilot stocks, respectively. The coefficient on *Treatment Intensity* is negative and significant for the sample including only pilot stocks, whereas the coefficient is positive and significant for the sample of nonpilot stocks. Both specifications are robust to the inclusion of the size of the stock positions.

2.6.6 Large vs. Small Firms

Grullon et al. (2015) show that small pilot firms are affected most by Reg SHO. Small pilot firms were sold short more frequently and performed negatively with abnormal returns of about -9% over the two years after the announcement of the Pilot program. They further reduced capital expenditures and issued less equity. According to these finding, this section investigates whether fund managers traded small and large firms differently after the announcement of Reg SHO.

Fund holdings are generally characterized by few large firms representing a large fraction of holdings. Splitting the firms in the sample first at the median of their market capitalization would result in one large sample of few large firms with many holding positions and a second small sample of many small firms with few holding positions. Hence, I use all holdings, assign the respective market capitalization of the firm, and split the sample at the median of the market capitalization. This results in two more evenly distributed samples. As a robustness check, I remove the tercile in the middle of the distribution and include only holdings in the highest and lowest tercile.

Table 2.9: Interference Effects in Large and Small Stocks

This table reports results of regressions of the change of stocks' holding size of mutual funds on the *Pilot* dummy, *Treatment Intensity*, and the interaction of both for different sub-samples of large and small firms. All stock holdings are split at the median of firms' market capitalization (Columns (1), (2), (5), & (6)). In columns (3), (4), (7), & (8), I only include holdings belonging to the highest or lowest tercile of firms' market capitalization. The dependent variable in columns (1) to (4) is the quarterly change in the market-value-weighted holding position of stock i in fund j between t and *t+1* ($\Delta\%TNA_{i,j,t,t+1}$). The dependent variable in columns (5) to (8) is the percentage change of shares $Ln(Shares_{i,j,t+1}/Shares_{i,j,t})$. *Pilot* is an indicator variable which equals one if the stock is exempted from short sales price tests and zero otherwise. *Treatment Intensity* is the market-value-weighted proportion of pilot stocks in a mutual fund on a report date. Control variables of fund and stock characteristics are the same as in Table 2.3. All regressions include an intercept. Standard errors are clustered at firm level and t-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	ΔProportion				% Shares			
	Median		Tercile		Median		Tercile	
VARIABLES	Large (1)	Small (2)	Large (3)	Small (4)	Large (5)	Small (6)	Large (7)	Small (8)
Pilot	0.147***	0.081***	0.172***	0.051*	0.057**	0.095***	0.077***	0.107***
	(5.04)	(3.78)	(4.83)	(1.84)	(2.57)	(3.96)	(2.80)	(3.44)
Pilot × Treatment Intensity	-0.470***	-0.233***	-0.551***	-0.146*	-0.184***	-0.265***	-0.251***	-0.312***
	(-4.11)	(-3.52)	(-3.81)	(-1.75)	(-2.63)	(-3.60)	(-2.95)	(-3.25)
Treatment Intensity	0.122**	0.338***	0.196**	0.391***	-0.059	0.234***	-0.016	0.314***
	(2.06)	(8.54)	(2.50)	(8.51)	(-1.44)	(5.82)	(-0.31)	(6.45)
Observations	85,175	97,316	56,569	65,803	61,796	66,715	42,096	45,007
Adjusted R-squared	0.459	0.377	0.480	0.357	0.004	0.007	0.005	0.010
Prob. Equal Pilot	0.07		0.01		0.25		0.48	
Prob. Equal Interaction	0.07		0.02		0.43		0.63	
Prob. Equal Treat. Intensity	0.00		0.03		0.00		0.00	

I use $\Delta\%TNA$ and $\Delta\%Shares$ as dependent variables. I apply the basic regression framework used in Table 2.4 and estimate regressions for each sub-sample separately. Then, I test for the equality of the three most important explanatory variables *Pilot*, *Treatment Intensity*, and *Pilot* $\times$ *Treatment Intensity*.

Table 2.9 shows results of regressions estimated for the different sub-samples of large and small firms separately. Columns (1) to (4) show results from regressions that use the quarterly change of the value-weighted holding positions of stocks ($\%\Delta TNA$) as dependent variable. Columns (5) to (8) present results from regressions that use the percentage change of shares held by a given fund ($\%\Delta Shares$) as dependent variable. Results shown in columns (1) to (4) are in line with the findings in Table 2.4. Interference occurs in both large and small stocks. The coefficients of *Pilot* and *Treatment Intensity* are both significant and positive. The coefficient of the interaction term *Pilot* $\times$ *Treatment Intensity* is again significant and negative. However, the full marginal effect of *Treatment Intensity* on holdings of pilot stock is negative and equals about -0.2[15] in the sub-sample of large pilot firms. In contrast, the effect is positive and equals 0.19 in the sub-sample of small pilot firms.

Fund managers typically reduce pilot holdings of large firms and increase holdings of small pilot firms. Coefficients on *Pilot* $\times$ *Treatment Intensity* are -0.47 in the sub-sample of large firms and -0.23 in the sub-sample of small firms. An F-test of the equality of coefficients suggests that the coefficients of the interaction term are significantly different at the 10% level. Fund managers thus sell more holdings of large pilot firms than holdings of smaller pilot firms with increasing treatment intensity. The coefficients of *Pilot* support this finding as the coefficient in the sub-sample of large firms is significantly larger than the coefficient in the sub-sample of small firms. In contrast, coefficients of *Treatment Intensity* show a different picture. Fund managers increase stock positions of small nonpilot firms more than positions of large nonpilot firms. In fact, the p-statistic of equal coefficients is statistically significant.

Columns (5) to (8) use the change of shares held by a given fund ($\%\Delta Shares$) as dependent variable. The coefficients of *Pilot* and *Pilot* $\times$ *Treatment Intensity* show similar results as coefficients in columns (1) to (4). However, the differences between the sub-sample of large firms and the sub-sample of small firms are smaller. Differences between the coefficients of *Pilot* and *Pilot* $\times$ *Treatment Intensity* are statistically not different as the p-statistics ranges between 0.25 and 0.63. In contrast, the coefficients on *Treatment Intensity* of the sub-samples of small firms in columns (6) and (8) are significantly larger than the coeffi-

[15] The sum of the coefficients on *Pilot*, *Pilot* $\times$ *Treatment Intensity*, and *Treatment Intensity* equals -0.2 when the *Pilot* dummy takes on the value of one.

cients of the sub-samples of large firms in columns (5) and (7). These significant differences suggest that interference is large for small nonpilot firms and that they are heavily affected by Reg SHO.

2.7 Fund Level Change in Treatment Intensity

In this section, I turn to the aggregated fund level. Analyses on the fund level provide two main advantages. First, the trading behavior on the stock level that managers prefer nonpilot stocks when treatment intensities are high and vice verse should also be observable on the aggregate fund level. Secondly, reactions on the aggregate fund level are less prone to potential diversification effects, whereas trading behavior on the stock level might be more affected by other potential diversification purposes than short selling. Hence, such analyses provide indirect evidence for the presence of interference effects.

I first investigate the change of funds' treatment intensities. Next, I look into funds' diversification and how fund managers change the diversification of pilot and nonpilot stock holdings. Lastly, I explore two possible alternative explanations for fund managers' trading behavior. Fund managers can alter funds' cash holdings or their net assets which might both explain the observed patterns.

2.7.1 Change in Funds' Treatment Intensity

The first analysis uses cross-sectional regressions to investigate the change of funds' treatment intensity over the next three quarters. The dependent variable, Δ *Treatment Intensity*$_{j,t}$, is the difference between the treatment intensity of fund j in quarter t (*Treatment Intensity*$_{j,t}$) and the initial treatment intensity ($Treatment\ Intensity_{j,0}$) calculated as of June 30, 2004. The main explanatory variable is the initial *abnormal* treatment intensity, *Abnormal Treatment Intensity*$_{j,0}$, which is defined as *Treatment Intensity*$_{j,0}$ minus 30%.[16] Further control variables are size (*Ln(TNA)*), the concentration of ownership (*Ln(Holding HHI)*, the *Management Fee*, and the investment strategy (*Strategy FE*) of funds.

Columns (1) to (3) of Table 2.10 show results from such regressions of the change of treatment intensity on *Abnormal Treatment Intensity*$_{j,0}$. Column (1) presents results on the first-quarter change between the initial quarter on June 30, 2004 and the end of the first quarter on September 30, 2004. Columns (2) and (3) present results on the change be-

[16] Reg SHO treats randomly one-third of all stocks in the Russel 3000 as pilot stocks. Since the universe of stocks mutual funds can invest into, the number is slightly lower. The mean and median value of treatment intensity in the sample of mutual funds also equal 30%.

Table 2.10: Change in Treatment Intensity within Mutual Funds

This table reports results of regressions of the change of funds' treatment intensity on *Abnormal Treatment Intensity*. Columns (1) to (3) cover the change of funds' treatment intensity over the next three quarters compared to the initial treatment intensity on June 30, 2004. Regressions in columns (4) to (6) distinguish between different sources of these changes. Column (4) presents estimates on the quarterly change in treatment intensity of stocks hold in the current and subsequent quarter. Column (5) refers to stock positions completely disposed during a quarter. Column (6) presents results on positions newly bought during a quarter. Main explanatory variable in columns (1) to (3) is the initial $Abnormal\ Treatment\ Intensity_{j,0}$ on June 30, 2004, whereas the *Abnormal Treatment Intensity* at the beginning of a quarter is used in columns (4) to (6). Control variables of fund characteristics are *LN(TNA)*, *LN(Holding HHI)*, and *Management Fee*. All variables are formally defined in Appendix A. *Time FE* account for the respective reporting quarters. *Strategy FE* refer to the respective Lipper Objective Code. All regressions include an intercept. Standard errors are clustered at funds' Lipper Objective Code and t-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	ΔTreatment Intensity			Sources		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Abn. Treatment	-0.119**	-0.218***	-0.327***	-0.064***	0.712***	0.126
Intensity	(-3.76)	(-7.42)	(-8.82)	(-6.43)	(9.05)	(1.42)
Ln(TNA)	0.000	-0.001	-0.001	-0.001*	-0.008***	-0.003
	(0.19)	(-0.50)	(-0.50)	(-1.67)	(-2.79)	(-1.06)
LN(Holding HHI)	0.003	0.004	0.007	0.003**	-0.011	0.024**
	(1.66)	(0.60)	(1.84)	(2.16)	(-1.20)	(2.34)
Management Fee	-0.003	-0.000	-0.002	-0.000	0.012	-0.007
	(-1.22)	(-0.14)	(-0.60)	(-0.27)	(1.44)	(-0.91)
Observations	743	697	679	1,983	1,920	1,904
Adj. R^2	0.060	0.116	0.173	0.034	0.058	0.015
Time FE	NO	NO	NO	YES	YES	YES
Strategy FE	YES	YES	YES	YES	YES	YES

tween the initial quarter and the second and third quarters, respectively. Results across all three columns show negative and significant coefficients of $Abnormal\ Treatment\ Intensity_{j,0}$. This indicates that funds with high treatment intensities reduce their fraction of pilot stock holdings, whereas funds with low treatment intensities buy pilot and sell nonpilot stocks. Results from the first three specifications seem reasonable in terms of time dynamics and economic significance. The coefficients of -0.119, -0.218, and -0.327 indicate that the change in treatment intensity becomes stronger over time. This is to be expected as fund managers need time to adjust large portions of their holdings to avoid trading-induced price impacts. The effect is also significant in economic terms. A one standard deviations change of $Abnormal\ Treatment\ Intensity_{j,0}$ leads to a change of funds' treatment intensity by 0.8% in the first quarter, 1.5% over the first six months, and 2.2% over the first nine months. These magnitudes are large relative to the mean and median treatment intensity of 30%.

The second analysis is presented in columns (4) to (6) of Table 2.10 and decomposes the change in treatment intensity into three different parts. Column (4) uses the change in treatment intensity of holdings which are held in two consecutive quarters as dependent variable. Column (5) uses the treatment intensity of holdings which are completely sold in a given quarter as dependent variable. The treatment intensity of positions completely sold is calculated using prices and stock positions at the beginning of each quarter because actual trades during a quarter are not observable. Column (6) implements the treatment intensity of holdings which are newly bought into a fund in a given quarter as dependent variable. Treatment intensity of stocks newly bought is calculated based on the prices and stock positions at the end of a quarter. All regressions are performed on the fund level. The main explanatory variable is the $\textit{Abnormal Treatment Intensity}_{j,t-1}$ at the end of the previous quarter. Control variables are the same as in columns (1) to (3).

In column (4) of Table 2.10, the coefficient on $\textit{Abnormal Treatment Intensity}_{j,t-1}$ is negative and significant. Fund managers buy more nonpilot than pilot stocks with increasing treatment intensity. This supports the findings presented in columns (1) to (3). In column (5), the coefficient on $\textit{Abnormal Treatment Intensity}_{j,t-1}$ is positive and significant. Mutual fund managers sell more holdings of pilot stocks than holdings of nonpilot stocks with increasing treatment intensity of funds' portfolio. The last specification presented in column (6) shows an insignificant coefficient on $\textit{Abnormal Treatment Intensity}_{j,t-1}$. Fund managers thus buy into diversified holdings which is in line with the motive to balance the benefits and disadvantages of short selling. Purchasing well-diversified portfolios alter the overall treatment intensity of funds' portfolios towards well-balanced diversification.

2.7.2 Diversification of Funds

The analysis in the previous section presents evidence that suggests that fund managers alter the treatment intensity of their funds' portfolios towards levels which balance advantages and disadvantages of short selling activities. This section addresses the question whether fund managers change the degree of diversification within their portfolios. I use the regression framework on the fund level from the previous section. Dependent variables are the change in the concentration of portfolios' holdings over the first, second, and third quarter measured by the Herfindahl-Hirschman-Index (HHI). The more positions in a portfolio and the more equal the holding positions are distributed, the lower is the Herfindahl-Hirschman-Index. The change is the difference between the concentration in the last quarter prior to the announcement of Reg SHO and the following quarters. I calculate the change for all holdings and for pilot and nonpilot stocks separately to analyze which positions are affected

Table 2.11: Change of Fund Concentration

This table reports the results of regressions of the change of funds' concentration over the next three quarters on the initial *Abnormal Treatment Intensity*. Columns (1) to (3) present results of the sub-sample of all stock holding, whereas columns (4) to (6) and (7) to (9) shows results of sub-samples of nonpilot and pilot stocks, respectively. The first column of each sub-sample uses the first-quarter change as dependent variable. The second and third columns uses the change over two and three quarters instead. Main explanatory variable the initial $Abnormal\ Treatment\ Intensity_{j,0}$ on June 30, 2004. Control variables of fund characteristics are *LN(TNA)*, *LN(Holding HHI)*, and *Management Fee*. All variables are formally defined in Appendix A. *Strategy FE* refer to the respective Lipper Objective Code. All regressions include an intercept. Standard errors are clustered at funds' Lipper Objective Code and t-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	Total			Nonpilot			Pilot		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Abn. Treatment	-0.001	-0.002	-0.004	0.001	0.003	0.002	-0.001	-0.005***	-0.007***
Intensity	(-0.60)	(-0.91)	(-0.92)	(0.24)	(1.11)	(0.49)	(-1.20)	(-6.25)	(-5.92)
Ln(TNA)	0.000	0.000	0.000	-0.000	0.000	0.000	0.000	0.000	-0.000
	(0.16)	(2.17)	(0.62)	(-0.33)	(0.40)	(0.46)	(1.34)	(0.61)	(-0.31)
LN(Holding HHI)	-0.000	0.000	-0.000	-0.000*	-0.000	-0.001	-0.000	0.000	0.000
	(-1.26)	(0.53)	(-1.39)	(-2.76)	(-0.83)	(-1.07)	(-0.22)	(1.31)	(0.64)
Management Fee	0.000	0.000*	0.001	0.000	0.000**	0.000	-0.000	-0.000	0.000
	(0.46)	(2.53)	(1.50)	(1.01)	(4.29)	(1.44)	(-0.83)	(-0.02)	(0.56)
Observations	743	697	679	743	697	679	743	697	679
Adj. R^2	0.004	0.023	0.017	0.012	0.018	0.009	-0.001	0.044	0.059
Strategy FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

most. The main explanatory variable is again *Abnormal Treatment Intensity*$_{j,0}$. Control variables are *Ln(TNA)*, *Ln(Holding HHI)*, *Management Fee*, and fund's investment strategy (*Strategy FE*). All variables are calculated as of the end of the last quarter prior to the announcement.

Columns (1) to (3) of Table 2.11 show results of the regressions on the change in diversification of *Abnormal Treatment Intensity*$_{j,0}$ for all stock positions. Columns (4) to (6) and (7) to (9) present results from the same regressions estimated for nonpilot and pilot stock holdings separately. Columns (1), (4), and (7) present results on the first-quarter change and columns (2), (5), and (8) on the second-quarter change. Coefficients of *Abnormal Treatment Intensity*$_{j,0}$ are insignificant in columns (1) to (3). Fund managers do not change the overall diversification of their funds. They substitute old stocks against new stocks but keep their relative position size fairly constant. A similar pattern is shown for nonpilot stock holdings in columns (4) to (6). The diversification of nonpilot stocks does not change upon the introduction of the pilot program. This further supports the argument that fund managers hold on to their original diversification decision.

Results are different for holdings of pilot stock. Coefficients of *Abnormal Treatment Intensity*$_{j,0}$ are negative and significant at the 1% level for the two-quarter and three-quarter change of diversification (Columns 8 and 9). This indicates that fund managers diversify the holdings of their pilot stocks more with increasing treatment intensity. Since the Pilot program was announced in the mid of the first quarter, it is reasonable to find no significant coefficient in column (7). Moreover, the effect increases between the second (column 8) and third quarter (column 9) which shows that fund managers take some time to adjust their stock positions. In conclusion, fund managers with high treatment intensities do not only reduce their pilot assets but also diversify their holdings of pilot stocks more.

2.7.3 Alternative Explanations

There are two important concerns which may drive results. The first concern is that mutual fund managers can alter their cash holdings in response to their treatment intensity. Fund managers that face high treatment intensities in their funds' portfolio could primarily sell holdings of pilot stocks and increase their cash holdings. In contrast, fund managers facing low treatment intensities could use some of their cash holdings to invest into pilot stocks in order to increase their treatment intensity. Such behavior of fund managers would result in the same empirical pattern, namely that the abnormal initial treatment intensity is negatively correlated with future changes of treatment intensity.

Table 2.12: Possible Alternative Explanation of Change in Treatment Intensity

This table reports results of regressions of the change in cash holdings and the change in total net assets of mutual funds over the next three quarters on the initial *Abnormal Treatment Intensity*. Columns (1) to (3) use the change of cash holdings as dependent variable, whereas columns (4) to (6) applies the change in total net assets as dependent variable. The first column of each sub-sample (Columns (1) and (4)) uses the first-quarter change as dependent variable. The second and third columns uses the change over two and three quarters instead. Main explanatory variable is the initial *Abnormal Treatment Intensity*$_{j,0}$ on June 30, 2004. Control variables of fund characteristics are *LN(TNA)*, *LN(Holding HHI)*, and *Management Fee*. All variables are formally defined in Appendix A. *Strategy FE* refer to the respective Lipper Objective Code. All regressions include an intercept. Standard errors are clustered at funds' Lipper Objective Code and t-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	ΔCash Holdings			ΔTotal Net Assets		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Abn. Treatment	0.632	0.964	0.181	-0.078	-0.260	-0.429
Intensity	(0.24)	(0.49)	(0.07)	(-0.49)	(-1.04)	(-0.83)
Ln(TNA)	0.004	0.092	0.014	-0.003	-0.009	-0.022
	(0.05)	(2.16)	(0.11)	(-0.88)	(-1.25)	(-1.47)
LN(Holding HHI)	-0.324	0.361	0.053	-0.001	0.004	0.012
	(-1.14)	(1.92)	(0.20)	(-0.11)	(0.25)	(0.43)
Management Fee	-0.379	-0.377	-0.468	-0.024	-0.047**	-0.105*
	(-1.30)	(-2.23)	(-1.75)	(-2.06)	(-3.48)	(-2.37)
Observations	740	691	674	743	697	679
Adj. R^2	0.002	0.000	0.002	0.013	0.036	0.038
Strategy FE	YES	YES	YES	YES	YES	YES

To address this concern, I re-estimate the regressions from the previous section using the change in funds' cash holdings over the first, second, and third quarters as dependent variable. Columns (1) to (3) of Table 2.12 show results. The coefficients on *Abnormal Treatment Intensity*$_{j,0}$ are insignificant across all three specifications indicating that the initial treatment intensity does not induce changes in cash holdings.

A second concern is that investors invested in mutual funds with high treatment intensities expect a negative fund performance in the future such that they withdraw money from these funds. Managers of funds with high treatment intensities would then sell holdings of pilot firms to pay out investors. In this case, funds' net asset value should be systematically related to treatment intensity. Columns (4) to (6) present results from regressions of the change of total net assets of mutual funds over the next one, two, and three quarters on *Abnormal Treatment Intensity*$_{j,0}$. None of the coefficients on *Abnormal Treatment Intensity*$_{j,0}$ are significant, suggesting that this alternative explanation is unlikely to cause results.

In conclusion, results above show that fund managers reallocate their portfolios by changing stock holdings. They do not change cash holdings nor do they have to deal with abnormal inflows or outflows as a result of different treatment intensities. Hence, they focus mainly on the trade-off between the advantages and disadvantages of short sellers.

2.8 Conclusion

Interference effects can be significantly large such that they heavily bias coefficients. They often represent side-effects of a new policy or regulation. Hence, they are important to be understood. Reg SHO has the potential to affect the treated and control group. One potential channel through which such interference effects can occur is the trading behavior of mutual fund managers. Reg SHO generates asymmetric incentives for fund managers to reallocate their portfolios. My results suggest that fund managers prefer to increase the share of pilot stocks when their portfolio includes only few pilot stocks and thus is only hardly affected by Reg SHO. However, they invest into nonpilot stocks when treatment intensity of their portfolio is high. This is evidence for interference. Neglecting the impact of interference effects would falsely lead to the conclusion that fund managers are indifferent between pilot and nonpilot stocks.

From an econometric perspective, mutual funds provide a useful setup to uncover interference effects. They lend themselves to estimations of within-group interference effects as mutual funds can be considered to operate as separate, independent groups. One can exploit fund managers' trading behavior at the single stock level because many funds typically hold stocks of the same firm. The changes of these holdings can be compared to isolate the effect of the treatment intensity on fund managers' trading behavior. There is one major limitation of this setup. It is not possible to estimate the «true» interference effect since super-control groups (e.g., Crépon et al., 2013) do not exist.

2.9 Appendix A: Variables

Variable	Definition
Dependent Variables	
$\%TNA_{i,j,t+1} - \%TNA_{i,j,t}$	Change of value-weighted proportion of stock i in fund j between quarter t and $t+1$
$\%Shares\ Outstanding_{i,j,t+1} - \%Shares\ Outstanding_{i,j,t}$	Change of proportion of stock i's shares outstanding held by fund j between quarter t and $t+1$
$Ln(Shares_{i,j,t+1}/Shares_{i,j,t})$	Percentage change of shares of stock i held by fund j between quarter t and $t+1$
Main Explanatory Variables	
Pilot	Dummy variable which equals one if stock is assigned to be exempted from short sale price tests by Reg SHO and zero otherwise.
Treatment Intensity	Value-weighted proportion of pilot stocks in a fund calculated at the end of a quarter
Fund Control Variables	
Ln(TNA)	Natural logarithm of fund j on quarter t
Ln(Holding HHI)	Fund concentration calculated as the natural logarithm of Herfindahl-Hirschman-Index of holdings within a fund.
Management Fee	Percentage points which holders have to pay to fund managers (CRSP Mutual Fund Database)
% Ind	Sum of value-weighted industry holdings based on Fama-French 48 divided by total fund holdings
Stock Control Variables	
ME	$Ln(prc \times shrout)$ at the end of a quarter
Past Return	$r_{past} = [\prod_{t-1}^{t-12}(1+r_t)]^{\frac{1}{11}} - 1$
Leverage	*(dltt + dlc) / at × 100*
Return on Equity	*ib / seq × 100*
Dividend Yield	*dv / (csho * prcc_f) × 100*
Earning-Price-Ratio	*ib / (csho * prcc_f)*
Book-to-Market-Ratio	*(seq + txdb) / (csho * prcc_f)*
Big Four	Indicator variable which equals one if $au \in [4, 5, 6, 7]$ and zero otherwise
Fixed Effects	
Time FE	Time fixed effects refer to each reporting quarter.
Strategy FE	Strategy fixed effects refer to the Lipper Object Code (G = Growth Funds, GI = Growth and Income Funds, MC = Mid-Cap Funds, SG = Small-Cap Funds)
Change Type FE	Capture whether a particular stock holding is changed or completely disposed within a quarter

3 Market Attention around Hedge Fund Activism

Nicolas Kube [1]

Abstract

I investigate information free riding around hedge fund activism. I find that market participants download activist announcement of hedge funds about 23% more often than filings of other types of activist investors. Market participants also review other filings of target firms, such as annual reports, if the activist investor is a hedge fund. The results suggest that hedge fund activism is studied more carefully at the beginning of a campaign. In the longer run, attention to firms' historical and newly filed filings targeted by hedge funds increases. However, large firms experience much more attention, whereas small firms experience a drop in attention. This result emphasizes that information free riding takes place in firms which are expensive to monitor and in which benefits from monitoring are relatively small.

Keywords: Information Free Riding, Hedge Funds, Public Attention, Activist Investors, EDGAR Log Data.

JEL Classification Numbers: G14, G34

[1] I am grateful for comments by Alexander Hillert, Iwan Meier, Markus Schmid, and Simon Straumann and participants at the research seminar in Davos for helpful comments. I thank Felix von Meyerinck for sharing the SharkRepellent dataset. All errors are my own.

3.1 Introduction

Attention to firms is seen as beneficial in the stock market. It accelerates the incorporation of new information into stock prices (e.g., Ben-Rephael, Da, & Israelsen, 2017; Da, Engelberg, & Gao, 2011; Drake, Roulstone, & Thornock, 2015). Attention also works as a governance mechanism to discipline managers. Managers' actions become widely known and are assessed by the market and the firms' investors when attention is high. This outside evaluation of managers' decisions can create pressure on managers to run the firm efficiently and exert effort. However, Hirshleifer and Teoh (2003) argue that attention of market participants is limited. Monitoring firms is costly and market participants have only limited resources to conduct market research. They have to prioritize their resources to spend them most effectively.

This paper follows the idea of Hirshleifer and Teoh (2003) and investigates whether market participants alter their attention to target firms after the entrance of an activist investor. In particular, I assess differences between hedge fund activists and other types of activist investors. Hedge funds are generally considered to be the investors with the most sophisticated monitoring abilities compared to other institutional investors (Brav, Jiang, Partnoy, & Thomas, 2008). Other market participants are generally considered to be less effective monitors. This situation provides incentives for information free riding. I employ a measure based on filing downloads from the Security Exchange Commission's (SEC) Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) as a proxy for attention (e.g., Ben-Rephael et al., 2017; Drake et al., 2015). This measure captures the interest of market participants in a particular firm filing. I investigate the relationship between activist investors and attention to target firms at two points in time. First, I test whether the attention to particular activist filings, i.e., SC 13D filings, is higher for hedge fund activist investors than other types of activists. Second, I explore whether market participants lower their attention to target firms in the aftermath of hedge fund activism.

I find that activist filings filed by hedge funds attract more downloads by EDGAR users on the filing date. Filings by hedge funds are about 23% more often downloaded compared to filings of other types of activist investors. This result indicates that market participants monitor and evaluate the potential impact of hedge funds more carefully than that of other activist investors. In line with more intense monitoring of hedge funds, the probability that other target firm filings are downloaded is significantly higher around the entrance of a hedge fund activist than other activists. EDGAR users most often review annual and quarterly reports as well as proxy statements. However, it is rather uncommon that EDGAR users download other activist filings which indicates that they mainly rely on information on the target firm. Joint downloads of SC 13D filings and other filings of the target firm by at least three IP addresses occur in one third of all activist events. There are even less EDGAR users which jointly download the SC 13D filing and other historical SC 13D filings of the same activist investor. Such a pattern is only present in 11% of all events indicating that EDGAR is mainly used to acquire information on a specific activist filing.

I also find that attention to target firms, on average, increases relatively more in the 120 days after a hedge fund acquires a stake compared to acquisitions of other types of activist investors. More EDGAR users download historical 8-K filings, annual reports, and proxy statements. This indicates that these filings still provide relevant information although they were filed prior to the activist filing. I find stronger results for newly filed 8-K reports but not for new quarterly reports. Thus, EDGAR users seem to be more focused on material ad hoc news than fundamental financial information. Exploring the heterogeneity of the long-term effect shows that this result is solely driven by large firms. Smaller firms experience a decrease in attention. Information free riding is thus present in small firms which are costly to monitor and whose impact on the market is rather weak. In contrast, the finding that attention increases in larger firms indicates that market participants are interested in future actions of large target firms.

I contribute to the growing literature on investor attention in general (e.g., Ben-Rephael et al., 2017; Da et al., 2011) and the use of the EDGAR log data as a proxy for market attention in particular (e.g., deHaan, Shevlin, & Thornock, 2015; Drake et al., 2015). In contrast to most papers which focus on the effect of market attention on stock prices, I focus on the change of attention when cash flow problems are expected to decrease (e.g., Brav et al., 2008; Jensen, 1986). Nevertheless, I also find a positive relationship between filings' download volume and cumulative abnormal returns.

I show that there are two different monitoring regimes. SC 13D filings are hosted twice at EDGAR: under the CIK of the activist investor and the CIK of the respective target firm. Most of the filings are accessed through the target firms' EDGAR page. This effect is larger for hedge fund which are mainly downloaded from the EDGAR pages of the target firms. In contrast, EDGAR users access more SC 13D filings from the activist investors' page if the investor is not a hedge fund. The correlation between filing requests from both sources equals -0.3. This is evidence that hosting such filings on both sources has a positive impact on the distribution of information to the market.

I lastly contribute to the literature on activist investors and their future consequences for target firms. Brav et al. (2008) argue that hedge funds have superior and distinctive monitoring abilities compared to other types of activist investors. Klein and Zur (2009) find a high success rate of 60% of enforcing intended deal purposes. From cost-benefit considerations and the idea of limited attention (Hirshleifer & Teoh, 2003), other (more passive or less sophisticated) market participants are expected to reduce attention to target firms after the entrance of a hedge fund. The reason is that their monitoring abilities are less sophisticated than those of hedge funds. Thus, hedge funds provide positive externalities for investors with limited attention. On the other hand, Drake, Jennings, Roulstone, and Thornock (2017) show that industry shocks sharpen attention to such industries and that large and visible firms draw the most attention. In fact, my analyses show that market participants review activist filings of hedge funds more carefully than those of other types of activist investors. I also find that target firms, on average, experience more attention after the investment of a hedge fund. However, attention to small target firms decreases, whereas attention to large target firms increases. These findings are in line with cost-benefit considerations since market participants can benefit most from future actions of large target firms. They typically affect a whole industry (e.g., by increasing competition). In contrast, small firms are typically more expensive to monitor so that the expected profit from monitoring small firms targeted by hedge funds is low or even negative.

The remainder of this paper is structured as follows. Section 3.2 reviews the relevant literature and briefly discusses SEC's EDGAR system. Section 3.3 provides an overview of the data and sample collection. It also presents summary statistics of the target firm sample and the log file data. Section 3.4 shows various analyses on the effect of hedge fund activism on download activities. Section 3.5 analyse the impact of hedge funds on the future attention to target firms. Section 3.6 discusses several robustness tests. Section 3.7 concludes.

3.2 Literature Review and the EDGAR System

3.2.1 Activist Investors

Section 13(d) of the Exchange Act of 1934 requires that investors which beneficially own at least 5% of issuer's equity securities and are willing to actively influence this firm have to file Schedule 13(D) (SC 13D) with the SEC within 10 days after passing the threshold of 5%. The filing contains, among other things, information about the acquired security, the investor's identity and background, the purpose of the acquisition and the size of stake. Most acquirers are institutional investors. Klein and Zur (2009) distinguish between hedge funds and other activist investors like private equity funds, asset managers, or individuals. Brav et al. (2008) argue that hedge funds have distinctive abilities to target firms compared to other types of activist investors since their incentive programs and their organizational form (e.g., unrestricted investment policy) are designed to support their role as informed activist monitors.

Several studies find positive stock returns around the announcement of activist investors' activism. Holderness and Sheehan (1985) find positive cumulative abnormal returns (CAR) of 1.77% in target companies in the (t, t + 1) event day for the entrance of one of the six biggest corporate 'raiders'. CAR in the (t - 40, t + 40) event window around the publication date equal 6.73%. Mikkelson and Ruback (1985) find similar returns of 2.88% in the two-day event window for corporate investors. For a more recent sample of SC 13D filers, Collin-Dufresne and Fos (2015) estimate abnormal buy-and-hold returns of 2.5% in the two days around the release of the filings and about 9% in the longer run of (t - 40, t + 40) days.

Stock market reactions to activist filings are characterized by large heterogeneity. Reactions are found to be much more positive for hedge fund activists. Brav et al. (2008) estimate positive CAR of targets' stock prices in the range of 7% to 8% for hedge fund activism. Klein and Zur (2009) find similar abnormal returns of about 10%. Similar to hedge funds, Allen and Phillips (2000) document CAR of 7% for corporate investors' purchase announcements. Another important factor which drives target firms' stock prices is the activist investors' deal purpose. Target firms which are forced to be acquired or merged in the aftermath of the activism experience the highest abnormal returns (Greenwood & Schor, 2009). Allen and Phillips (2000) find that returns are significantly larger for strategic investments indicating synergies as one main driver. Brav et al. (2008) complement these findings by showing that changes in the business strategy or the sale of the target company are associated with positive abnormal returns of 8.5%. Activism related to the capital structure or corporate governance does not yield significantly positive returns. Denes, Karpoff, and McWilliams (2017) find large differences in market reactions upon activists' tactics to target firms. Announcements of activists which acquire large stakes in target companies are followed by higher abnormal returns. Such activists are more likely to implement their planned strategies. Tactics involving other shareholders or the management such as shareholder proposals or negotiations are associated with low abnormal returns. In contrast, more powerful tactics such as proxy fights yield highly positive returns instead.

Prior research emphasizes three potential channels which can explain positive stock market reactions. Activist investors, in particular hedge funds, demonstrate superior monitoring abilities. Klein and Zur (2009) argue that hedge funds address potential cash flow problems as argued in Jensen (1986). Brav et al. (2008) show that hedge funds implement more equity-based compensation schemes. Greenwood and Schor (2009) find that target companies reduce their capital expenditures and increase leverage. Moreover, they undertake fewer acquisitions, divest more assets, and improve operating profitability (Bethel, Liebeskind, & Opler, 1998). Klein and Zur (2009) find that hedge funds have high success rates of 60% in terms of enforcing their transaction purposes. This finding is in line with higher abnormal returns of target firms' stocks if activist investors acquire larger stakes (Denes et al., 2017). The second channel explains shareholder gains through wealth transfer. Klein and Zur (2011) find negative short-term and long-term effects of hedge fund activism on bondholders. Bondholders experience abnormal bond returns of -3.9% around the publication date of SC 13D filings. They further lose about 4.5% in the following year. In addition, Xu and Li

(2010) find that target companies have to pay higher spreads on private loan agreements and that banks ask for more collateral and implement more restrictive covenants after an activist investor entered a firm. Target firms are also more likely to be downgraded (Xu & Li, 2010). These negative bond returns and caution of private lenders are mainly driven by higher risk of the target companies. The risk increases due to higher dividend payments, more share repurchases, and higher leverage. Another source of wealth transfer is shown by Brav et al. (2008). Hedge funds reduce total compensation of target firms' managers which is then be allocated towards shareholders.

A third channel is the selection of target firms by activist investors. Bethel et al. (1998) find that activist investors target poorly performing and diversified firms. In contrast, hedge funds typically invest into value firms which are profitable and generate stable cash flows (Brav et al., 2008). Takeover defenses of target firms do not deter activists from acquiring shares (Bethel et al., 1998). Brav et al. (2008) and Denes et al. (2017) show that target firms typically have even more takeover defenses such that activist investors act as a substitute for the missing market of corporate control. Brav et al. (2008) also find that hedge funds typically cooperate with target firms' management and that the median holding period equals roughly one year. Becht, Franks, Mayer, and Rossi (2008) show longer median holding periods of more than two and a half years which are even longer for confrontational campaigns. Hence, activist investors seek to earn long-term shareholder gains and are less interested in short-term stock picking.

3.2.2 EDGAR Search Traffic

Investors' attention is regarded as beneficial for incorporating news into stock prices and to monitor firms closely. Da et al. (2011) introduce the Google search volume index (SVI) which measures retail investors' attention to firms. Increasing Google search volumes predict short-term outperformance of stocks. In contrast, Ben-Rephael et al. (2017) investigate the collection of information through Bloomberg terminals which is, due to high costs, attributed to institutional investors. They find that institutional investors respond more quickly to news announcements than retail investors and that stock prices adjust permanently when institutional investors trade on these news.

Another recent measure of investors' attention and which is also used in this study is the EDGAR search volume. EDGAR, the Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) of the Security Exchange Commission (SEC), hosts all publicly available company filings which can be requested though the Web. Each request to open a filing at EDGAR is registered as an entry in the server log data. This data can be downloaded from the SEC's website.[2] Drake et al. (2015) find that the majority of EDGAR users only request filings occasionally and focus on a small subset of filings such as 10-K, 10-Q, or 8-K filings. Firm events such as earnings announcements, announcements of restatements, or announcement of acquisitions drive EDGAR search volume. Additionally, search volume increases after days with high negative abnormal returns. It is also higher for large, highly leveraged, and mature firms, as well as for firms with high institutional ownership.

Drake et al. (2015) further find that stock market reactions to earnings announcements are more positive for high search volume and post-earnings-announcement drifts are lower. Loughran and McDonald (2017) examine to what extent individual investors use financial information from EDGAR to conduct fundamental research. They find that company filings are rarely consummated. On average, annual reports of publicly listed firms are downloaded about 28 times within the first two days. Reports of private firms are even downloaded less. During the first two days, reports of private firms are read 14 times only. Even for firms in the highest size quintile, the average (median) download volume over the first four days is 96 (56). The download pattern over the subsequent 12 months shows that about 41% of all downloads occur during the first quarter. Cong, Du, and Vasarhelyi (2017) show that in more recent years, EDGAR users access machine-readable XBRL filings more often than human-readable HTML filings.

deHaan et al. (2015) use abnormal download volume of 8-K filings as a proxy for investors' attention. They focus on 8-K filings which contain firms' earnings announcements. They find that EDGAR users access filings more frequently on Fridays but less often after the stock market is closed and when several earnings announcements are released on the same day. Related to earnings announcements, Chapman (2018) shows that more often down-

[2] https://www.sec.gov/dera/data/edgar-log-file-data-set.html

loaded earnings notifications are associated with higher returns prior to the release of the actual earnings announcement, whereas returns around the release date are lower. Drake, Roulstone, and Thornock (2016) show that market participants also use historical financial reports (10-K and 10-Q reports) to gather qualitative and more detailed information on a firm. They in particular do this when current reports are complex, managers report higher amounts of accounting discretion, when firms announce negative earnings shocks, and after large stock price movements. In contrast, Dechow, Lawrence, and Ryans (2015) find that 80% of companies' Comment Letters are not downloaded at all on the publication day. Such letters contain companies' answers to SEC's questions on their financial reports. Bozanic, Hoopes, Thornock, and Williams (2017) find that the US tax authority (Internal Revenue Service) downloaded financial reports more often if such reports likely contain more tax-related information which are not already known by the IRS.

Search behavior of EDGAR users also predicts stock price movements. Drake et al. (2017) find that industry attention predicts the search intensity of particular stocks in the respective industry. This comovement of attention is also associated with stronger comovement of equity stock returns and industry returns. F. W. Li and Sun (2018) find that higher numbers of abnormal distinct IP addresses searching for a particular firm are associated with more positive future returns. An investment strategy which invests into highly searched firms and short sells rarely searched firms generates an alpha of 52 to 82 basis points per month.

Lee, Ma, and Wang (2015) emphasize that the search behavior of non-robot EDGAR users can also be used to form meaningful peer groups. EDGAR users frequently search for information of related firms. Forming groups based on this search behavior shows a better out-of-sample prediction in stock returns, growth, or leverage compared to other industry classifications. Firms within such peer groups share, in addition to similar business characteristics, a high comparability of financial characteristics (e.g., return on equity, leverage, R&D). Madsen (2017) focuses on the customer-supplier relationship and shows that EDGAR users acquire customer information before the respective suppliers disclose their earnings announcements. Users, therefore, access EDGAR to refine their expectations about supplier firms.

3.2.3 Release of EDGAR Filings

The SEC maintains two systems through which company filings can be accessed. EDGAR is publically available through the Web. The second system is called public dissemination system (PDS) and provides access to paying subscribers. Filings are uploaded by companies and the SEC runs some semantic and consistency checks first. According to Rogers, Skinner, and Zechman (2017), the processed filings are then simultaneously passed onto EDGAR and to the PDS. They find that about 57% of Form 4 filings (i.e. insider trading) are published faster by the PDS than EDGAR and other filings are affected, too. Although the PDS is faster in expectation, information of new filings are still much earlier available from both sources compared to other information providers. E. X. Li, Ramesh, and Shen (2011) document a delay of about 2.3 weekdays between the publication of an SEC filing and the posting on Dow Jones Newswires. It takes on average 14 weekdays until new quarterly financial data are available in COMPUSTAT (D'Souza, Ramesh, & Shen, 2010) and often, there are discrepancies between the numbers in the XBRL filings and those in COMPUSTAT (Chychyla & Kogan, 2014). Hence, it seems reasonable to observe such a tremendous increase of download activities on EDGAR in recent years (e.g., Cong et al., 2017; Loughran & McDonald, 2017).

3.3 Data and Summary Statistics

3.3.1 Sample of Activist Investors

I follow the cleaning procedure used in Collin-Dufresne and Fos (2015). I start with the collection of all SC 13D filings in EDGAR. I include only filings which were filed between January 1, 2007 and December 31, 2016 to match them with EDGAR server log data. This procedure yields 18,479 filings. SC 13D filings typically appear twice in EDGAR. They can be found under the activist investors' and target firms' CIK. I parse all filings to distinguish between targets and activists. This information is given on the index site of each filing.[3]

[3] https://www.sec.gov/Archives/edgar/data/921669/000092846415000094/0000928464-15-000094-index.htm provides an example where Xerox Corp is the target firm (subject) and Carl C. Icahn is the activist investor (filer).

Each filing has to occur twice in EDGAR to compare how internet users access filings. This requirement reduces the sample to 17,972 unique filings.

It is common that different activist investors target a firm together or follow each other such that they file separate filings. This investment behavior leads to multiple filings within a short time period or even on a particular day and would confound results on search data. Collin-Dufresne and Fos (2015) address the problem of multiple events by requiring no other SC 13D filing in the time period between 120 days prior to and 40 days after a SC 13D filing. I implement the same requirement which reduces the sample to 9,256 events.

In the next step, I match each filing with the "Center for Research in Security Prices" (CRSP) data set. I parse through all filings and search for the target firms' CUSIP which is given in the description. I then match them with the historical CUSIPs collected by CRSP. I was able to identify 4,119 filings which can be matched with common stocks (shrcd 10 & 11) from the CRSP data set. To estimate abnormal returns, the stock market had to be open on the filing date and the stock had to be tradable (trdstat = 'A'). These requirements reduce the sample to 4,033 filings. I remove all stocks with share prices below $1 or above $1,000 and filings which cannot be linked to Compustat using the CCM Linking Table. These requirements reduce the sample to 3,709 filings.

To obtain deal characteristics and characteristics of activist investors, I merge the SC 13D sample with the activist data set maintained by Shark Repellent. The intersection results in 1,064 events. I assign control variables from the Compustat Annual and Quarterly Database. Quarterly data must not be older than 100 days. In addition, I exclude filings of firms in the financial industry (SIC 6000 - 6999) or in the public sector (SIC 9000 - 9999). I also require that firms were traded in the previous 12 months. These requirements result in a sample of 871 events.

I then estimate cumulative abnormal returns (CAR) using the procedure proposed by Greenwood and Schor (2009). They estimate abnormal returns around activist announcements using factor loadings of target firms' returns on market return, SMB, and HML factors (Fama & French, 1993). Loadings are estimated between 110 and 10 days prior to the actual announcement.[4] I exclude 17 events since their trading stopped after the entrance of

[4] I also estimate a market model and a four factor model (Carhart, 1997) as robustness checks.

Table 3.1: Sample Selection of Activist Investors

This table presents the cleaning procedure of activist events. I first follow the procedure conducted in Collin-Dufresne and Fos (2015) and constructed then the intersection with Shark Repellent to obtain detailed data of the activist events.

Number of Events	Filter
18,479	All SC 13D Filings between January 1, 2007 and December 31, 2016
17,972	Filing for subject and filer (Two Filings)
13,855	Only ONE filing per day
11,129	No other SC 13D filing in the previous 120 days
9,256	No other SC 13D filing in the 40 days after
5,075	CUSIP in CRSP appears in filing
4,119	Valid links with share codes 10 or 11
4,052	U.S. common stock was trading on filing date (trdstat = 'A')
4,033	Market was open on acceptance date
3,716	Share Price between $1 and $1,000
3,709	Valid Link to Compustat
1,064	Intersection with Shark Repellent
871	COMPUSTAT Quarterly Data not older than 100 days
845	Abnormal Returns available
845	**Full Sample**

the activist investor.

3.3.2 Log Data

All firms in the U.S. which are required to publicly disclose mandatory information have to upload and publish their filings on EDGAR. Such filings are accessible through the Web and are hosted by SEC's EDGAR servers. Web servers collect page requests as log data entries which contain information about the requesting IP address. Information are, among other things, the IP address, the timestamp of the request, an indicator code whether the request was successful, as well as the accessed CIK and accession number of the filing. The SEC published the EDGAR log file data for the time period between June 2003 and June 2017. Since data was sparse in 2003 and files between September 2005 through May 2006 have been shown to be of poor quality (Loughran & McDonald, 2017), I choose January 1, 2007 as the starting point of the sample.

I follow the cleaning procedure in Loughran and McDonald (2017). I remove self-identifying web crawlers because they typically belong to search engines (e.g., Google, Yahoo). I keep only log data entries with server codes lower than 300. Higher server codes identify relocated files (*300s*), client errors (*400s*), or server errors (*500s*). I remove all index page requests since index pages contain only few financial information (e.g., Drake et al., 2015; Loughran & McDonald, 2017). I assign the respective filing form (e.g., SC 13D, 10-K, 10-Q) to each log data entry. I focus only on the most common and important filings such as 10-K, 10-Q, 8-K, SC 13D and SC 13G.[5] Lee et al. (2015) argue that TXT filings are mostly downloaded by web crawlers and that nonrobot users typically request HTML filings. Hence, I keep human-readable requests only (i.e, HTM, HTML, and pdf files). I remove observations with missing data items. The whole cleaning process is summarized in Table 3.2.

Table 3.2: EDGAR Log File Data

This table presents the cleaning steps of the EDGAR log file data. There is one file with log data for each day. Number of observations are aggregated over all days in the time period between January 1, 2007 and June 30, 2017.

Number of Observations	Cleaning Step
26,026,627,338	All Log Data between January 1, 2007 and June 30, 2017
24,902,633,194	No Crawler (e.g., Google, Yahoo): *Crawler* is equal to 0
20,477,898,471	Successful Access: *Code* lower than 300
10,784,870,669	No Index Page: *IDX* is equal to 1
7,434,571,696	Forms: 10-K, 10-Q, 8-K, DEF 14A, SC 13D, SC 13G, & 4
7,434,570,232	Missing Values
1,670,017,020	Only human-readable sites (.htm, .html, .pdf)
1,670,017,020	**Full Sample**

3.3.3 Robots vs. Nonrobots

Most of the web traffic on EDGAR can be attributed to autonomous web crawlers. Nonrobot requests represent only a small fraction of searches. The fraction of robot searches increased tremendously in the past, whereas the number of nonrobot requests remained rather stable (Loughran & McDonald, 2017). As the log data do not provide a reliable indicator whether a certain IP address is a nonrobot user or a web crawler, researchers developed four classification algorithms. Lee et al. (2015) classify IP addresses which access

5 I include 10-K, 10-Q, 8-K, and DEF 14 as filings containing firms' financial information (e.g., deHaan et al., 2015; Lee et al., 2015; Loughran & McDonald, 2017). SC 13D and SC 13G cover large investor positions.

more than 50 unique firms' filings on a particular day as robots. Loughran and McDonald (2017) label IP addresses with more than 50 requests per day as robots. Drake et al. (2015) employ two indicators. They categorize IP addresses which either request more than five filings per minute or more than 1,000 requests per day as robots. The most recent classification scheme was introduced in Ryans (2017). IP addresses with more than 25 requests per minute, more than three different CIK per minute, or IP addresses with more than 500 requests per day are assigned to robots. My main analyses are based on the classification scheme proposed in Ryans (2017) since his classification procedure is tested on more recent log data. However, I run robustness checks to study whether variation in the classification procedure alters the results. The actual classification of IP addresses as robots is run on the log data after removing unsuccessful requests, i.e., request code equal to or larger than 300, and self-identified crawlers (see step 3 in Table 3.2).

3.3.4 Summary Statistics of Activist Sample

I first provide summary statistics of the activist investors' and deal characteristics in Table 3.3. The sample consists of 845 events. Activist ownership as presented in Panel A is slightly right-skewed with a mean of 7.79% and a median of 6.34%. Panel B.1 shows the distribution of activist types. *Hedge funds* are involved in 525 cases and represent the largest group, whereas *Investment advisers* take part in 195 deals. Individuals represent a small group of 50 deals.[6] Panel B.2 shows the figures on professional support used in the deals. Only 15 activist investors took advantage of professional financial support indicating that activist investors are financially sophisticated. In contrast, legal advisors of activist investors are involved in 333 deals. Professional support by financial and legal advisors of target firms is more evenly distributed at target firms, which made use of financial and legal counseling in 160 and 192 cases, respectively. Panel C.1 and C.2 present the most frequent deal purposes and tactics. The most popular deal purposes are asking for strategic alternatives, seeking a sale, merger, or liquidation, returning cash to the shareholders, and to break up the company. The most common tactic of activist investors is to publicly disclose a letter to the board or management. Two other important tactics are threatening target firms with a

[6] Other types are not listed separately as their frequency is low.

proxy fight and to nominate a slate of directors. Panel D shows the occurrence of deals over the years. Most deals took place in 2007, hence prior to the financial crisis. The number of deals went down to only 54 deals in 2009 and 59 deals in 2010. Afterwards, the number increased steadily to a persistent level of about 90 deals per year since 2014. Number of deals is more equally distributed across months (see Panel E). There are slightly more deals between May and July. The distribution of deals is more distinctive on certain weekdays (see Panel F). Most activist investors disclose their investment on Mondays followed by Thursdays and Fridays.

Table 3.4 presents summary statistics of target firms. I focus on the most important variables determining both filing requests on EDGAR and abnormal returns which are presented in Panel A. Drake et al. (2015), Lee et al. (2015), and Drake et al. (2016) argue that firms' visibility is one important factor. It is approximated by firms' market capitalization *(Ln(MVE))* and firms' age. Market capitalization is highly skewed as the median equals USDm 295, whereas the mean is USDm 1,285. Hong, Lim, and Stein (2000) stress the role of analysts in transmitting news and information to the market. They help to incorporate negative news which otherwise disseminate gradually and slowly. The median number of analysts covering a firm in IBES is five which means that the majority of firms is monitored closely by analysts. Firms' profitability and expected performance are further drivers of search activity on EDGAR (see Drake et al., 2015; Klein & Zur, 2011; Lee et al., 2015). They are captured by the enterprise value-to-sales ratio (EV-sales ratio), return on net operating assets (RONOA), R&D expenses, dividend payments, past abnormal returns, and short selling interests. Most target firms show a highly negative abnormal stock performance in the previous year. Their return on net operating assets is on average 1.3% indicating that their profitability is low.[7] 47% of all target firms have positive R&D expenses and only 24% pay dividends. On average, 6.0% of the stocks outstanding are sold short. The median value is smaller and equals 3.9%.

The median value of the enterprise value-to-sales ratio is 5.4 indicating that firms hold five times their sales in assets. Hence, they have lots of assets employed to run their business.

[7] The average return on net operating assets of firms in the Compustat universe at the same time and with property, plant, and equipment of at least USDm 5 equals 8.5%. The median value is 2.7%.

Table 3.3: Summary Statistics of Activist Investors

This table presents summary statistics of activist and deal characteristics. Panel B to F shows absolute numbers of observations of the total sample size of 845. Panel A shows the distribution of activist investors' ownership at the announcement. Panel B characterizes the type of investor and indicates support by professional advisers. Panel C lists different deal purposes and tactics of investors. Panel D to E show the distributions over time.

Panel A: Activist Ownership

	5^{th}	25^{th}	Median	Mean	75^{th}	95^{th}	N
Ownership	5.00%	5.30%	6.34%	7.79%	9.10%	16.38%	845

Panel B.1: Type		Panel B.2: Professional Support	
Hedge Fund	525	Financial Advisor (Activist)	15
Investment Adviser	195	Legal Adviser (Activist)	333
Individual	50	Financial Advisor (Target)	160
Other	75	Legal Advisor (Target)	192

Panel C.1: Purpose		Panel C.2: Tactics	
Strategic Alternatives	159	Letter to Stockholders	63
Seek Sale/Merger/Liquidation	147	Nominate Slate of Directors	108
Potential Acquisition	34	Publicly Disclosed Letter to Board/Mgmt	259
Others	253	Proxy Fight	112
Not stated	252	Other Tactics	73

Panel D: Years

2007	145	2009	54	2011	67	2013	78	2015	92
2008	97	2010	59	2012	72	2014	91	2016	90

Panel E: Months

January	63	April	64	July	79	October	72
February	63	May	82	August	73	November	65
March	75	June	87	September	61	December	61

Panel F: Weekdays

Monday	243	Wednesday	121	Friday	171
Tuesday	125	Thursday	185		

Moreover, firms' leverage (Lee et al., 2015) and cash holdings (Klein & Zur, 2009) are factors related to the free cash flow problem (Jensen, 1986). The sample consists of many zero-leverage firms and median leverage equals only 16.5%. Cash holdings are relatively high with a median value of 14.0%. Both variables indicate some potential free cash flow problems.

Panel B of Table 3.4 presents characteristics related to governance. 211 target firms had a poison pill in place prior to the investment of the activist investor. 369 target firms had classified boards. Panel C shows the ten most frequent industries based on the two-digit SIC Industry Classification.[8] Deals are spread across many different industries. The three most frequent industries in the sample do not share the same first digit of the industry classification.

Table 3.4: Summary Statistics of Target Sample

This table presents summary statistics of target firms. Panel A shows financial characteristics of target firms. All variables are formally defined in Appendix 3.13. Panel B presents indicator variables of target firms' corporate governance. Panel C shows the distribution across different two-digit SIC industry classification (Drake et al., 2017). All continuous variables are winsorized at the 2.5$^{\text{th}}$ and 97.5$^{\text{th}}$ percentile.

Panel A: Financial Characteristics

	5^{th}	25^{th}	Median	Mean	75^{th}	95^{th}	N
Market Capitalization	29.1	118.9	295.1	1,284.7	1,252.2	5,938.8	845
EV-sales ratio	1.1	2.8	5.4	8.7	10.2	26.1	813
Leverage	0.0%	0.0%	16.5%	59.3%	77.7%	319.9%	828
RONOA	-19.0%	-2.1%	1.9%	1.3%	5.6%	19.3%	821
Cash holdings	0.6%	4.0%	14.0%	21.4%	32.8%	68.4%	845
R&D (Dummy)	0.0	0.0	0.0	0.47	1.0	1.0	845
Dividends (Dummy)	0.0	0.0	0.0	0.24	0.0	1.0	845
Short Interests	0.1%	1.4%	3.9%	6.0%	8.7%	19.8%	845
Nr. Analysts	0.0	2.0	5.0	6.3	9.0	19.0	845
One-year BHAR	-66.3%	-36.6%	-16.7%	-11.7%	7.0%	68.8%	845

Panel B: Governance

Prior Poison Pill	211	Classified Board	369

Panel C: Industries (Two-digit SIC)

Business Services (73)	144
Electronic And Other Electrical Equipment And Components (36)	91
Chemicals And Allied Products (28)	79
Industrial And Commercial Machinery And Computer Equipment (35)	65
Measuring and Analyzing Instruments (38)	54
Health Services (80)	36
Communications (48)	32
Eating And Drinking Places (58)	24
Oil And Gas Extraction (13)	24
Miscellaneous Retail (59)	23

8 Drake et al. (2017) show the importance of this industry classification in predicting attention comovement.

3.3.5 Summary Statistics of Abnormal Returns and Log Data

Table 3.5 summarizes cumulative abnormal returns (CAR) and filing requests around the release of the activist filing. Panel A presents CAR for different event windows. The average (median) announcement effect in the (t - 10, t + 10) day event window equals 5.5% (5.54%). This magnitude is in line with previous findings (e.g., Allen & Phillips, 2000; Brav et al., 2008), but slightly lower. The pre-announcement effect equals 0.38% in the (t - 10, t - 5) window and 0.96% in the (t - 10, t - 2) window and is lower compared to other studies. The announcement returns in the three days around the release of the SC 13D filings (i.e., (t - 1, t + 1), (t, t + 1), and (t, t + 2)) range from 2.84% to 3.18%. The post-announcement effect is again low. In the (t + 2, t + 10) window, the average CAR equal 1.31%. In the (t + 5, t + 10) event window, CAR lower to 0.93% which indicates that market participants are fast in incorporating the news into stock prices.

Panel B of Table 3.5 shows the distribution of filing requests on the day of release. On average, each filing is requested around 40 times. The median value is, however, lower and equals 13. Similar to findings in Chapman (2018), some filings are not downloaded at all by nonrobot IP addresses. There is also a distinctive difference in the download behavior in target firms and activist investors.

Most filings are accessed through target firms' EDGAR site. The mean (median) requests equal 30 (5), whereas the download volume is low on activist investors' EDGAR site. There are slightly more requests by IP addresses which were active at least 10 minutes before the SC 13D filing was released (*Downloads Pre-Active IPs*). The median value of requests equals 8. In contrast, *Downloads New IPs*, i.e., IP addresses which access EDGAR 10 minutes before or after the release of a particular SC 13D filing, have median requests of 4 but are more right-skewed. The last five variables are indicator variables. These are equal to one if a SC 13D filing and the respective other filing form indicated in the variable name are downloaded both by at least three different IP addresses.[9] Such measures are proxies for the deal complexity and whether EDGAR users require more information from other filings. In 37% of all deals, EDGAR users downloaded the SC 13D filings and another 8-K filing.

[9] I choose a threshold of three because it seems reasonable that the other downloaded filing contains related and valuable information.

Table 3.5: Summary Statistics of Event Study

This table presents summary statistics of cumulative abnormal returns (CAR) in Panel A and downloads of filings from EDGAR in Panel B. Panel A shows first the event window followed by the median and average cumulative abnormal returns (CAR) in the respective event window. CAR are estimated using the Fama-French model (Fama & French, 1993). Panel B shows different variables of EDGAR search traffic. All variables are defined in Appendix 3.13 and winsorized at the 2.5$^{\text{th}}$ and 97.5$^{\text{th}}$ percentile.

Panel A: Cumulative Abnormal Returns

	Median	Mean		Median	Mean		Median	Mean
(t-10, t+10)	5.54%	5.50%	(t-1, t+1)	2.33%	2.94%	(t, t+10)	3.94%	4.38%
(t-10, t-5)	0.57%	0.38%	(t, t+1)	2.26%	2.84%	(t+2, t+10)	0.99%	1.31%
(t-10, t-2)	1.77%	0.96%	(t, t+2)	2.80%	3.18%	(t+5, t+10)	0.83%	0.93%

Panel B: Log Data

	5^{th}	25^{th}	Median	Mean	75^{th}	95^{th}	N
Total Downloads	0	2	13	39.63	33	154.20	845
Total Downloads Target	0	0	5	29.81	22	114.40	845
Total Downloads Activist	0	0	0	9.84	1	38.60	845
Downloads Pre-Active IPs	0	1	8	18.34	20	80	845
Downloads New IPs	0	0	4	21.29	14	75.80	845
Downloads Target 8-K	0	0	0	0.37	1	1	845
Downloads Target 10-K	0	0	0	0.30	1	1	845
Downloads Target 10-Q	0	0	0	0.33	1	1	845
Downloads Target DEF 14A	0	0	0	0.31	1	1	845
Downloads Activist SC 13D	0	0	0	0.11	0	1	845

The fraction is lower for 10-K and 10-Q reports and equals 30% and 33%, respectively. Similarly, the fraction of combined downloads of SC 13D and proxy statements equals 31%. Surprisingly, there are only few downloads of other SC 13D. The fraction of downloads of other activist investors' SC 13D filings equals only 11%.

3.4 Attention on Hedge Fund Activism

3.4.1 Total Downloads

I first examine whether SC 13D filings of hedge funds attract different market attention than SC 13D filings from other types of activist investors. To evaluate the effect of hedge fund activism on filing requests, I estimate cross-sectional regressions of *Total Downloads* on the *Hedge Fund* indicator variable.

$$\text{Total Downloads} = \alpha + \beta_1 \text{ Hedge Fund} + \beta_2 X + \gamma + \theta + \zeta + \epsilon \tag{3.1}$$

Total Downloads is the natural logarithm of one plus the total number of downloads of a SC 13D filing on the publication day ($Ln(1+Requests)$). I only consider nonrobot IP addresses based on the classification methodology of Ryans (2017). *Hedge Fund* is an indicator variable which is equal to one if the activist investor is a hedge fund and zero otherwise. γ and θ refer to the year and weekday of the release date, respectively. ζ is an indicator variable (*After Market*) which is equal to one if the filing was released after 4 p.m. Previous literature shows many other factors related to activist investors and their impact on abnormal returns which might also impact the number of downloads. These are all included in matrix X. First, I control for several activist characteristics. According to findings in Denes et al. (2017), I include activist investors' ownership in the target firm and an indicator variable indicating a potential proxy fight. I further control for the most important activists' deal purpose, i.e., potential acquisition, strategic alternatives, and sale of the firm (e.g., Brav et al., 2008; Greenwood & Schor, 2009). Besides activist characteristics, I include several characteristics of the target firms. Large and older firms as well as firms with high leverage and many analysts are highly visible in the market and known for more downloads (e.g, Drake et al., 2016; Lee et al., 2015). Abnormal returns in the previous year, return on net operating assets (RONOA), R&D expenses, and short interests proxy higher attention based on expectations about firms' future performance (e.g., Drake et al. (2015); Klein and Zur (2011); Lee et al. (2015)). Dividend payments and cash holdings controls for potential cash flow problems (e.g., Denes et al., 2017; Jensen, 1986; Klein & Zur, 2009, 2011). There is some evidence that shareholder proposals induce firms to restructure their poison pill (Bizjak & Marquette, 1998). I include an indicator variable which equals one if the target firm has a poison pill in place and zero otherwise. I also include the cumulative abnormal return on the publication day, which is estimated by a Fama French three factor model (Fama & French, 1993). Drake et al. (2015) and Chapman (2018) show that the number of downloads and abnormal returns are positively related.

Table 3.6: Download Activity around Hedge Fund Activist Filings

This table presents results of the regression of the number of downloads of SC 13D filings, *Total Downloads*, on the *Hedge Fund* indicator variable and several control variables. *Total Downloads* are defined as the natural logarithm of one plus the number of downloads of nonrobot IP addresses on the filing day. Nonrobot IP addresses are classified using the definition of Ryans (2017). Cumulative abnormal returns (CAR) in the (t+0, t+1) event day window are estimated using a three-factor Fama-French model (Fama & French, 1993). Remaining control variables are defined in Appendix 3.13. A constant as well as year FE, weekday FE, and after market FE are included in each regression. All continuous variables are winsorized at the 2.5^{th} and 97.5^{th} percentiles. In each column, I report estimated coefficients and their heteroskedasticity-robust standard errors (in parentheses). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Hedge Fund	0.256***	0.293***	0.245**	0.232**
	(0.092)	(0.096)	(0.095)	(0.094)
Activist Ownership		0.030	-0.044	-0.065
		(0.124)	(0.131)	(0.129)
Proxy Fight		-0.187	-0.147	-0.157
		(0.137)	(0.143)	(0.144)
Potential Acquisition		0.526*	0.650**	0.564*
		(0.270)	(0.293)	(0.291)
Strategic Alternatives		0.135	0.079	0.051
		(0.171)	(0.173)	(0.174)
Sale/Merger/Liquidation		-0.298	-0.203	-0.219
		(0.184)	(0.189)	(0.190)
CAR(0,1)				1.754**
				(0.806)
Adj. R^2	0.39	0.40	0.44	0.44
No. observations	845	845	793	793
Target Firm Controls	NO	NO	YES	YES
Year FE	YES	YES	YES	YES
Weekday FE	YES	YES	YES	YES
After Market FE	YES	YES	YES	YES

Table 3.6 presents the results. Column (1) only includes the *Hedge Fund* indicator variable and the different fixed effects. Column (2) additionally controls for deal and activist characteristics. In column (3), I also include control variables related to target firm characteristics. Column (4) shows the most saturated model which accounts for the cumulative abnormal return on the publication day.

Across all columns, the coefficients of *Hedge Fund* are positive and significant at the 5% level or better. Economically, activist filings filed by hedge funds are associated with about 23.2% more downloads on the publication day compared to other types of activist investors.

Thus, the economic magnitude of this relationship is large. The coefficients are rather stable across the different specifications indicating the robustness of this relationship.
The coefficient of CAR(0,1) is significant and equals 1.75. A one standard deviation increase of CAR(0,1) increases the download volume by 11.3%. This finding is in line with Drake et al. (2016) who show that the download volume of historical annual reports is higher for both positive and negative stock price shocks. The coefficient of *Potential Acquisitions* is also positive and significant at the 10% level. The announcement of a potential acquisition is associated with about 56% more downloads. This finding is supported by findings in Greenwood and Schor (2009) showing that potential take over targets experience abnormally positive stock returns. Coefficients of other deal purposes or tactics are insignificant. There might be two main explanations for the insignificance. First, they do not attract more market participants to explore the target firms as they are of less relevance. Second, market participants do not know ex ante the content of SC 13D filings such that they download the filings irrespective of the deals' tactics and purposes. The positive coefficients of *Potential Acquisition* are not necessarily evidence against the second reason as Greenwood and Schor (2009) show a strong anticipation effect of potential acquisitions and any effect on other purposes.
In conclusion, EDGAR users are much more interested in hedge fund activism than activism of other investors, as shown by a higher total download volume around the disclosure of hedge funds' activist filings. This result finds support by previous literature which shows that hedge funds play a distinct role as activist investors (e.g., Brav et al., 2008; Denes et al., 2017).

3.4.2 New Users

This section discusses potential differences in the observation of filings by hedge funds between two different types of EDGAR users. I distinguish EDGAR users into two groups. The first group are users which gather information on EDGAR at least 10 minutes before a SC 13D filing is released (*Pre-Active IPs*). Such users are expected to be more sophisticated as they spent more time on EDGAR and search also for other filings. The second group

Table 3.7: Impact on Different Types of Internet Users

This table presents results of the regression of the number of downloads of SC 13D filings on the *Hedge Fund* indicator variable and distinguishes between two types of EDGAR users. A *Pre-Active IP* is an IP address which accessed filings from other firms than the target firm at least 10 minutes before the respective SC 13D filing was released. *New IP* refer to IP addresses which access the respective SC 13D filing and are not classified as a *Pre-Active IP*. *Downloads Pre-Active IPs* and *Downloads New IPs* are both defined as the natural logarithm of one plus the number of downloads from the respective nonrobot IP addresses on the filing day. Nonrobot IP addresses are classified using the definition of Ryans (2017). Columns (1) and (2) show results on *Pre-Active IP*. Columns (3) and (4) show results on *New IP*. Cumulative abnormal returns (CAR) in the (t+0, t+1) event day window are estimated using a three-factor Fama-French model (Fama & French, 1993). Remaining control variables are defined in Appendix 3.13. A constant as well as year FE, weekday FE, and after market FE are included in each regression. All continuous variables are winsorized at the 2.5^{th} and 97.5^{th} percentile. In each column, I report estimated coefficients and their heteroskedasticity-robust standard errors (in parentheses). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	Pre-Active IPs		New IPs	
	(1)	(2)	(3)	(4)
Hedge Fund	0.208***	0.198**	0.314***	0.299***
	(0.079)	(0.078)	(0.082)	(0.081)
Activist Ownership	-0.079	-0.098	0.125	0.099
	(0.108)	(0.107)	(0.112)	(0.110)
Proxy Fight	-0.156	-0.165	-0.057	-0.069
	(0.120)	(0.120)	(0.125)	(0.125)
Potential Acquisition	0.520**	0.448*	0.677**	0.572**
	(0.244)	(0.243)	(0.271)	(0.263)
Strategic Alternatives	0.110	0.087	0.100	0.066
	(0.142)	(0.143)	(0.159)	(0.160)
Sale/Merger/Liquidation	-0.210	-0.223	-0.082	-0.101
	(0.155)	(0.156)	(0.168)	(0.168)
CAR(0,1)		1.490**		2.142***
		(0.667)		(0.686)
Adj. R^2	0.49	0.49	0.44	0.45
No. observations	793	793	793	793
Target Firm Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Weekday FE	YES	YES	YES	YES
After Market FE	YES	YES	YES	YES

contains more reactive EDGAR users (*New IPs*) which access EDGAR just before or after the release of a SC 13D filing. *Downloads Pre-Active IPs* are defined as the natural logarithm of one plus the number of downloads of *Pre-Active IPs*. All other IP addresses are labelled as *New IPs* and *Downloads New IPs* are calculated as the natural logarithm of one plus the number of downloads of *New IPs*.

Table 3.7 presents regression estimates from regressions of either the number of downloads by *Pre-Active IPs* (columns (1) & (2)), or downloads by *New IPs* (columns (3) & (4)) on the *Hedge Fund* indicator variable. Control variables are the same as in Table 3.6. Coefficient estimates of *Hedge Funds* are significant and positive in all specifications. About 20% more pre-active IP addresses downloaded the activist filings of hedge funds. The pattern is similar but more distinct for new IP addresses. Filings of hedge fund activists are on average 30% more downloaded than those of other types of activists. This indicates that filings of hedge funds are more important for both types of IP addresses than filings of other activists. As the effect is more distinct for new IP addresses, results emphasize that EDGAR users get more often notified or react more often when hedge funds release a filing.

3.4.3 Monitoring of Activist vs. Target Firm

SC 13D filings are different from earnings announcements or annual and quarterly reports as they can be accessed through the target firms' as well as the activist investors' EDGAR page. This parallel filing provides the opportunity to test whether market participates monitor potential activist investors and target firms differently.

In Table 3.8, *Total Downloads* is split into its two sources. *Total Downloads Target* is the natural logarithm of one plus the number of downloads from target firms' EDGAR page. *Total Downloads Activist* is calculated in the same way but considers only downloads from the activist investors' EDGAR page. Control variables are the same as in the regressions presented in Table 3.6.

Coefficient estimates of *Hedge Fund* show two different patterns. The coefficients are positive and significant in columns (1) and (2). Both columns refer to the download volume from the target firms' EDGAR page. EDGAR users download more filings from the target firms in the case that the activist investor is a hedge fund. The effect is large in economic terms. The download volume from the target firms' page is about 60% higher for hedge funds. The effect is different for downloads from the activist investors' EDGAR page presented in columns (3) and (4). Coefficients of *Hedge Fund* are significantly negative. EDGAR users download filings about 45% less often from hedge funds' EDGAR page compared to other

Table 3.8: Sources of Downloads

This table presents results of the regression of the number of downloads of SC 13D filings on the *Hedge Fund* indicator variable and distinguishes between downloads accessed through the target firms' and activist investors' EDGAR website. *Downloads Target* is calculated as the natural logarithm of one plus the number of downloads of nonrobot IP addresses on the filing day through the target firms' EDGAR site. *Downloads Activist* is calculated as the natural logarithm of one plus the number of downloads of nonrobot IP addresses on the filing day through the activist investors' EDGAR website. Nonrobot IP addresses are classified using the definition of Ryans (2017). Columns (1) and (2) show results on *Downloads Target*. Columns (3) and (4) show results on *Downloads Activist*. Cumulative abnormal returns (CAR) in the (t+0, t+1) event day window are estimated using a three-factor Fama-French model (Fama & French, 1993). Remaining control variables are defined in Appendix 3.13. A constant as well as year FE, weekday FE, and after market FE are included in each regression. All continuous variables are winsorized at the 2.5^{th} and 97.5^{th} percentile. In each column, I report estimated coefficients and their heteroskedasticity-robust t-values (in parentheses). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	Downloads Target		Downloads Activist	
	(1)	(2)	(3)	(4)
Hedge Fund	0.608***	0.601***	-0.446***	-0.453***
	(0.106)	(0.106)	(0.086)	(0.086)
Activist Ownership	-0.121	-0.134	0.023	0.011
	(0.143)	(0.142)	(0.110)	(0.110)
Proxy Fight	0.096	0.090	-0.210*	-0.215*
	(0.169)	(0.170)	(0.120)	(0.120)
Potential Acquisition	0.547	0.496	0.037	-0.010
	(0.346)	(0.346)	(0.239)	(0.239)
Strategic Alternatives	0.193	0.177	-0.159	-0.174
	(0.199)	(0.200)	(0.127)	(0.127)
Sale/Merger/Liquidation	-0.307	-0.316	0.088	0.080
	(0.206)	(0.206)	(0.127)	(0.127)
CAR(0,1)		1.036		0.953
		(0.921)		(0.641)
Adj. R^2	0.33	0.33	0.24	0.24
No. observations	793	793	793	793
Target Firm Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Weekday FE	YES	YES	YES	YES
After Market FE	YES	YES	YES	YES

types of activist investors. These results indicate that EDGAR users search more on the target firms' EDGAR page if the activist investor is a hedge fund. Thus, they seem less interested in other information about the hedge fund which can only be acquired on the EDGAR page of the hedge fund.

The correlation between total downloads from the activist investors' and target firms'

EDGAR pages is negative and equals -0.3. This indicates that downloads occur often either on one of the both websites and rarely on both. Thus, hosting SC 13D filings at the activist investors' and target firms' EDGAR page is beneficial from a market perspective as it supports the dissemination of new information into the market.

3.4.4 Monitoring Intensity of Other Filings

This section extends the previous section and investigates whether EDGAR users monitor target firms more carefully if the activist investor is a hedge fund. The idea is that SC 13D filings which are downloaded together with other filings of the same firm by the same IP address are an indicator of more intense monitoring. Drake et al. (2016) show, for example, that historical 10-K reports can be helpful to evaluate new annual reports by providing detailed historical information.

I construct indicator variables for target firms' 8-K, 10-K, 10-Q, and DEF 14A filings and activist investors' SC 13D filings. These filings contain typically the financially most important information. The indicator variables are equal to one if at least three IP addresses download a SC 13D filing together with one of the previous mentioned filings of the same target firm. I then run probit regressions of each indicator variable on the *Hedge Fund* indicator variable and the same control variables as in the baseline regression presented in Table 3.6. The filing forms are indicated above each column in Table 3.9.

The coefficient of *Hedge Fund* is insignificant on 8-K filings. Although 8-K filings are the form type which is most often downloaded together with SC 13D filings (see Table 3.5), EDGAR users do not download them more often if the activist investor is a hedge fund. Column (2) of Table 3.9 presents a significantly positive coefficient of *Hedge Fund*. EDGAR users are more likely to jointly download the activist investor's filing and an annual report of the target firm if the activist investor is a hedge fund. The average marginal effect is 6.6%. The pattern is similar for quarterly reports presented in column (3) and proxy statements in column (4). However, the effect is lower in statistical and economic terms. Quarterly reports are 5.6% more likely to be downloaded. The results indicate that EDGAR users assess target firms more closely if the activist investor is a hedge fund. They assess target firms' financial circumstances more intensively compared to other types of activist investors. These findings complement the findings from the previous section that EDGAR users typically download filings from the target firms' EDGAR page. These findings are also in line with findings in Drake et al. (2016) that EDGAR users request historical filings to assess the information from new filings. It is reasonable to expect the largest effect for annual reports (10-K filings) as they contain the most comprehensive financial information.

Table 3.9: Monitoring Intensity through Requesting Other Target Filings

This table presents results of the regressions of various indicator variables whether IP addresses downloaded the SC 13D filing together with other target firms' filings on the *Hedge Fund* indicator variable and several control variables. *Downloads Target 8-K*, *Downloads Target 10-K*, *Downloads Target 10-Q*, and *Downloads Target DEF 14A* are indicator variables which equal one if at least three different IP addresses access the SC 13D and the respective other (e.g., 8-K, 10-K) filing. *Total Downloads* are defined as the natural logarithm of one plus the number of downloads from nonrobot IP addresses on the filing day. Cumulative abnormal returns (CAR) in the (t+0, t+1) event day window are estimated using a three-factor Fama-French model (Fama & French, 1993). Remaining control variables are defined in Appendix 3.13. A constant as well as year FE, weekday FE, and after market FE are included in each regression. All continuous variables are winsorized at the 2.5^{th} and 97.5^{th} percentile. In each column, I report estimated coefficients and their heteroskedasticity-robust t-values (in parentheses). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	8-K	10-K	10-Q	DEF 14A	SC 13D
	(1)	(2)	(3)	(4)	(5)
Hedge Fund	0.189	0.546***	0.427**	0.322*	-0.486***
	(0.135)	(0.184)	(0.173)	(0.168)	(0.143)
Average Marginal Effect	[3.9%]	[6.6%]	[5.6%]	[3.9%]	[-3.6%]
Pseudo R^2	0.26	0.37	0.38	0.35	0.24
No. observations	793	793	793	793	793
CAR(0,1)	YES	YES	YES	YES	YES
Target Firm Controls	YES	YES	YES	YES	YES
Activist Investor Controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Weekday FE	YES	YES	YES	YES	YES
After Market FE	YES	YES	YES	YES	YES

Column (5) presents results on the download of other SC 13D filings by the same activist investor. Older SC 13D filings might provide information about the past behavior of the activist investor. In contrast to the results in columns (2) to (4), the probability to download other SC 13D filings is lower for hedge funds. However, this result should be treated with caution. There are only 37 events where EDGAR users also downloaded another SC 13D filing of the same activist investor (see Table 3.5). Thus, it is in general rare that EDGAR users acquire additional information about the activist investor by downloading other activist investor filings at the same time.

3.5 Change in Attention

Hedge funds have certain abilities to impact their target firms' future perspectives as activist investors. First, they typically address potential cash flow problems (e.g., Brav et al., 2008; Klein & Zur, 2009). Second, their targets and strategies are well-chosen as their success rate reaches about 60% (Klein & Zur, 2009). Lastly, their monitoring of firms is distinctively better than that of other investors (Brav et al., 2008). In this regard, this section explores the impact of hedge funds targeting a firm on the future attention of market participants on the target firm. Hirshleifer and Teoh (2003) and Drake et al. (2017) argue that market participants have only limited resources to monitor the market such that they have to focus on those stocks which promise the highest benefit from monitoring. In this sense, attention should decrease after the investment of a hedge fund expecting that hedge funds have the most sophisticated monitoring abilities and the intention to maximize future stock performance. On the other hand, market participants might monitor firms targeted by a hedge fund more closely if they want to acquire information on future actions of the target firm and the activist investor. This is in particular important if target firms have the potential to change the competition within their industry. Market participants would then spend more time to evaluate such target firms. Drake et al. (2017), for example, show that industry shocks enhance public attention and that this effect is especially pronounced in large and visible stocks.

3.5.1 Main Results

To estimate whether the attention to target firms of hedge funds changes in the longer run, I again run cross-sectional regressions which estimate the difference in attention between hedge funds and other types of activist investors. However, I now use dependent variables which measure attention in a longer time window around the activist investors' filing. I calculate two dependent variables similar to the procedure in deHaan et al. (2015). I compare the downloads of certain filing forms prior to and after the release of a SC 13D filing. The pre-period lasts from (t - 120) to (t - 10) days. The post period covers a symmetric time span (t + 10, t + 120) after the release. I exclude the time period (t - 9, t + 9) to avoid downloads directly related to downloads of the respective SC 13D filing. The first type of

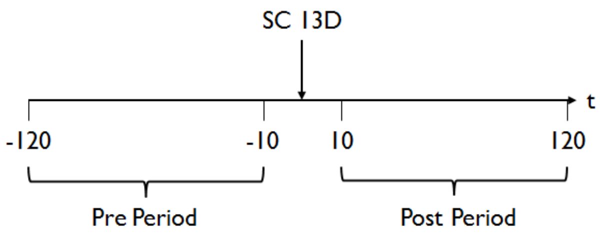

Figure 3.1: This figure shows the time periods which are selected to compare filing requests.

dependent variables compares the change of the download volume of historical filings. This approach is similar to the idea presented in Drake et al. (2016) that historical annual reports are used to gather detailed firm information. Historical filings are older than five days and must be filed in or prior to the pre-period. I calculate the average number of downloads for each filing form (e.g., 8-K, 10-K) in the pre- and post-period and then take the difference between the two periods. This procedure captures the abnormal interest of EDGAR users in historical filings.

$$\text{Abnormal Requests} = \frac{1}{N}\sum_{i=1}^{N}\sum Requests_{i,j,post} - \frac{1}{N}\sum_{r=1}^{N}\sum Requests_{i,j,pre} \tag{3.2}$$

where i refers to a particular activist event and j represents the form of the filing (e.g., 10-K, 8-K). *Pre* and *post* indicate whether the filing was released in the pre-period before or in the post-period after the release date of the respective SC 13D filing. N is the number of different filings of the respective filing form j. I consider 8-K, 10-K, 10-Q, and DEF 14A filings as they contain material financial information about the target firms.

The second type of dependent variables compares the number of downloads in the first five days after a filing is published between the pre-period and the post-period. This variable is based on the procedure described in Drake et al. (2015) which compares the download volume of historical 8-K reports with the download volume of new 8-K filings. It captures whether more EDGAR users are interested in new filings and new information about the target firms (see deHaan et al., 2015). I only consider 8-K filings and 10-Q reports for this variable because they are frequently filed and their occurrence in the pre-period and post-period can be expected for most of the activist events.

I then regress the different measures of *Abnormal Requests* on the *Hedge Fund* indicator variable and the several control variables presented in Equation 3.1. Additionally, I include the average download level of the respective filing in the pre-period to control for the overall activity of EDGAR users in the target firm.

$$\text{Abnormal Requests} = \alpha + \beta_1 \text{ Hedge Fund} + \beta_2 X + \gamma + \theta + \zeta + \epsilon \tag{3.3}$$

Table 3.10 shows results of the regressions of change in attention to target firms on the *Hedge Fund* indicator variable and various control variables. Coefficients of *Hedge Fund* are positive and significant in five out of six regression specifications. EDGAR users thus spend more attention to the different filing types of target firms after a hedge fund has invested into the target firm compared to other types of activist investors. The first column refers to the historical 10-K filings. The coefficient of *Hedge Fund* equals 0.828 and is significant. EDGAR users download historical 10-K filings, on average, 0.83 more often in the (t + 11, t + 120) day period than in the (t - 120, t - 11) day period if the activist investor is a hedge fund. The economic magnitude of this result is large as this is an increase of the download volume by 12.7%. The average download volume of 10-K filings equals 6.63 in the pre-period. Column (2) shows the effect of hedge fund activism on the download volume of quarterly reports (10-Q). The coefficient is 0.306 and significant at the 10% level. On average, download volume increases by 7.6% more after hedge fund activism as mean downloads of 10-Q reports equal 4.03 in the pre-period. Effects of hedge fund activism are similar for 8-K and DEF 14A filings in columns (3) and (4), respectively. In the pre-period, they are downloaded 4.13 and 1.42 times, respectively such that the download volume of 8-K filings increases by 10% more for hedge fund activism. DEF 14A statements are requested 18.8% more often. Column (5) presents coefficient estimates on the second type

Table 3.10: Impact of Hedge Funds on Future Attention

This table presents results of regressions of the change in public attention on the *Hedge Fund* indicator variable and several control variables. *Historical Filings* consider 10-K, 10-Q, 8-K, and DEF 14A filings which were published prior to the release of the respective SC 13D filing and older than five days. I calculate the difference between the average downloads of each filing type prior to and after the release of the respective SC 13D filing. *New Filings* refer to filings published after the release of the respective SC 13D filing. I calculate the difference between the average downloads of each filing type in the first five days after the publication prior to and after the release of the respective SC 13D filing. The time period to calculate all differences lasts from 120 days prior to the entrance of the activist investor to 120 days after. I exclude the 10 days before and after the release of the respective SC 13D filing to avoid confounding search behavior directly related to the activist investor. Remaining control variables are defined in Appendix 3.13. A constant as well as year FE, weekday FE, and after market FE are included in each regression. All continuous variables are winsorized at the 2.5^{th} and 97.5^{th} percentile. In each column, I report estimated coefficients and their heteroskedasticity-robust standard errors (in parentheses). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Historical Filings				New Filings	
	10-K	10-Q	8-K	14A	8-K	10-Q
	(1)	(2)	(3)	(4)	(5)	(6)
Hedge Fund	0.828***	0.316*	0.415**	0.263***	5.165***	4.049
	(0.238)	(0.169)	(0.173)	(0.050)	(1.873)	(4.024)
Activist Ownership	0.465	0.227	0.784***	0.061	5.136**	3.888
	(0.294)	(0.237)	(0.249)	(0.062)	(2.532)	(5.799)
Proxy Fight	0.401	0.316	0.580**	0.197***	-0.150	-5.121
	(0.370)	(0.259)	(0.265)	(0.066)	(2.555)	(6.577)
Potential Acquisition	0.046	-0.233	0.269	0.106	10.991**	-12.397
	(0.653)	(0.408)	(0.448)	(0.128)	(4.591)	(8.074)
Strategic Alternatives	0.488	0.394	0.453	0.022	5.888*	0.824
	(0.479)	(0.317)	(0.321)	(0.093)	(3.381)	(8.125)
Sale/Merger/Liquidation	-0.301	0.014	-0.292	0.010	-0.008	4.622
	(0.454)	(0.290)	(0.289)	(0.087)	(3.161)	(8.000)
Adj. R^2	0.08	0.05	0.10	0.14	0.27	0.04
No. observations	793	793	793	793	748	439
CAR(0,1)	YES	YES	YES	YES	YES	YES
Target Firm Controls	YES	YES	YES	YES	YES	YES
Pre-Download Volume	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Weekday FE	YES	YES	YES	YES	YES	YES
After Market FE	YES	YES	YES	YES	YES	YES

of dependent variable which captures new filings. The coefficient of *Hedge Fund* equals 5.51 and is significant at the 1% level. New 8-K filings attract, on average, 5.5 more EDGAR users than in the time before a hedge fund revealed its investment. In the pre-period, the mean download volume of 8-K filings is 36.38 such that the relative increase of the download volume equals 15.1%. I do not find any significant effect on 10-Q reports.

The results presented above provide evidence that market participants monitor target firms much more closely after a hedge fund has invested into this firm compared to other types of activist investors. This cannot be explained with limited and costly attention (Hirshleifer & Teoh, 2003). In line with the findings in Hirshleifer and Teoh (2003), market participants are expected to reduce monitoring activities on firms controlled by hedge funds as hedge funds are considered to be the most effective monitors (Brav et al., 2008).

3.5.2 Large vs. Small Firms

Drake et al. (2016) show that large and more visible firms are more sensitive to changes in industry attention. Large firms are also more important to replicate benchmark portfolios and have the potential to impact their whole industry. The costs for investors to monitor small firms are much higher compared to large firms as information must be collected and preprocessed first. According to these arguments, there might be differences in the change of market attention between small and large firms after a hedge fund invested into a target firm.

Table 3.11 presents results of the regression of change in attention on the interaction term of the *Hedge Fund* indicator variable and target firms' market capitalization and various control variables. The main variables of interest are *Hedge Fund* and the interaction term of *Hedge Fund* × *Ln(MVE)*. Dependent variables and the remaining control variables are the same as in Table 3.10. The coefficients of *Hedge Fund* turn negative and are significant on historical 10-K reports, 8-K filings, and DEF 14A proxy statements as well as on newly filed 8-K filings. This indicates that market participants download fewer filings if the activist investor is a hedge fund. The effect is large in terms of economic magnitude. The download volume of historical annual reports reduces by 2.1 downloads or 32% considering average downloads of 10-K reports in the pre-period of 6.61. The effects for 8-K and DEF 14A filings equal about 37% and 29%, respectively. New 8-K filings are download 15.1 times less often. On average, new 8-K filings are downloaded 36.9 times on the first day such that the download volume decreases by about 41% after hedge fund activism. However, the interaction term *Hedge Fund* × *Ln(MVE)* is positive and significant. This indicates

Table 3.11: Impact of Hedge Funds on Future Attention of Large Firms

This table presents results of regressions of the change in public attention on the *Hedge Fund* indicator variable, the interaction term, *Hedge Fund* $\times$ *Ln(MVE)*, *Ln(MVE)*, and several control variables. *Historical Filings* consider 10-K, 10-Q, 8-K, and DEF 14A filings which were published prior to the release of the respective SC 13D filing and older than five days. I calculate the difference between the average downloads of each filing type prior to and after the release of the respective SC 13D filing. *New Filings* refer to filings published after the release of the respective SC 13D filing. I calculate the difference between the average downloads of each filing type in the first five days after the publication prior to and after the release of the respective SC 13D filing. The time period to calculate all differences lasts from 120 days prior to the entrance of the activist investor to 120 days after. I exclude the 10 days before and after the release of the respective SC 13D filing to avoid confounding search behavior directly related to the activist investor. Remaining control variables are defined in Appendix 3.13. A constant as well as year FE, weekday FE, and after market FE are included in each regression. All continuous variables are winsorized at the 2.5^{th} and 97.5^{th} percentile. In each column, I report estimated coefficients and their heteroskedasticity-robust standard errors (in parentheses). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Historical Filings				New Filings	
	10-K	10-Q	8-K	14A	8-K	10-Q
	(1)	(2)	(3)	(4)	(5)	(6)
Hedge Fund	-2.057**	-0.537	-1.556**	-0.413**	-15.068**	-10.472
	(0.817)	(0.623)	(0.635)	(0.179)	(6.732)	(15.789)
Hedge Fund x Ln(MVE)	0.498***	0.147	0.339***	0.117***	3.453***	2.510
	(0.155)	(0.119)	(0.117)	(0.033)	(1.232)	(2.718)
Ln(MVE)	-0.021	0.141	0.050	0.044	0.983	4.955
	(0.191)	(0.121)	(0.133)	(0.042)	(1.268)	(3.315)
Activist Ownership	0.524*	0.244	0.821***	0.074	5.634**	4.492
	(0.292)	(0.237)	(0.249)	(0.062)	(2.574)	(5.785)
Proxy Fight	0.355	0.301	0.550**	0.186***	-0.459	-5.292
	(0.365)	(0.258)	(0.260)	(0.065)	(2.550)	(6.541)
Potential Acquisition	-0.096	-0.274	0.172	0.073	9.983**	-12.983
	(0.638)	(0.406)	(0.444)	(0.129)	(4.812)	(8.085)
Strategic Alternatives	0.510	0.401	0.465	0.027	5.992*	1.133
	(0.476)	(0.317)	(0.317)	(0.093)	(3.305)	(8.185)
Sale/Merger/Liquidation	-0.348	0.001	-0.323	-0.001	-0.180	4.301
	(0.446)	(0.289)	(0.285)	(0.086)	(3.103)	(8.055)
Adj. R^2	0.10	0.05	0.11	0.16	0.28	0.04
No. observations	793	793	793	793	748	439
Target Firm Controls	YES	YES	YES	YES	YES	YES
Pre Download Volume	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Weekday FE	YES	YES	YES	YES	YES	YES
After Market FE	YES	YES	YES	YES	YES	YES

that attention increases in firm size. The coefficient of *Hedge Fund* $\times$ *Ln(MVE)* in the first specification on historical 10-K reports equals 0.498. A one standard deviation increase of *Ln(MVE)* increases the download volume of historical 10-K filings by 0.8. For historical 8-K and DEF 14A filings, the coefficients equal 0.339 and 0.117, respectively. A one standard deviation change increases the average filing requests by 0.55 and 0.19, respectively. The effect is much larger for new 8-K filings. A one standard deviation increase raises the number of requests by 5.56.[10]

These results show that market participants alter their monitoring differently after the entrance of hedge funds. They turn away their monitoring activities from small firms which are typically expensive to monitor. One the other hand, they intensify their monitoring in larger firms which play a more dominant role in the market. Such behavior may reflect a rational cost-benefit analysis as larger firms potentially affect other firms in the market and market participants can profit from more intensive monitoring.

3.6 Robustness Checks

This section presents robustness checks that address concerns that my results are affected by the classification procedure used to identify IP addresses that belong to robots. Specifically, I first check whether the effect on *Total Downloads* in Table 3.6 is affected by the procedure to classify IP addresses as robots. I use three different robot classification algorithms presented in Drake et al. (2015), Loughran and McDonald (2017), and Lee et al. (2015) to re-estimate the impact of hedge fund activism on total downloads. Second, I use the same three classification algorithms and re-estimate the change in attention presented in Tables 3.10 and 3.11. For the sake of brevity, I present all regression tables of the robustness checks in the Appendix.

Appendix 3.14 presents results on *Total Downloads*. Column (1) refers to the baseline result using the classification procedure in Ryans (2017). Column (2) presents the coefficient of *Hedge Fund* using the procedure in Loughran and McDonald (2017). The coefficient equals 0.248 and is similar to the baseline result in column (1). Columns (3) and (4) support the previous results. They employ the classification procedure from Lee et al. (2015) and Drake et al. (2015), respectively. Coefficient estimates are again significant and close to the

[10] The effect on new 8-K filings cannot be explained by events with no new 8-K filings in the pre-period. Re-estimating the regressions including observations with average downloads of at least 5 or 10 in the pre-period yields similar results.

baseline results.

Results presented in Tables 3.10 and 3.11 might also be sensitive to the classification of robots. I again re-estimate regressions presented in Table 3.10 and use the classification procedures presented in Drake et al. (2015), Lee et al. (2015), and Loughran and McDonald (2017) instead of the one in Ryans (2017). Appendix 3.15 shows coefficient estimates of the main explanatory variable *Hedge Fund*. Results are similar to those presented in Table 3.10. On average, target firms of hedge funds experience higher attention on both historical filings and new 8-K filings. Only the coefficient of *Hedge Fund* on historical 10-Q filings is not significant anymore for the classification used in Lee et al. (2015). However, this coefficient is the least significant coefficient in the baseline model (see Column (2) of Table 3.10). Appendix 3.16 shows results from re-estimating the regressions presented in Table 3.11. Again, I use the classification procedures presented in Drake et al. (2015), Lee et al. (2015), and Loughran and McDonald (2017). Results support the baseline coefficient estimates in Table 3.11. Coefficients of *Hedge Fund* are consistently negative and significant as in Table 3.11. Coefficients of the interaction term *Hedge Fund* $\times$ *Ln(MVE)* are positive and significant. Hence, the results indicate that the change in attention is robust to the different classification procedures presented in the literature.

3.7 Conclusion

In this paper, I show that activist filings from hedge funds are downloaded more often from EDGAR than similar filings from other types of activist investors. Market participants also explore more other target firms' filings containing financially valuable information if the activist investor is a hedge fund. Similar results are found for the source of downloads. Most downloads occur on the target firms' EDGAR page and the effect is much stronger for hedge fund activists. However, the correlation between downloads from the target firms' and activist investors' EDGAR page is highly negative indicating that there are two distinct patterns how to monitor activist filings. Information on activism of other types than hedge funds disseminates more often through downloads from the activist investors' EDGAR page. Thus, hosting activist filings on the EDGAR pages of both parties is beneficial in terms of information efficiency.

In line with findings in Brav et al. (2008) who find that hedge funds have distinct monitoring abilities, I find heterogeneous effects in future attention to target firms. Attention depends on the size of target firms. Small firms experience less attention if the activist investor is a hedge fund compared to other types of activist investors. This pattern is reasonable since other market participants are expected to have less sophisticated monitoring abilities than hedge funds and the monitoring costs of small firms are high. Thus, information free riding is present in small firms. On the other hand, I find that attention increases in firm size indicating that market participants monitor future actions of the activist investor more carefully. Such actions might be more relevant for competitors and the market than actions of small firms.

3.8 Appendix B: Variable Definition

Appendix 3.12: Definition of Dependent Variables

This table presents definitions of log data variables employed in the empirical analyses. They are based on human-readable and successful requests on the SEC's EDGAR system.

Variable	**Definition**
Total Downloads	Natural logarithm of one plus the number of nonrobot requests
Downloads Target	Natural logarithm of one plus the number of nonrobot requests on the target firms' EDGAR site
Downloads Activist	Natural logarithm of one plus the number of nonrobot requests on the activist investors' EDGAR site
Downloads Pre-Active IPs	Natural logarithm of one plus the number of nonrobot requests of IP addresses which were active at EDGAR at least 10 minutes before the SC 13D filing was released
Downloads New IPs	Natural logarithm of one plus the number of nonrobot requests of IP addresses which are not *Pre-Active IPs*
Downloads Target 8-K	Indicator variable which equals one if at least three IP addresses accessed both the respective SC 13D filing AND a target firm's 8-K filing and zero otherwise
Downloads Target 10-K	Indicator variable which equals one if at least three IP addresses accessed both the respective SC 13D filing AND a target firm's 10-K filing and zero otherwise
Downloads Target 10-Q	Indicator variable which equals one if at least three IP addresses accessed both the respective SC 13D filing AND a target firm's 10-Q filing and zero otherwise
Downloads Target DEF 14A	Indicator variable which equals one if at least three IP addresses accessed both the respective SC 13D filing AND a target firm's DEF 14A filing and zero otherwise
Downloads Activist SC 13D	Indicator variable which equals one if at least three IP addresses accessed both the respective SC 13D filing AND another activist investor's SC 13D filing and zero otherwise

Appendix 3.13: Definition of Control Variables

This table presents definitions of variables employed in the empirical analyses. *COMPQ* and *COMPA* refers Compustat's quarterly and annual reports, respectively. *SHORTINT* stands for Compustat's short interest data. *SharkRep* refers to Shark Repellent. [1], [2], [3], [4], [5], and [6] refer to *COMPQ*, *COMPA*, *SHORTINT*, *I/B/E/S*, and *SharkRep*, respectively.

Target Firm Controls	Log(MVE)	[1] $\ln(prccq \times cshoq)$	Lee et al. (2015)
	Enterprise value-to-sales ratio	[1] $\ln(prccq \times cshoq + dlttq)/saleq$	Lee et al. (2015)
	Leverage	[1] $dlttq/seqq$	Lee et al. (2015)
	Return on net operating assets	[1] $oiadpq/\big(ppentq + actq - lctq\big)$	Lee et al. (2015)
	R&D (Dummy)	[1] xrdq ≥ 0	Lee et al. (2015)
	Cash holdings	[1] $\ln(cheq/atq)$	Klein and Zur (2009)
	Age	[2] $\ln\big(\text{Days in Compustat}\big)$	Drake et al. (2016)
	Dividends (Dummy)	[2] dvpsx_f ≥ 0	Klein and Zur (2011)
	One year Abnormal Return	[3] $\prod ret - \prod vwretd$	Klein and Zur (2011)
	Short Interest	[4] $\ln\big(shortint/cshoq\big)$	Drake et al. (2015)
	Analysts	[5] $\ln\big(1 + \text{Analysts}\big)$	Drake et al. (2016)
Deal Controls	Initial Stake	[6] $\ln\big(\text{\% of shares bought}\big)$	Denes et al. (2017)
	Hedge Fund	[6] Indicator variable	Denes et al. (2017)
	Proxy Fight	[6] Indicator variable	Denes et al. (2017)
	Prior Poison Pill	[6] Indicator variable	Bizjak and Marquette (1998)
	Acquisition	[6] Indicator variable	Brav et al. (2008)
	Alternative Strategy	[6] Indicator variable	Brav et al. (2008)
	Sale/Merger	[6] Indicator variable	Brav et al. (2008)

3.9 Appendix C: Tables of Robustness Checks

Appendix 3.14: Robustness: Impact of Hedge Fund Activism on EDGAR Attention using Different Procedures to Classify Robots

This table presents results of the regression of the number of downloads of SC 13D filings, *Total Downloads*, on the *Hedge Fund* indicator variable and several control variables. *Total Downloads* are defined as the natural logarithm of one plus the number of downloads of nonrobot IP addresses on the filing day. *Ryan* refers to the robot classification procedure in Ryans (2017). *LM* (Loughran/McDonald), *LMW* (Lee/Ma/Wang), *DRT* (Drake/Roulstone/Thornock) stand for the classification schemes presented in Loughran and McDonald (2017), Lee et al. (2015), and Drake et al. (2015), respectively. Cumulative abnormal returns (CAR) in the (t+0, t+1) event day window are estimated using a three-factor Fama-French model (Fama & French, 1993). Remaining control variables are defined in Appendix 3.13. A constant as well as year FE, weekday FE, and after market FE are included in each regression. All continuous variables are winsorized at the 2.5th and 97.5th percentile. In each column, I report estimated coefficients and their heteroskedasticity-robust standard errors (in parentheses). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	Ryan	LM	LMW	DRT
	(1)	(2)	(3)	(4)
Hedge Fund	0.232**	0.248***	0.252***	0.213**
	(0.094)	(0.086)	(0.090)	(0.096)
Adj. R^2	0.44	0.47	0.45	0.44
No. observations	793	793	793	793
Deal Characteristics	YES	YES	YES	YES
Activist Investor Controls	YES	YES	YES	YES
Target Firm Controls	YES	YES	YES	YES
CAR(0,1)	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Weekday FE	YES	YES	YES	YES
After Market FE	YES	YES	YES	YES

Appendix 3.15: Robustness: Impact of Hedge Funds on Future Attention

This table presents results of regressions of the change in public attention on the *Hedge Fund* indicator variable and several control variables. *Lee/Ma/Wang*, *Loughran/McDonald*, and *Drake/Roulstone/Thornock* refer to the respective algorithm to determine IP addresses as robots. *Historical Filings* consider 10-K, 10-Q, 8-K, and DEF 14A filings which were published prior to the release of the respective SC 13D filing and older than five days. I calculate the difference between the average downloads of each filing type prior to and after the release of the respective SC 13D filing. *New Filings* refer to filings published after the release of the respective SC 13D filing. I calculate the difference between the average downloads of each filing type in the first five days after the publication prior to and after the release of the respective SC 13D filing. The time period to calculate all differences lasts from 120 days prior to the entrance of the activist investor to 120 days after. I exclude the 10 days before and after the release of the respective SC 13D filing to avoid confounding search behavior directly related to the activist investor. Remaining control variables are defined in Appendix 3.13. A constant as well as year FE, weekday FE, and after market FE are included in each regression. All continuous variables are winsorized at the 2.5^{th} and 97.5^{th} percentile. In each column, I report estimated coefficients and their heteroskedasticity-robust standard errors (in parentheses). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Historical Filings				New Filings	
Type: Lee/Ma/Wang	10-K	10-Q	8-K	14A	8-K	10-Q
Hedge Fund	0.579***	0.155	0.259**	0.177***	4.708***	5.767
	(0.190)	(0.129)	(0.120)	(0.035)	(1.457)	(3.676)
Adj. R^2	0.07	0.03	0.09	0.12	0.24	0.06
Type: Loughran/McDonald	10-K	10-Q	8-K	14A	8-K	10-Q
Hedge Fund	0.353***	0.153**	0.160**	0.133***	3.913***	2.529
	(0.100)	(0.068)	(0.076)	(0.024)	(1.091)	(1.649)
Adj. R^2	0.13	0.03	0.10	0.11	0.24	0.06
Type: Drake/Roulstone/Thornock	10-K	10-Q	8-K	14A	8-K	10-Q
Hedge Fund	0.881***	0.324*	0.485**	0.292***	4.628**	1.386
	(0.252)	(0.195)	(0.203)	(0.056)	(2.128)	(4.627)
Adj. R^2	0.08	0.07	0.11	0.15	0.28	0.06
No. observations	793	793	793	793	748	439
Deal Characteristics	YES	YES	YES	YES	YES	YES
Activist Investor Controls	YES	YES	YES	YES	YES	YES
Target Firm Controls	YES	YES	YES	YES	YES	YES
CAR(0,1)	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Weekday FE	YES	YES	YES	YES	YES	YES
After Market FE	YES	YES	YES	YES	YES	YES

Appendix 3.16: Robustness: Impact of Hedge Funds on Future Attention of Large Firms

This table presents results of regressions of the change in public attention on the *Hedge Fund* indicator variable, the interaction term, *Hedge Fund* × *Ln(MVE)*, *Ln(MVE)*, and several control variables. *Lee/Ma/Wang*, *Loughran/McDonald*, and *Drake/Roulstone/Thornock* refer to the respective algorithm to determine IP addresses as robots. The definition of the dependent variables is the same as in Appendix 3.15. Remaining control variables are defined in Appendix 3.13. A constant as well as year FE, weekday FE, and after market FE are included in each regression. All continuous variables are winsorized at the 2.5^{th} and 97.5^{th} percentile. In each column, I report estimated coefficients and their heteroskedasticity-robust standard errors (in parentheses). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Historical Filings				New
Lee/Ma/Wang	10-K	10-Q	8-K	14A	8-K
Hedge Fund	-1.341*	-0.296	-1.085**	-0.260**	-12.277**
	(0.692)	(0.481)	(0.435)	(0.124)	(5.330)
Hedge Fund×Ln(MVE)	0.331**	0.078	0.231***	0.075***	2.897***
	(0.132)	(0.093)	(0.081)	(0.023)	(0.978)
Adj. R^2	0.08	0.03	0.10	0.13	0.25
Loughran/McDonald	10-K	10-Q	8-K	14A	8-K
Hedge Fund	-1.057***	-0.228	-0.567**	-0.223***	-9.189**
	(0.353)	(0.248)	(0.281)	(0.086)	(3.950)
Hedge Fund×Ln(MVE)	0.243***	0.066	0.125**	0.061***	2.234***
	(0.066)	(0.046)	(0.053)	(0.016)	(0.713)
Adj. R^2	0.14	0.03	0.10	0.13	0.25
Drake/Roulstone/Thornock	10-K	10-Q	8-K	14A	8-K
Hedge Fund	-1.977**	-0.401	-1.899**	-0.434**	-18.297**
	(0.893)	(0.737)	(0.757)	(0.201)	(7.711)
Hedge Fund×Ln(MVE)	0.493***	0.125	0.411***	0.125***	3.913***
	(0.168)	(0.139)	(0.140)	(0.037)	(1.404)
Adj. R^2	0.10	0.07	0.12	0.16	0.28
No. observations	793	793	793	793	748
Deal Characteristics	YES	YES	YES	YES	YES
Activist Investor Controls	YES	YES	YES	YES	YES
Target Firm Controls	YES	YES	YES	YES	YES
CAR(0,1)	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Weekday FE	YES	YES	YES	YES	YES
After Market FE	YES	YES	YES	YES	YES

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