Governance under the Gun: Spillover Effects of Hedge Fund Activism[◆]

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ABSTRACT

Hedge fund activism is a potent governance device associated with substantial improvements in the performance and governance of targets. In this paper, we investigate whether the managers of peer firms view activism activity in their industry as a threat that motivates them to undertake real policy changes to fend off activists. We find that peers with fundamentals similar to those of previous targets reduce agency costs and improve operating performance along the same dimensions as actual targets in the same industry. These effects are distinct from those of product market competition or time-varying industry conditions. We show that the peers' positive policy responses are anticipated by the market and reflected in valuations. Finally, we demonstrate that these policy and valuation improvements lower the peers' ex-post probability of being targeted, suggesting that this "do-it-yourself" activism is indeed effective. Taken together, our results imply that shareholder activism, as a monitoring mechanism, reaches beyond the target firms.

Keywords: Shareholder activism, Corporate governance, Hedge funds, Institutional investors

JEL classification: G12, G23, G32, G34

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1. Introduction

Hedge fund activism is an important governance mechanism consistently associated with marked improvements in the performance and governance of target firms (see Brav, Jiang, Partnoy, and Thomas, 2008; Becht, Franks, Mayer, and Rossi, 2008; Brav, Jiang, and Kim, 2013).[1] These positive effects often come at the expense of managers and directors who see a sizeable reduction in compensation and a higher likelihood of being replaced.[2] More importantly, a recent *New York Times* article suggests that shareholder activism has replaced hostile takeovers as the major disciplining force in the market for corporate control: "Today, hostile deals are on the wane, but a new threat has emerged that has put boardrooms on edge: activist investors."[3]

Unlike hostile takeovers, however, the *threat of activism* is more potent and difficult to defend against. Chris Young, head of contested situations at Credit Suisse, says, "There are no longer structural defenses. […] there is no moat to build around your company anymore."[4] As a result, executives of yet-to-be-targeted firms are taking a more proactive approach and hiring advisors to help in evaluating potential vulnerabilities such as "whether the company's stock is trading at a discount to its peers, whether it has excess cash on the balance sheet"[5], etc. Such advisors include both big-league investment banks such as Deutsche Bank AG, Barclays Plc., Goldman Sachs Group Inc., Morgan Stanley, and JPMorgan Chase & Co. as well as smaller firms such as Moelis & Co., Evercore Partners Inc., and Lazard Ltd.[6] Potential targets are advised to monitor activism at their peer firms, "with a view toward minimizing vulnerabilities to attacks by activist hedge funds."[7]

Anecdotes suggest that this "activist fire drill" approach leads to real policy changes such as "spinning off divisions or instituting return of capital programs to quell dissent before it begins."[8] The *New York Times* article gives the example of EMC, a leading data storage provider, which started paying a dividend in part to detract activist attention from its large cash balance. These anecdotes also indicate that managers see activism at their peer firms as a sign of threat and proactively seek to institute policy changes that may help prevent future attacks by activists.

[1] Recent academic work has shown that among activist investors, hedge funds achieve better success as monitors than
[2] Brav et al. (2008) show that CEO pay drops by $1 million and CEO turnover goes up by 10% in the year following an activist intervention. In the context of proxy contests (not necessarily initiated by hedge fund activists), Fos and Tsoutsoura (2014) show that board members who lose seats in proxy contests tend to also lose seats on other boards.
[3] See "Boardrooms Rethink Tactics to Defang Activist Investors", *The New York Times*, November 11, 2013.
[4] Ibid.
[5] Ibid.
[6] See "Bankers Pitching Avoidance Advice as Activists Amass Record Cash", *Bloomberg*, January 6, 2014.
[7] See "Key Issues for Directors in 2014" by Martin Lipton of Wachtell, Lipton Rosen and Katz, *The Harvard Law School Forum on Corporate Governance and Financial Regulation*, December 16, 2013.
[8] See "Boardrooms Rethink Tactics to Defang Activist Investors", *The New York Times*, November 11, 2013.

In this paper, we provide large-scale evidence in support of this “do-it-yourself” activism. We use the full panel of U.S. firms between 2000 and 2011 to investigate the role of activism threat in prompting policy changes at the peers of activist targets and examine whether such proactive responses are effective at fending off activists. Our study complements previous work in hedge fund activism, which has focused mainly on examining changes in corporate policies at actual targets. In their survey of the literature, Brav, Jiang, and Kim (2010) show that typical changes at targets include increases in payout and leverage, and decreases in capital expenditures, consistent with lower agency costs, as well as improvements in return on assets and asset utilization. We offer novel evidence that similar policy improvements also spill over to yet-to-be-targeted but threatened peers, thereby shedding new light on hedge fund activism as a governance device. Absent these spillovers, the extant literature does not fully capture the impact of activism.

Our main findings can be summarized as follows. First, we show that peers with fundamentals similar to those of previous targets feel threatened by recent activism activity in their industry and respond by reducing agency costs and improving operating performance in the same way as the targets. Second, we find that these positive policy changes are anticipated by the market and reflected in the threatened peers’ valuations. Third, these policy and valuation improvements reduce the peers’ ex-post probability of being targeted, indicating that the proactive approach they take is indeed effective.

We use the industry dimension to define peer firms and classify an industry as threatened if its target frequency (that is, the number of activist campaigns divided by the total number of firms in the industry) exceeds the sample mean for the first time in the preceding three years or has experienced two consecutive increases over that period. This definition captures the salience of activism activity in an industry. The first outburst and persistent uptrend in activism are also easily ascertainable by the managers and directors of yet-to-be-targeted firms.

Identifying the impact of activism threat from other confounding factors is difficult. Even in the absence of threat, peer firms may change their policies in response to product market competition or time-varying industry conditions. For example, peer firms may need to adjust their policies to react to the improved competitive position of activist targets and avoid a deterioration in performance (Aslan and Kumar, 2013). To isolate the effects of threat, we use a difference-in-differences design. We start by estimating a baseline target probability model that combines the influence of different firm fundamentals on activist targeting, and then compare the response to activism threat between peers with high baseline target probability (that is, firms with characteristics similar to those of previous targets) and peers with low target probability. As long as the effects of product market competition are not positively correlated with activism threat, the differential improvements in corporate policies that we identify must occur through the threat channel.

In order to capture the multidimensional nature of hedge fund activism, we condition the threat for a given policy on whether the majority of targets in an industry change this policy in the direction of less agency or better performance. Such consistency in the targets' policy responses may indicate that activists have identified a common problem in the industry and offered a common prescription for dealing with it. This common prescription may vary by industry, inducing peers in different industries to respond to the threat of activism in different ways (Brav, Jiang and Kim, 2013).

We demonstrate that consistent with the postulated proactive approach, peer firms in threatened industries change their policies in the same way as actual targets. These changes are in the direction of reducing agency costs and improving operating performance. For example, peers in threatened industries, in which most activist targets increase leverage, also increase leverage. Similarly, on an industry-by-industry basis, threatened peers also follow targets by increasing shareholder payout and decreasing capital expenditures, in line with the general predictions of agency theory. In terms of operating performance, we find that threatened peers improve their return on assets, return on sales and asset utilization.

Our empirical design isolates the impact of activism threat from that of changing industry conditions that have a common effect on all firms in the industry. However, we recognize that industry conditions may have a differential impact on firms with different initial levels of corporate policies and performance. For example, firms with lower leverage will have better ability/greater need to increase leverage, in line with changing industry trends (that may affect both activist targets and peers). Aslan and Kumar (2013) demonstrate that firms with more slack, such as lower leverage and more cash, are also better able to respond to changes in the competitive environment while peers with less slack experience lower profitability and cash flows. We control for a firm's flexibility in changing its policies and find that the effect of activism threat is not driven by firms with more slack.

Next, we investigate the market returns of peer firms around the time of activism threat. We find evidence that the market anticipates the disciplining effect of either activism threat or activism itself. In the quarter in which the signs of threat becomes apparent, peer firms with high baseline target probability (likely targets) experience 0.6% higher monthly abnormal returns compared to their low probability counterparts (unlikely targets). These abnormal returns are about a third in magnitude of those observed in actual targets.

Finally, we confirm that firms that proactively correct potential vulnerabilities are less likely to be targeted in the future, indicating that the "activist fire drill" approach advocated by investment bankers and corporate lawyers is effective. Our results show that the impact of activism threat on the probability of becoming a target is indeed weaker ex-post for peers that (a) improve more or (b) experience a larger increase in valuation, suggesting the presence of a feedback effect. Peer firms that are most vulnerable to activism are most likely to improve, and due to these improvements, we do not observe ex-post that these firms are most likely to be targeted. Thus, the positive financial, investment, and operating policy changes that we document above seem to alleviate the need for activist monitoring or raise market valuations, making it more costly for an activist to enter.

We make two important contributions to the literature. First, we contribute to the broad corporate governance literature by providing evidence of a new disciplining force in the marketplace – the threat of activism. Previous work has focused mainly on the threat of control contests (Servaes and Tamayo, 2013; Song and Walkling, 2000). However, Zhu (2013) presents evidence of substantial time variability in the threat effect of takeovers. A recent *New York Times* article makes a similar argument: "The hostile takeover is on life support, if it's not dead altogether. […] The real concern from the decline of a hostile takeover is that its disciplining effect will disappear. […] But unlike hostile takeovers, there is a real fear on Wall Street of activists."[9]

Second, our results demonstrate positive real externalities of hedge fund activism, establishing that the impact of activism reaches beyond the firms being targeted and may have been underestimated in previous studies (Brav et al., 2008, among others.) These externalities have been an important but missing ingredient in the hotly contested debate on whether hedge fund activism is good or bad for the economy.[10] We show that managers rationally respond to the threat of activism by reducing agency costs and improving operating performance. This proactive mentality advocated by bankers and lawyers has positive real effects, which lower the need for activist monitoring and therefore the ex-post probability of being targeted. Our results complement the findings of Fos (2013) who studies the disciplining role of future proxy contests and Zhu (2013) who compares the preventive effects of activism and takeovers. Unlike these authors, we define threat at the industry dimensions and establish a direct industry-by-industry link between the changes advocated by activists at target firms and the preemptive policy changes implemented by their peers.

The rest of the paper proceeds as follows. Section 2 provides a review of the literature and formulates specific hypotheses for our analysis. Section 3 describes the hedge fund activist sample and motivates our definition of activism threat. Section 4 investigates the role of activism threat in prompting real policy changes at the peers of targeted firms. We also study whether such proactive responses are effective in preventing future attacks by activists. Section 5 examines whether the market anticipates the disciplining effect of activism threat. Section 6 explores the long-term implications of our results and Section 7 concludes.

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[9] See "With Fewer Barbarians at the Gate, Companies Face a New Pressure", *The New York Times*, July 30, 2013.
[10] For example, see "Don't Run Away from the Evidence: A Reply to Wachtell Lipton" by Lucian Bebchuk, Alon Brav, and Wei Jiang, *The Harvard Law School Forum on Corporate Governance and Financial Regulation*, September 17, 2013.

2. Literature review and hypotheses development

In this paper, we empirically investigate the role of activism threat in motivating real policy changes at peer firms. We hypothesize that peers will preemptively improve performance and reduce agency costs along the same dimensions as actual targets. Our goal is to provide evidence of these spillover effects and ultimately contribute to a better understanding of shareholder activism as a governance mechanism. We will also examine whether such proactive responses are effective in preventing future attacks by dissident shareholders.

Previous work has studied the disciplining effects of threat in the contexts of proxy solicitations and takeovers. Fos (2013) demonstrates that the threat of a proxy contest induces real changes in firm policies. In the takeover market, Song and Walkling (2000) show that merger rivals experience high abnormal returns and that these returns are positively correlated with firm fundamentals that determine takeover probability. Servaes and Tamayo (2013) find that industry peers respond to control threats by changing certain firm policies.

Our study complements this literature by examining spillovers resulting from the threat of activism. The anecdotal evidence presented in the introduction suggests that past activist events pose a potent threat to other firms in the industry. This threat is plausible as the positive changes at activist targets often come at the expense of managers and directors. For example, Brav et al. (2008) show that "hedge fund activism is not kind to CEOs of target firms" (p. 1732). CEO pay drops by about $1 million and CEO turnover increases by 10% in the year following an intervention. Managers of yet-to-be-targeted rivals rationally expect an increase in the probability that their firms will be targeted and that they may be fired. As a result, the threat of becoming the next activist target prompts them to undertake some positive changes to fend off activists.

We define peer firms naturally as companies that operate in the same industry as a previous target of hedge fund activism. This industry dimension to the threat channel is supported by the theoretical literature. For example, Jensen (1986) and Shleifer and Vishny (1988) show that the free-cash flow problem is an industry, rather than a firm, characteristic. Raff (2011) argues that knowledge spillovers could benefit the monitoring activities of pension funds and hedge funds intervening in multiple firms with common industry conditions. Finally, activism threat can induce policy changes only if the managers of peer firms perceive the threat in the first place. Benchmarking against industry peers is a common practice in setting manager compensation, measuring performance, etc.

Our definition of activism threat is intended to capture the salience of activism activity in an industry and be easily ascertainable by the managers and directors of yet-to-be-targeted firms. Consequently, we refrain from using model-based definitions. Instead, we consider an industry as threatened if its target frequency (i.e., the number of activist campaigns divided by the total number of firms in the industry) exceeds a certain threshold for the first time (over a number of years) or has recently accelerated. We recognize that this definition is not without problems but it captures both the initial outburst and following trend in an industry's activism and works well across industries. Our underlying assumption is that policy changes are costly and peers will only make changes if they perceive industry activism as sufficiently threatening.

We recognize that identifying the impact of activism threat is difficult and therefore formulate explicit hypotheses here to aid in isolating the threat channel from other confounding factors. Specifically, peer firms may change their policies (even in the absence of activism threat) if they respond to product market competition or time-varying industry conditions. First, positive improvements of target firms are likely to induce an intra-industry response from rivals through their competition for resources, talent or consumer demand.[11] Theoretically, Acharya and Volpin (2010) and Dicks (2012) model positive governance externalities due to competition for scarce managerial talent. Empirically, Aslan and Kumar (2013) use business segment data to show that peers of activist targets experience negative abnormal returns as well as lower profitability and cash flows.[12] Second, Mitchell and Mulherin (1996) relate clustering of acquisition activity within industries to common industry shocks and Harford (2005) shows that merger waves result from industry-level shocks, especially in liquid markets. Dong, Hirschleifer, Richardson, and Teoh (2006) establish a relationship between valuation multiples and takeover probabilities.

We identify the effects of activism threat from those of product market competition and time-varying industry conditions by using the cross-section of threatened peers. In particular, we expect that the threat channel will affect more strongly rivals whose fundamentals are similar to those of previous targets. We capture the combined influence of firm characteristics on the targeting decision using a baseline target propensity model and compare changes in corporate policies between firms with high and low target propensities (that is, likely and unlikely targets), competing in the same product market and subject to the same industry conditions. This allows us to examine the differential effect of threat among firms with high and low probability of becoming a target in the same threatened industry.

Based on the above difference-in-differences design, we formulate the following three hypotheses:

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[11] A long theoretical literature relates competition to agency costs - Hart (1983), Holmstrom (1982), Nalebuff and Stiglitz (1983), Schmidt (1997), Allen and Gale (2000), Raith (2003). Empirically, Giroud and Mueller (2011) and Brav, Jiang, and Kim (2013) examine the interaction between product market competition and shareholder activism.

[12] Mietzner, Schweizer, and Tyrell (2011) also explore the competition hypothesis among rivals of German targets.

H1: Peer firms respond to the threat of activism by improving performance and reducing agency costs. Within the same industry, these changes will be positively related to firm characteristics affecting target choice.

The preemptive policy changes at peers should be similar to those observed at actual targets. Previous work has shown that target firms reduce non-value maximizing behavior – increase leverage and shareholder payout, and decrease capital expenditures. These findings are supported by the theoretical literature on agency costs which argues that high leverage and payout limit a firm's ability to engage in value destroying activities (see Grossman and Hart, 1982; Easterbrook, 1984; Jensen, 1986; and Lambrecht and Myers, 2007). Empirically, Brav, Jiang, and Kim (2010) show that targets increase payout, CEO turnover, and pay-performance sensitivity. Both Clifford (2008) and Klein and Zur (2009) document increases in leverage and dividend yield, which they interpret as evidence of lower agency costs.

The literature also finds improvements in the operating performance of targets. Brav, Jiang, and Kim (2013) demonstrate that targets raise output, asset utilization, and productivity. Clifford (2008) also finds a statistically significant improvement in industry-adjusted return on assets, which he attributes to better asset utilization. Aslan and Kumar (2013) show that hedge fund activism leads to substantial increases in the market shares and cost markups of target firms. We explore all of these dimensions at threatened industry peers in a way that tightly links the peers' policy changes to the common changes experienced by the targets in the same industry.

We expect that the presence of spillovers from hedge fund activism will also be detectable in the market returns of peer firms. The share price response to the threat of activism should be positive due to the market's anticipation that peers will improve their policies and operations in response to the announcement of activism at target firms, or because of a higher likelihood that the peers which do not improve will become future activist targets.

H2: The threat of being targeted results in a positive share price response of industry peers. Within the same threatened industry, firms with characteristics shown to affect targeting experience a stronger market response.

This hypothesis is supported by the literature on hedge fund activism, which shows that activists generate significant abnormal returns in their targets, both in absolute terms and in comparison to non-activist investing. Brav et al. (2008) report that the average hedge fund activist in 2001-2006 earned 14% higher return than the size-adjusted value-weighted portfolio of stocks. Clifford (2008) shows that activist hedge funds in 1998-2005 generated 22% higher annualized returns on their activist holdings than on their passive investments. Boyson and Mooradian (2011) compare aggressive activist and non-activist hedge funds and find similar results.

A similar positive market reaction could be observed when the activist's monitoring of a target firm reveals to its peers new information about common industry conditions – *monitoring spillover hypothesis* (Raff, 2011). Under this alternative, any changes in firm policies at peer firms could be attributed to learning from the activist's monitoring rather than to the threat of becoming a future target. We will attempt to differentiate the threat channel from the monitoring spillover hypothesis, as well as other confounding explanations, by comparing the price responses of rivals with low and high probabilities of being targeted (based on characteristics common among target firms). Since these other hypotheses do not rely on the threat of activism, their effects should not differ significantly between peers with high and low propensities of becoming a target.

Another important implication of the threat channel is that firms facing high levels of threat would respond by instituting value-enhancing changes, which in turn will reduce the effects of the threat on their likelihood of being targeted. This *feedback effect* could result from two sources: (1) The improvements at peer firms may alleviate or eliminate the problems which would have required the involvement of an activist, and/or (2) these changes would push up the peer firms' market values, which would make it more costly for an activist to initiate a campaign. It is important to note that if the feedback effect is complete, then we should not observe the presence of threat at all; managers will act to completely eliminate the need for an activist intervention. In reality, due to institutional and market frictions, it is reasonable to expect that the feedback effect will only be partial.

H3: Improvements in firm policies or the market's anticipation of such improvements reduce a firm's probability of being targeted.

This feedback effect has been shown both theoretically and empirically in different contexts. In a survey of the literature, Bond, Edmans, and Goldstein (2012) argue that the informational role of (secondary) market prices has a feedback effect on the actions of decision makers. In the context of blockholder models, Edmans (2009) shows that a blockholder increases price informativeness by trading on private information, which affects the manager's incentives to improve long-term investment. Edmans and Manso (2011) show that a multiple blockholder structure is optimal when governing through exit because competitive blockholders' trading increases price informativeness.[13] In both papers, the threat of exit disciplines managers whose rational actions in turn eliminate the blockholders' need to carry through with the threat.

Empirically, Edmans, Goldstein, and Jiang (2012) show that the anticipation of a takeover attenuates the relationship between a target's valuation and its probability of being acquired. They also suggest that the market's anticipation of a takeover or an activist engagement raises prices, which in turn deters the intervention. Bradley, Brav, Goldstein, and Jiang (2012) examine the

[13] On the other hand, Maug (1998) and Kahn and Winton (1998) show that low price efficiency facilitates blockholder formation and increases the likelihood of activist monitoring.

feedback loop between the discounts of closed-end mutual funds and open-ending attempts by arbitrageurs. They find evidence of a reduction in discounts not only through direct targeting but also through an indirect 'anticipatory' channel which forces fund managers to take actions that lower the discount.

The above three hypotheses summarize the expected spillover effects resulting from the threat of activism. Threatened firms with fundamentals similar to those of previous targets will change their policies in order to minimize the probability of being targeted, which will raise their valuations and reduce their ex-post probability of becoming targets.

3. Sample construction and variable definitions

3.1 Hedge fund activism sample

The primary dataset used in this study is a hand-collected list of hedge fund activist campaigns between 2000 and 2011. The collection procedure combines data from regulatory filings and SharkRepellent.net and is described in more detail in Gantchev (2013). The primary data source is Schedule 13D (and 13D/A), which must be filed with the US Securities and Exchange Commission (SEC) by any person or institution that acquires more than 5% of the voting stock of a public firm with the intention of influencing its operations or management. The list of (intended) activities requiring disclosure in Schedule 13D includes mergers and acquisitions, reorganizations, asset sales, recapitalizations, changes in dividend policies, board structure, charter or bylaws, exchange listing, and other similar actions.[14]

The full sample of activist targets with PERMNO and GVKEY links consists of 1,507 campaigns in the twelve-year sample period. We exclude repeat targets within the same year, reducing the number of events to 1,397. For our industry-level analysis, we impose some additional restrictions such as requiring that each industry-year must have at least 5 firms.[15] These further reduce the sample size to 1,283 target-years. Finally, we require that targets have sufficient data from CRSP, Compustat and Thomson Reuters to calculate the necessary variables for our multivariate analysis, which leaves us with a final sample of 1,034 unique target-years.

The typical target of hedge fund activism differs from the average firm in the CRSP/Compustat

[14] An alternative filing with less stringent disclosure requirements is Schedule 13G, which is filed by large shareholders who intend to remain passive investors.
[15] These restrictions ensure that the main variable of interest in this study – target frequency, defined as the number of targeted firms in an industry divided by the total number of firms in the industry – has well-behaved cross-sectional and time-series distributions.

universe along several valuation, performance, and ownership dimensions. Consistent with the findings of the previous literature[16], Table 1 shows that the average target in our sample is significantly smaller than the average non-target firm, with a mean (median) market capitalization of \$946 (\$146) million. The typical target tends to have a lower valuation, with a mean (median) Tobin's Q of 1.87 (1.33) compared to 2.26 (1.46) for the average non-target firm. This undervaluation is especially evident in terms of the targets' recent stock market performance, with a mean (median) target stock return of 0.01 (-0.07) versus 0.12 (0.02) for other firms. Targets tend to have somewhat higher stock turnover.[17] They also have lower book leverage and shareholder payout but higher capital expenditures, suggesting higher agency costs than the average non-target firm.

[Insert Table 1]

In terms of their operational performance, targets have similar return on assets as the median firm but lower median return on sales (0.08 for targets versus 0.11 for other firms) and sales growth (0.05 versus 0.08). Finally, we confirm findings in the previous literature that hedge funds tend to approach firms with large institutional ownership (as reported by Thomson Reuters). The average target has a substantially higher mean (median) institutional ownership – 0.51 (0.52) versus 0.45 (0.44) for the average non-target firm.

In summary, the results in Table 1 confirm that hedge funds typically target firms with fundamentals that are different from those of the average firm. This suggests that it is critical to consider firm characteristics in determining a firm's probability of becoming an activist target. Our subsequent analysis will take into account the combined influence of these fundamentals on the targeting decision using a propensity score model. More importantly, the presence of firms with the 'right' characteristics in certain industries may also confound the role of activism threat. As a result, we will identify the effect of threat by comparing changes in policies between firms with high and low target propensities (that is, high and low activism threat) in the same threatened industry.

3.2 Activism threat

Anecdotal evidence shows that financial advisors and corporate lawyers advocate a so-called "do-it-yourself activism", which involves "critically examining [a] company's portfolio, balance sheet, and governance in much the same way that an activist investor would, and then preemptively

[16] See Brav, Jiang, and Kim (2010) for a survey of the literature, including the general characteristics of target firms.
[17] To the extent that turnover proxies for liquidity, this finding is consistent with Edmans, Fang, and Zur (2013).

making necessary changes"[18]. Such an examination typically consists of benchmarking against industry peers on "industry-specific operating metrics and qualitative screens" as well as quantitative measures such as "valuation discounts, historical total shareholder return, cash and operating margins, financial policies, and balance sheet profiles"[19]. We take this industry dimension as a natural starting point of our definition of activism threat.

Past activist events in a firm's industry present a threat to yet-to-be-targeted firms. CEOs and directors must perceive such threat as potent in order to take preemptive efforts in fending off future attacks. Consequently, our definition of activism threat should capture the salience of recent activism but also work across industries with heterogeneous structures. In addition, we avoid model-based definitions of threat in favor of metrics easily observable by a firm's executives and directors.[20]

Our definition of activism threat consists of two dimensions that capture the outburst and recent trend in an industry's target frequency. Specifically, we consider an industry as threatened if its target frequency (i) exceeds the sample average of 2.5% for the first time in the preceding three years, or (ii) has experienced two consecutive increases up to the current year. This definition reflects the salience of activism in an industry (for example, the media often focuses on the number of recent targets or changes in an industry's target frequency) and has the additional advantage of working well in industries with different numbers of firms. Alternative definitions, which extend the look-back period or raise the frequency threshold produce qualitatively similar results and do not affect our conclusions.

Panel A of Figure 1 illustrates the definition of threat across three example industries. The first chart depicts the electronic components industry (SIC 367), a very large industry in terms of the average number of firms during the sample period (mean of 191). The height of the solid (blue) bars represents the annual target frequency and the dashed (red) rectangles show the years in which the industry is classified as threatened. We define 2005 as a threatened industry-year because the target frequency exceeds 2.5% for the first time in the sample period. The industry target frequency stays above this threshold until 2008 when it reaches 5.9% (representing 11 campaigns). Year 2008 (as well as 2003) is also classified as a threatened industry-year because of the two consecutive positive changes in the industry's target frequency in the preceding two years.

[Insert Figure 1]

[18] See "Do-It-Yourself Activism" by Gerry Hansell of The Boston Consulting Group, posted on *The Harvard Law School Forum on Corporate Governance and Financial Regulation*, March 13, 2014.
[19] Ibid.
[20] An earlier version of the paper defined threatened industries as those that experienced an abnormally high number of activist campaigns in the past year, as indicated by the positive residuals from a panel AR(1) model of target frequency. The results from this model-based definition of threat were quantitatively and qualitatively similar.

In contrast, the second chart depicts a smaller industry - eating and drinking places (SIC 581) – with an average of 70 firms over the sample period. The target frequency in this industry exceeds (or equals) the sample mean of 2.5% in 11 of the 12 years. We classify as threatened only 2000 (the first time the industry target frequency exceeds 2.5%) and 2005 and 2006 (due to two consecutive positive changes in the target frequency). Similarly, the third chart presents activism threat in an even smaller industry – engineering (SIC 871). Due to the very small number of firms (15, on average), even 1 or 2 campaigns are visible in this industry and arguably pose a viable threat to yet-to-be-targeted peers. We classify as threatened 2001, 2007 and 2011 because the target frequencies in these years exceed the sample average (for the first time in the preceding three years).

Panel B of Figure 1 presents some additional evidence that our definition of activism threat appears to describe well the future rate of targeting in an industry. We split industries into two groups – threatened and unthreatened – based on the above definition. Then, we report the actual rate of targeting in the following year. The figure clearly shows that threatened industries see high future target frequencies, on average. The only exception is 2010, in which we have only 7 threatened industries against 43 unthreatened ones. However, this evidence should be considered with caution. First, it should be the threat perceived by the peers' managers that matters, even if the managers' perceptions may not always coincide with the subsequently realized rate of activism. Second, due to the evidence of preemptive policy improvements that we present later, the actual activism activity following the emergence of threat may be attenuated.

To summarize, our definition of activism threat accounts for both the initial outburst and following trend in an industry's target frequency. Generally, in smaller and infrequently targeted industries, an abnormally high number of targets (outburst) captures well the potential threat to peer firms. In larger or frequently targeted industries, acceleration in targeting (trend) better measures the uptick from normal levels and hence the potency of threat to peer firms.

Table 2 presents the annual panel of threatened firms and industries, consisting of 50,970 firm-year observations. There is a significant time variation in the number of activist campaigns, which exceeds the average frequency in 2005-2008 but is substantially lower at the beginning and end of the sample period.[21] In most of our subsequent analysis, we control for the average rate of targeting in each year by using year fixed effects.

[Insert Table 2]

Table 2 also shows that about one-third of three-digit SIC industries get targeted each year. The

[21] Burkart and Dasgupta (2013) argue that increases in the net leverage of targeted firms and performance sensitivity of hedge fund investor flows generate pro-cyclicality in hedge fund activism.

number of targeted industries is higher in the years with above-average number of campaigns (2005-2008). However, in the time-series, the number of targeted industries varies less than proportionally with the number of targeted firms, suggesting that activism activity is, in part, scaled up and down within the same industry. The last column shows that about 10% of industries and 35% of targeted industries are classified as threatened based on our definition. In the time series, two important patterns deserve attention. First, the numbers of threatened industries and firms are disproportionately higher in the early part of the sample. This is due to the first component of our definition (initial outburst), which emphasizes the first sign of threat. Second, very few industries are classified as threatened in 2009-2011. This is due to the high activism rates in 2005-2008 and the dramatic drop during and after the Great Recession.

3.3 Activism threat in the cross-section

We have shown that target firms differ from the average firm in the CRSP/Compustat universe along many valuation, performance, and ownership dimensions. Firm fundamentals affect not only the propensity that a firm will become an activist target but also the extent to which it may feel threatened by activist activity in its industry. A high level of threat does not imply that all firms in the industry experience the same increase in their likelihood of being targeted. Specifically, we expect that the threat channel will affect more strongly rivals whose fundamentals are similar to those of actual targets. Therefore, we will identify the effects of the threat channel from other confounding explanations (such as product market competition and time-varying industry conditions) by using the cross-sectional differences in the peers' "similarity-with-targets".

We capture the combined influence of firm characteristics on the targeting decision using a propensity model of activist targeting. Table A.1 in the Appendix presents estimates of a baseline probit model, which predicts a firm's propensity to become a target as a function of (lagged) firm fundamentals *only*. The independent variables used in this model follow Brav, Jiang, and Kim (2010) and Edmans, Fang, and Zur (2013)[22] and are summarized in Table 1. Our results are consistent with the previous literature; a firm's market capitalization, *Q*-ratio, stock return, and sales growth are negatively correlated with target propensity whereas return on assets, decreasing payout, distance to default, and institutional ownership have a positive correlation with targeting. As reported at the bottom of Table A.1, the unconditional baseline probability of becoming an activist target is 2.7% per year.

The model specification in Column (3) controls for the average rate of targeting by industry and

[22] In order to improve the model's predictive power, we use logarithms or dummy versions of some firm characteristics.

year with the inclusion of industry and year fixed effects. We use this model, setting the estimated fixed effects to zero, to calculate the baseline propensity that a firm, conditional on its fundamental characteristics, will be targeted in a given year. To evaluate the model performance in the context of our study, we sort all firm-year (industry-year) observations based on their estimated target propensities (or, average estimated target propensities for industries) into halves (above- and below-median) and track the numbers of targeted and threatened firms (industries) in each half. Panel A of Table A.2 in the Appendix reports the results for the pooled probability classifications. The target frequencies increase as we move from low to high probability groups, confirming that our baseline model fits the data well.

In Panel B of Table A.2 in the Appendix, we sort firms into halves within each industry-year. These groupings are highly correlated with the pooled classifications as seen in the *Agreed* column, which presents the proportion of firms for which within-industry sorts are consistent with the pooled sorts in Panel A. This suggests that much of the variation in target propensity is within industry-year. This feature is important as we use these *within-industry-year* propensity classifications (which by construction contain an equal number of firms in each industry-year) to identify the spillover effects that occur through the threat channel. The idea is that within the same threatened industry, firms with high baseline target probability should respond more strongly to activism threat than those with low baseline target probability. This research design allows us to differentiate the threat channel from the competitive channel and the common effects of time-varying industry shocks.

[Insert Table 3]

In Table 3, we split the peer firms in our sample into two groups – high (above-median) and low (below-median) propensity of being targeted. The summary statistics confirm that high target probability firms (Panel A) have fundamentals similar to those of previous targets whereas low target probability firms (Panel B) do not. Comparing the two panels, we see that firms with high target propensity have substantially lower market capitalization, Tobin's *Q*, and stock return than firms with low target probability. High propensity firms also have lower book leverage and shareholder payout as well as lower return on assets, return on sales and sales growth. Finally, firms with high target probability also have considerably higher institutional ownership.

4. Policy changes

In this section, we investigate the role of activism threat in motivating real policy changes at the peers of targeted firms. We hypothesize that threatened peers with fundamentals similar to those of previous targets will attempt to mitigate the effect of threat by reducing agency costs and improving operating performance along the same dimensions as the targets (hypothesis *H1*).

4.1 Policy changes at activist targets

Before we test hypothesis *H1*, we confirm findings in the previous literature that hedge fund activism creates value at target firms by improving operating performance and reducing agency costs. Brav, Jiang, and Kim (2010) show that targets experience improvements in *Q*-ratio and dividend payout. They also report statistically significant changes in operating performance (return on assets) after correcting for sample selection.[23] Clifford (2008) also finds a statistically significant improvement in industry-adjusted return on assets in the two years following activism and attributes most of this improvement to better asset utilization. Both Clifford (2008) and Klein and Zur (2009) document post-event increases in leverage and dividend yield, which they interpret as evidence of lower agency costs.

We start our analysis of the effect of activism on the policies of targeted firms with Figure 2, which plots mean and median changes in select firm policies in the five-year period around the activist campaign (from *t-2* to *t+2*, where year *t* contains the start of the engagement). Consistent with the previous literature, we document that on average, targets increase their book leverage from 0.296 in *t-2* to 0.323 in *t+2*, with a peak in *t+1* of 0.329. Targets also raise their payout yield, defined as the sum of dividends and share repurchases divided by stock market capitalization, from an average of 0.0197 in *t-2* to an average of 0.0254 in *t+2*. During the same window, the targets' average capital expenditure ratio decreases from 0.100 to 0.076. All three variables reach (almost) peak levels by year *t+1*. These results suggest that targets substantially reduce agency costs, with most of the changes happening within one year of the activist intervention.

[Insert Figure 2]

In terms of performance measures, targets see a worsening in their return on assets, return on sales and asset turnover between years *t-2* and *t*, followed by a sizeable improvement in all three metrics in *t+1* and *t+2.* For example, mean return on assets improves from 0.029 in year *t* to 0.042 in year *t+2*; return on sales and asset turnover see similar improvements. It is interesting to note that these operational changes take longer to materialize (until year *t+2*) than the period required to observe improvements in financial and investment policies.

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[23] Brav, Jiang, and Kim (2010) point out that one-fifth of their sample disappears from Compustat within two years of intervention, which induces a negative bias in measuring post-event performance as the missing firms most likely represent successful outcomes of activism.

We confirm these results in a multivariate setting in Panel A of Table 4, which reports OLS regressions of policy levels on year dummies (from *t-2* to *t+2*). All specifications include industry and calendar year fixed effects as well as policy quintile fixed effects to capture the flexibility of a target to change a given policy. We also add a dummy to control for firms that experience a default on their fixed income obligations (according to data from Mergent FISD) from *t-2* to *t+2*, where year *t* is the year of the activist campaign.

[Insert Table 4]

Column (1) shows that targets substantially raise their book leverage in the year after the start of the campaign. The coefficient of *Year t+1* is statistically significant at 5% and the change between *Year t-1* and *Year t+1* is statistically significant at 10%. As seen in Columns (2) and (3), targets also increase their payout yield and reduce their capital expenditures ratio, with the coefficients of both *Year t+1* and *Year t+2* statistically significant. The change between *Year t-1* and *Year t+1* is statistically significant at 1% for both ratios, suggesting that most of the reduction in agency costs happens within one year of the activist intervention. In economic terms, an average target increases its book leverage by about 1.6%, increases its payout yield by about 0.6%, and decreases its capital expenditures ratio by about 0.9% from one year before to one year after the initiation of an activist campaign.

Columns (4)-(6) look at changes in operating performance variables. Two observations are worth noting. First, targets appear to have experienced significant pre-event deterioration in return on assets, return on sales and asset turnover as evidenced by the statistical significance of some of the pre-event year dummies. This result is consistent with the findings of Brav, Jiang and Kim (2013) for US manufacturing firms. Second, the statistical significance and large magnitude of the coefficient changes between *Year t* and *Year t+2* indicate that operational changes seem to take longer than financial and investment changes. In particular, operating performance appears to still drift downward in the year of campaign initiation and only sees significant improvement two years after. During this period, an average target increases its return on assets by about 2.1%, with both return on sales and asset utilization contributing to this improvement. Based on these results at targeted firms, we choose the event horizon *t-1* to *t+1* to study financial and investment policies and *t* to *t+2* to study operating performance at peer firms.

As suggested by the findings of Brav, Jiang and Kim (2013), hedge fund activism is multifaceted and activists may create value in various ways. Panel B of Table 4 provides some evidence consistent with this general conclusion. Even though targets across industries tend to improve both financial and performance variables, we see in Panel B that these results vary across industries. In some industries, the majority of firms improve certain policies but not others, suggesting that activists may sometimes follow a 'common prescription' for target firms in the same industry; in other industries, only a minority of firms improves these policies, implying that activists may sometimes tailor their recommendations to the specific circumstances of each target firm. That is, the activists' prescriptions have both an industry and a firm-specific component. For example, an average target increases book leverage by just 2.2% (first row) and only about 50% of all targets increase leverage (fourth row). However, if we group industries into those in which most targets increase leverage versus those in which most targets do not, an average target in the former group increases book leverage by as much as 12.0% and over 80% of the targets in this group increase their leverage. The same patterns can be seen across all six financial and performance metrics.

The above results also suggest that capturing the activists' common prescription for an industry would require conditioning on whether the majority of the targets in that industry change in the desired direction. Specifically, in estimating the effect of activism threat on the peers of targeted firms, we will focus on the effect of threat in industries in which the majority of previous targets improve a given policy. In addition, we will also control for the flexibility of a peer firm to change a given policy by including a control for 'policy slack', which captures how far a firm is from the industry optimum.

4.2 Policy changes at threatened peer firms

In this subsection, we examine whether threatened industry peers with fundamentals similar to those of previous targets attempt to mitigate the effect of threat by reducing agency costs and improving operating performance in the same way as the targets (hypothesis *H1*).

We start our analysis of the effects of activism threat on the policies of yet-to-be-targeted industry peers with Figure 3, which plots mean and median levels of select firm policies in the five-year period (from *t-2* to *t+2*) around the time when a firm's industry is classified as threatened. An industry is considered threatened if its target frequency (i) exceeds the sample average of 2.5% for the first time in the preceding three years, or (ii) has increases for two consecutive years leading up to the current year. For each policy, we further require that the majority of targets in the threatened industry improve that policy. As discussed earlier, activism is multifaceted and looking at average changes across industries may not fully capture the impact of activism threat on threatened peers. Therefore, we condition our analysis on whether the majority of targets in an industry change in the desired direction, which would indicate that activists may have identified a common industry problem and offer a common prescription for dealing with it.

[Insert Figure 3]

Consistent with our results for activist targets, we find that peers increase their mean book leverage from 0.300 in *t-2* to 0.310 in *t+2*. They also raise their average payout yield from 0.017 in *t-2* to 0.022 in *t+2* and reduce their average capital expenditure ratio from 0.135 in *t-2* to 0.110 in *t+2*. In terms of performance metrics, peers see an improvement in their mean return on assets from -0.065 in *t-2* to -0.016 in *t+2*. They also raise their mean return on sales from -0.524 in *t-2* to -0.142 in *t+2* and their asset turnover from 0.944 in *t-2* to 1.021 in *t+2*. These results are in line with the reduction in agency costs and improvement in performance observed at actual targets.

We confirm these findings in a multivariate setting in Table 5. Panel A reports OLS regressions of changes in corporate policies (from *t-1* to *t+1*) or performance metrics (from *t* to *t+2*) on dummies for whether a firm is in a threatened industry (*Threat*=1 based on the same definition as in Figure 3) and whether a firm is a likely activist target based on its fundamentals (*High target prob.*=1 if the firm has an above-median target propensity estimated by the probit model in Column (3) of Table A.1 in the Appendix). All specifications include industry and calendar year fixed effects as well as policy quintile fixed effects. The inclusion of policy quintile fixed effects controls for the distance in a firm's policy relative to the industry distribution of that policy. We also control for firms that experience a default on their fixed income obligations from *t-2* to *t+2*, where year *t* is the year of the activist campaign.

[Insert Table 5]

The term of interest is the interaction between *Threat* and *High target prob.*, which captures the differential impact of activism threat on firms with high baseline target propensity (likely targets) versus firms with low baseline target propensity (unlikely targets) in the same threatened industry. Before we discuss our results, it is helpful to summarize the rationale behind our research design. The idea is that within the same threatened industry, firms with high baseline target probability should respond more strongly to activism threat than those with low baseline target probability. The difference-in-differences design allows us to differentiate the threat channel from the common effects of product market competition or industry shocks on the firms' policy choices.

The results in Panel A of Table 5 show that the interaction between *Threat* and *High target prob.* is statistically significant for all three financial and investment policy variables. Threatened peers with high target propensity increase their book leverage and payout yield, and decrease their capital expenditure ratio. These changes are consistent with the predictions of agency theory and similar to the changes observed at actual targets (see Brav, Jiang, and Kim (2010), among others). In terms of economic magnitude, the increase in leverage is 1.5% greater among threatened firms with high baseline target propensity than among those with low baseline target propensity. This magnitude is slightly smaller than the leverage changes observed in the full sample of target firms (Table 4) and in firms in US states that increase state tax rates (Heider and Ljungqvist, 2013). Also, this magnitude is about 15% of the average change in leverage among targets in the industries in which the majority of targets increase leverage.

Similarly, threatened peers with high target propensity also increase their payout yield by 0.3% and reduce their capital expenditure ratio by 0.5% more than those in the low target propensity group. This magnitude is again about 15% of the corresponding average change among targets in the industries in which the majority of targets improve these policies. Our further investigation shows that the smaller average changes among threatened peers, compared to actual targets in the same industry, are due to the smaller fraction of peers that change in the desired direction rather than the smaller magnitude of change among those that do.

In terms of operational improvements, threatened peers with high target propensity significantly improve their return on assets and asset turnover, relative to their industry counterparts with low target propensity. Their return on sales also increases but this effect is not statistically significant. As for economic magnitude, the increase in return on assets is about 1.5% greater among threatened peers with high baseline target propensity than among those with low baseline target propensity. In relative terms, this is about half of the increase among targets in the industries in which the majority of targets improve return on assets. The improvement in return on assets comes from both the increase in return on sales and the increase in asset turnover, although each of these improvements appears smaller in relative terms.

In our context, it is difficult to isolate the changes in peer firms' policies resulting from activism threat from changes that the peers would have implemented even without the activists' involvement at actual targets in the same industry. Put differently, some may argue that hedge fund activists are very good at picking targets that would benefit the most from certain industry trends and peer firms may also change in response to such industry trends. If the expected changes are about the same among all threatened peers, then the effect of industry trends should have been differenced out between the high and low target propensity groups. However, it is reasonable to expect that the ability or need to adjust to industry trends may be greater among some peers than others; in this case, the effects will not be completely differenced out and may confound our results.

In addition, an activist's engagement at a certain firm may improve its competitive position within the industry and peer firms may be responding to the changed competitive landscape rather than to activism threat. Aslan and Kumar (2013) demonstrate that firms with more slack are better able to respond to the improved competitive position of activist targets while peers with less slack experience lower profitability and cash flows. Intuitively, firms with more slack in terms of certain policies have the ability to change these policies in response to competition. For example, peers with high leverage (relative to the other firms in the industry) are unlikely to increase their leverage in order to better compete. Similarly, firms with (relatively) low capital expenditure ratios would not have the flexibility to cut capital expenditures by much.

To isolate the effects of activism threat from those of changing industry conditions, we introduce a *Slack* dummy, which equals one for firms in the worst two quintiles of a given policy (bottom quintiles for all variables, except for capital expenditures). In Panel B of Table 5, we add an additional interaction between *Threat* and *Slack* to the specifications in Panel A.[24] Firms with more slack may change their policies in response to the improved competitive position of previous targets or in response to industry conditions that correlate with activist targeting. It is worth mentioning that a firm's level of policy slack also enters in the calculation of the baseline propensity model so the *High target prob.* dummy and the *Slack* dummy are likely to be highly correlated. For example, firms with lower leverage are more likely to be targeted (Table A.1 in the Appendix). Thus, our identification relies on the effect of target propensity above and beyond the effect of each policy slack. For the same amount of slack in a given policy, peers that are more vulnerable in dimensions other than that policy (e.g., smaller size, lower *Q*, and/or higher institutional ownership) may improve more than peers that are less vulnerable.

The significance of the interaction between *Threat* and *Slack* shows that threatened firms with more slack respond more forcefully, confirming the results in Aslan and Kumar (2013). However, threatened firms with high target probability also respond strongly, as indicated by the significance of the interaction between *Threat* and *High target prob.* The statistical significance and magnitude of the coefficients on the six policy changes remain virtually unchanged (relative to Panel A), suggesting that the effects of activism threat are not driven by firms with more slack.

Together, the results in Table 5 demonstrate that activism threat has a disciplining effect on peers, which respond by reducing agency costs and improving operating performance. These effects are similar to those documented by Fos (2013) who shows that firms exposed to potential proxy contests increase leverage, dividends and CEO turnover, and reduce capital expenditures. However, our results differ from the findings of Aslan and Kumar (2013) who demonstrate that rivals of activist targets experience significant deterioration in cash flows and return on assets as the targets become more competitive in their product markets. Our empirical design differences out the common competitive effects by comparing changes in corporate policies between firms with high and low target propensities (hence, high and low activism threat) in the same threatened industry. We also account for potentially differential competitive effects by controlling for slack in firm policies. Thus, the effects of activism threat on the policies of peer firms are distinct from the firms' responses to the improved competitive position of previous targets or to industry conditions that correlate with activist targeting.

[24] Note that the main term, *Slack* dummy alone, is subsumed by the policy quintile dummies in all specifications.

4.3 Policy feedback effect of activism threat

In this subsection, we examine whether the improvements implemented by threatened peers reduce their probability of becoming future targets (hypothesis *H3*). This feedback effect could result from two sources: (1) the improvements at peer firms may alleviate or eliminate the problems which would have required the involvement of an activist, and/or (2) these changes would push up the peers' market values, making it more costly for an activist to initiate a campaign.[25] It is important to note that in a perfectly rational world with no frictions, the feedback effect should completely eliminate activism threat so that the recent rate of activism in an industry is uninformative of future activism activities in that industry. Thus, our study is based on the assumption that due to some organizational and/or market frictions, policy and valuation changes are insufficient to completely eliminate the effect of threat.

Table 6 investigates the presence of a feedback effect among the peers of activist targets. We estimate linear probability models of activist targeting, where the dependent variable is a dummy equal to one if a hedge fund activist targets a firm within two years of being threatened. We measure a firm's average improvement in its financial and operational policies by using two proxies – *Avg. improvement quintiles* and *Avg. improvement z-score*. The first measure captures the average number of quintiles of improvement across the six financial and operational performance metrics. The second measure computes the average *z*-score of improvement across all policies, where the *z*-score for each policy is the ratio of the industry-adjusted change, normalized by the cross-sectional standard deviation within the industry-year. All models include firm-level controls (defined in Table A.1), industry and calendar year fixed effects.

[Insert Table 6]

In Columns (1) and (4), the coefficient on *Threat* is positive and statistically significant at 5%, suggesting that firms in threatened industries are more likely to become targets. Comparing Columns (2) and (3) and Columns (5) and (6), we see that the effect of threat is stronger (in both statistical and economic terms) for firms with high baseline target probability but statistically insignificant for firms with low baseline target probability. This confirms our initial conjecture that the threat channel operates largely in the high probability group (that is, among firms with characteristics similar to those of previous targets).

The coefficients on the two measures of policy improvements are negative in the full sample (Columns (1) and (4)) and even larger in magnitude in the sample of firms with high baseline target probability (in Columns (3) and (6)), but both effects are not statistically significant. More

[25] We will study separately the feedback effect of changes in the peers' valuations in subsection 5.2.

importantly, the interaction between *Threat* and the two measures of policy improvements is negative and statistically significant, indicating that policy improvements at threatened peers have significantly negative effects on the probability of being targeted. In economic terms, the average improvement quintiles and z-score for threatened peers are about 0.3, implying that an average peer manages to reduce its probability of being targeted by 0.005 to 0.009 (0.3 x -0.017 in Column (1) and 0.3 x -0.031 in Column (4)). This reduces the effect of activism threat by about 40-60%.

The significant coefficients on the interaction terms show that the policy improvements induced by the disciplining effects of activism threat mitigate, or in some cases, completely eliminate the need for activist involvement. However, the lack of significance for the main improvement terms suggests that such improvements, e.g. increasing leverage and reducing capital expenditures, are only effective in reducing the probability of being targeted when a firm's industry is already under activism theat. We conjecture (but do not test) that such policy improvements are potentially under the spotlight when peer firms are intensely scrutinized by activist investors and possibly the media.

The feedback effect we show here supports the overall idea that shareholder activism plays a disciplinary role in non-target firms. Activism threat motivates the managers of peer firms to implement some positive changes that they believe will reduce this threat. Here, we show that these improvements lower the *ex-post* probability that the threatened firms are targeted.

5. Returns

5.1 Effect of activism threat on the returns of peer firms

We continue our investigation of the response of peers to activism threat by examining whether the market anticipates the disciplining effect of this threat. We hypothesize that the share price response will be positive (hypothesis *H2*) due to the market's expectation that peers will improve their financial and operational policies in response to the heightened threat in their industry, or due to a higher likelihood that those peers, which do not sufficiently improve, will become future activist targets. Our conjecture follows from the findings of the previous literature that targets themselves experience significant positive returns at the announcement of activism.[26]

In Table 7, we investigate the stock market reaction to activism threat among peer firms. We estimate monthly returns over the five quarters around the threat quarter *t*. For each industry, the

[26] In their review of the literature, Brav, Jiang, and Kim (2010) report abnormal returns of 6% for the [-20, +20] daily window around announcement. Klein and Zur (2009) find a [-30, +30] market-adjusted return of 7.2% while Clifford (2008) estimates a [-2, +2] market-adjusted return of 3.39%. For longer horizons, Clifford (2008) reports three- and four-factor monthly alphas between 1.5% and 1.9% in the year following activism.

threat quarters include all quarters (in the threat year) in which at least one new target is announced and the rolling four-quarter target frequency is between 1% and 5%. Our intent is to capture the relatively short window in which the announcements of new targets are perceived as informative about the emergence of threat. In Columns (1) and (2), we adjust returns by the return on the CRSP value-weighted index whereas in Columns (3) and (4) we adjust returns using the matched Fama-French 25 value-weighted (FF25VW) and equally-weighted (FF25EW) size and style portfolios. All models include industry and year fixed effects.

[Insert Table 7]

Column (1) reveals that around the time that activism threat emerges (*Threat qtr. t* dummy), an average peer experiences a positive return of about 0.9%, which is marginally significant at 10%. This result does not differentiate the effects of activism threat from those of other confounding forces. For example, Aslan and Kumar (2013) show that due to product market competition, a target's improvement comes at the expense of rival firms, which suffer negative abnormal returns upon the announcement of activism at the target. Thus, the positive effects of threat and the negative effects of product market competition (and/or other changing industry conditions) may partially offset, rendering unclear the sign and magnitude of abnormal returns.

In Columns (2)-(4), we interact the *Threat qtr.* dummies with an indicator for firms with high baseline target propensity (*High target prob.* dummy). This interaction term captures the differential valuation effect of activism threat on firms with high baseline target propensity (likely targets) relative to firms with low baseline propensity (unlikely targets due to some of their fundamental characteristics). The use of the *High target prob.* dummy isolates the threat effect from the effects of other confounding factors. To the extent that such confounding factors are not correlated with the strength of activism threat, our specification is poised to pick up the threat effects as the coefficients on the interaction terms.

Regardless of the risk adjustment benchmark, the models in Columns (2)-(4) show that the market anticipates a positive valuation effect associated with the threat of activism. The coefficient on the interaction between *Threat qtr. t* and *High target prob.* ranges between 0.55% and 0.60% and is highly statistically significant. This finding suggests that the documented positive abnormal returns are driven primarily by peers in the high target propensity group, which experience higher returns of about 1.1% per month[27] compared to their low target propensity counterparts. Note that much of the valuation improvement associated with activism threat is complete within the quarter of the threat event, suggesting that such improvement is anticipatory and strongly related to the unfolding

[27] We sum the coefficient on the interaction term and that on the *Threat qtr t* dummy.

of activist campaigns. We do not observe any price reversals or any other indication that the abnormal returns we uncover are due to mechanical or behavioral biases.

The bottom of Table 7 also reports (as controls and to provide a benchmark for comparison) the respective returns for the targets of activist campaigns. We observe that targets experience negative abnormal returns in the two quarters leading up to the campaign, confirming findings in the previous literature. The mean targets' returns turn positive in the quarter of the activist campaign and range between 1.6% and 1.8% per month. Thus, peers seem to experience significantly lower but still sizeable returns in the quarter in which their industries become threatened.

The results so far demonstrate that the market anticipates an improvement in the valuation of those industry peers most likely to be targeted. Similar positive market reaction could be observed if the activists' monitoring reveals some new information about common industry conditions – *monitoring spillover hypothesis* (Raff, 2011). Under this alternative, any changes in firm policies at peer firms could be attributed to learning from the activists' monitoring of the targets rather than to the threat of becoming a future target. Since this hypothesis does not rely on the threat of activism, its effects should be observed in peers with both high and low probability of becoming a target. Therefore, the results in Table 7, which are obtained by differencing the returns of firms with high and low target probabilities, should be (mostly) clean from the monitoring spillover effects.

5.2 Return feedback effect of activism threat

In this subsection, we examine whether the valuation improvements associated with activism threat reduce the peers' probability of becoming future targets (hypothesis *H3*). In Table 8, we estimate linear probability models of activist targeting, where the dependent variable is a dummy equal to one if a hedge fund activist targets a firm within the next two years. We adjust returns using the matched Fama-French 25 value-weighted (FF25VW) size and style portfolios[28]. In the last three columns, we also control for a firm's average improvement of financial and operational policies by using its *Avg. improvement z-score* calculated across all six policies, as in Table 6. All models include firm-level controls (defined in Table A.1), industry and calendar year fixed effects.

[Insert Table 8]

We focus on Columns (4)-(6), which present simultaneously the effects of both valuation and policy improvements on the peers' probability of being targeted. As in Table 6, the coefficient on the *Threat* dummy is positive and statistically significant, suggesting that firms in threatened

[28] Our results are robust to the Fama-French 25 equally-weighted and the CRSP value-weighted benchmarks.

industries are more likely to become actual targets of hedge fund activism. Comparing Columns (5) and (6), we see that the effect of *Threat* is larger in magnitude for firms with high baseline target probability than for their low target probability counterparts.

More importantly, the coefficient on *Avg. abnormal return* is negative and highly statistically significant in all regressions, suggesting that a valuation improvement negatively affects the probability of a firm becoming an activist target. That is, a higher valuation makes it more costly for an activist to initiate a campaign. The coefficient on the interaction between *Threat* and *Avg. abnormal return* is negative and statistically significant in the full sample in Column (4) and in the sample of firms with low baseline target probability in Column (5). Although the sign and magnitude are largely the same, the statistical significance disappears in Column (6) for the sample of firms with high baseline target probability. This is due to the control for the peers' average policy improvement – *Avg. improvement z-score*, which is highly correlated with abnormal returns in this sample. Firms with high target propensity substantially improve their polices in order to mitigate the effect of threat, and the market strongly anticipates these improvements.

Together, the results in Tables 6 and 8 show that improvements in firm policies or the market's anticipation of such improvements (reflected in stock prices) reduce the peers' probability of being targeted. It is important to recognize that the above feedback results suggest that the net increase in the probability of being targeted (due to threat), the expected 'preemptive' policy improvements, and the market valuation are simultaneously determined. This is a fixed point problem in which the equilibrium is reached when all three rationally reflect each other, given other exogenous forces, such as the costs and frictions associated with policy changes, etc. Without a natural experiment or clean instrumental variables, we are left with somewhat imperfect tests. However, the economics suggest that the estimated feedback effects may be biased towards zero (against finding our results). Threatened peers with the highest increase in their probability of being targeted are more likely to make policy improvements and experience higher valuation effects. These positive associations should diminish the estimated negative effects of policy and valuation improvements.

6. Long-term implications

Our results so far have demonstrated that the threat of activism disciplines peer firms, which preemptively improve their financial, investment, and operating policies in the two-year period following the emergence of threat. These event-time results pose some interesting questions about the longer-term effects of threat on the evolution of the peers' policies. Do improved firms maintain their policy advantage over their unimproved peers (thus persistently reducing their target probability) or do they revert back to their old ways? If the peers' policy improvements are simply a form of window-dressing to temporarily fend off activists, then we should observe cyclicality in these firms' probability of being targeted. This would also suggest that activists are unlikely to run out of potential targets even if firms proactively change their policies to prevent activism. In this section, we will attempt to address some of these questions but urge caution in interpreting our results. The multi-faceted nature of activism and the relatively short time-series of activist events we use in this study make a robust econometric analysis challenging. Nevertheless, we hope that our exploratory analysis here will offer some ideas for future research.

We start by comparing the evolution of the policy gap between improving and non-improving threatened peer firms. We use the first two years of the sample period (2000 and 2001) to classify peers as threatened, according to our industry threat definition. For each policy, we fix the samples of improving and non-improving peers based on whether firms improve that policy by at least one industry quintile in the two-year period following threat. Then, we track the evolution of the policy gap between the two groups in the ten-year period between 2002 and 2011.

Starting with book leverage in the top left plot of Figure 4 Panel A, we see that the difference in leverage between improving and non-improving threatened peers is negative in 2000 (-10%) and 2001 (-5%), the two years in which we classify firms into the two groups. This policy gap in leverage turns positive in 2002 (5%) and reaches a peak in 2003 (10%), two years after the emergence of activism threat. However, the difference in leverage between improving and non-improving peers starts to decline in 2004 until it virtually disappears in 2009. These findings suggest that (1) peers attempt to pre-empt activism by raising their book leverage in the first few years after they feel threatened but (2) they revert back to their old ways within a few years (that is, the gap between the leverage of improving and non-improving firms disappears).[29] The two other corporate policies we study – payout and capital expenditures – follow a similar pattern of a sharp positive response to activism threat followed by a gradual reversal to a more minimal difference.

[Insert Figure 4]

In terms of their return on assets, improving peers start similarly with a negative gap of about 2% in 2000 and 2001 (the threat years) but turn this gap into a positive one (that is, improve their return on assets relative to non-improving peers) in the next few years, reaching a peak difference of 8% in 2004. Within the next few years, this positive gap gradually disappears. We observe roughly the same pattern in return on sales and asset turnover, even though we also see more cyclicality in these operating measures.

Overall, the results so far suggest that activism threat motivates real policy changes at threatened peers, with a substantial difference in the policies of improving and non-improving firms. However,

[29] An alternative explanation is that the initially non-improving peers eventually catch up.

this positive gap in financial, investment, and operating policies diminishes over time, suggesting that these firms should experience cyclicality in their probability of being targeted. Panel B of Figure 4 provides support for this conclusion. We plot the average target frequencies of improving (red striped bars) and non-improving (blue solid bars) peers and the cumulative difference between the two target frequencies. We aggregate across all six policies by defining peers as improving if they improve at least two policies following the activism threat in 2000-2001. Two findings emerge. First, in the first few years following activism threat, improving peers see lower target frequencies suggesting that their proactive policy changes are successful in fending off potential activist attacks. As a result, the cumulative difference in the probabilities of improving and non-improving peers increases. Second, this cumulative difference starts leveling off and gradually disappears, which coincides with the improving peers' reverting back to their old ways and becoming attractive targets once again.

Taken together, our exploratory analysis suggests that peers in threatened industries respond quickly to activism threat by improving their policies in the direction of less agency and better performance. These positive changes are effective at reducing the peers' probability of being targeted. However, the policy advantage of improving peers (relative to non-improving peers) gradually disappears, potentially returning the target probability of improved peers to the pre-activism threat level. This last observation suggests that the proactive changes implemented by peers are unlikely to eliminate the long-term need for activist monitoring. Put differently, activists are unlikely to run out of potential targets even in the face of the "do-it-yourself" activism advocated by bankers and lawyers.

7. Conclusion

This paper investigates the role of activism threat in prompting policy changes at peers of activist targets and examines whether such proactive responses are effective in fending off activists. We find that peers with fundamentals similar to those of previous targets feel threatened by recent activism activity in their industry and respond by reducing agency costs and improving operating performance in the same way as the targets. These effects are distinct from the peers' responses to the improved competitive position of the targets or to industry conditions that correlate with activist targeting. The peers' positive policy changes are anticipated by the market and reflected in stock valuations. Finally, the policy improvements and higher market valuations of the threatened peers reduce their ex-post probability of being targeted, indicating that the proactive approach they take is indeed effective.

Our results provide novel large-scale evidence of positive real externalities of shareholder activism on industry peers, establishing that the impact of activism reaches beyond the firms being directly targeted. Such externalities have been an important but missing ingredient in the hotly contested debate on whether hedge fund activism is good or bad for the economy.

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Figure 1: Activism Target Frequency and Threat

This figure plots annual target frequencies for a sample of industries (Panel A) and the annual average target frequencies for industries that are (are not) under threat of being targeted by hedge fund activists (Panel B). For each industry (SIC3)-year, target frequency is calculated as the number of firms targeted by hedge fund activists divided by the total number of firms. For each industry-year, threat equals one (that is, the industry is under threat) if target frequency (i) exceeds the sample average of 2.5% for the first time in the preceding three years, or (ii) has increased for two consecutive years leading up to the current year; threat equals zero, otherwise. Panel A plots annual target frequencies for SIC 367, 581, and 871. For each industry, the years in which threat equals one are identified by dashed red rectangles. Panel B plots the annual average target frequencies for industries with the lagged value of threat equal to one and industries with the lagged value of threat equal to zero. Only industry-years with at least 5 firms are included.

Panel A: Annual Target Frequency for Selected Industries

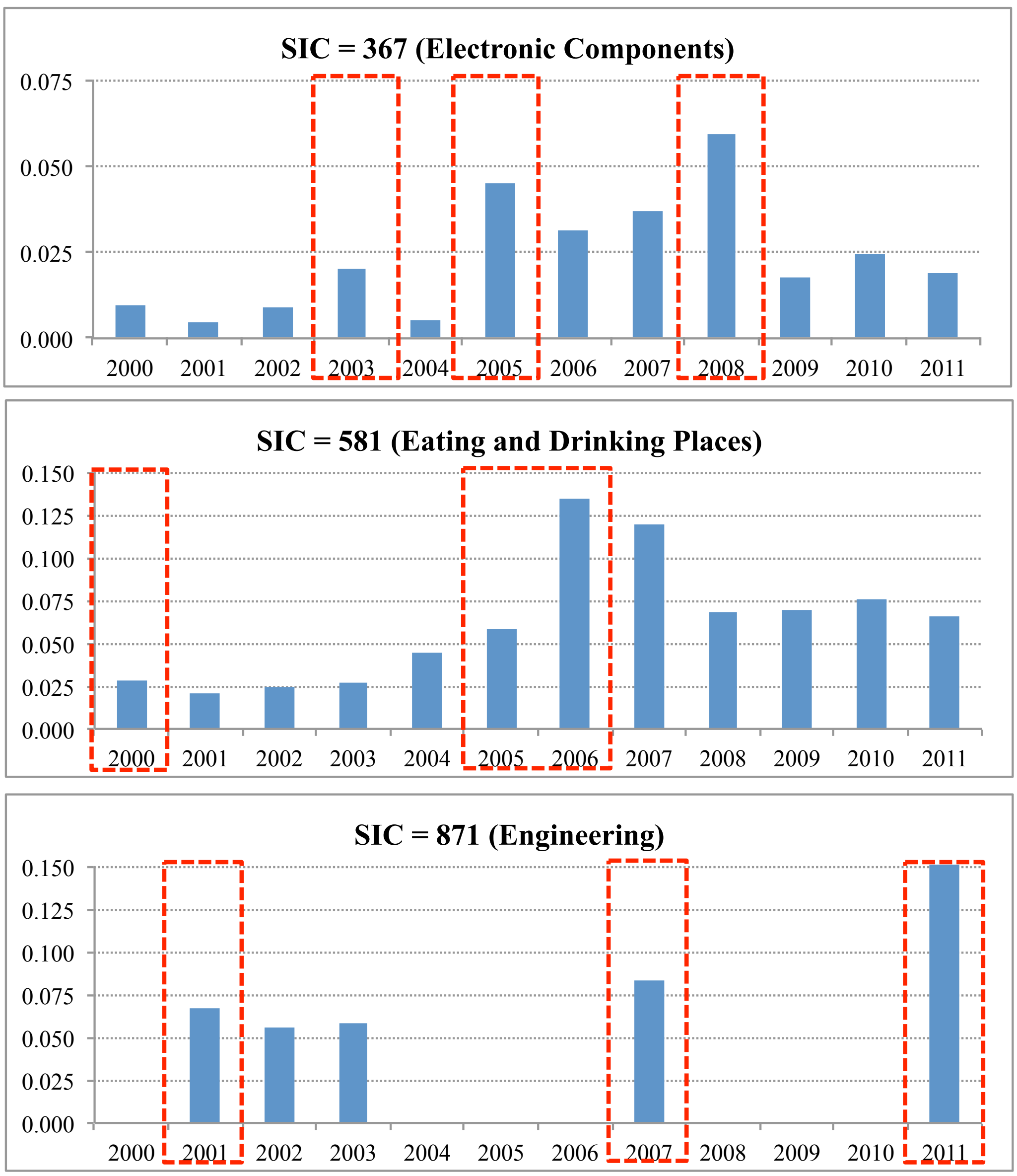

Figure 1, cont'd: Activism Target Frequency and Threat

Panel B: Annual Target Frequencies for Threatened and Unthreatened Industries

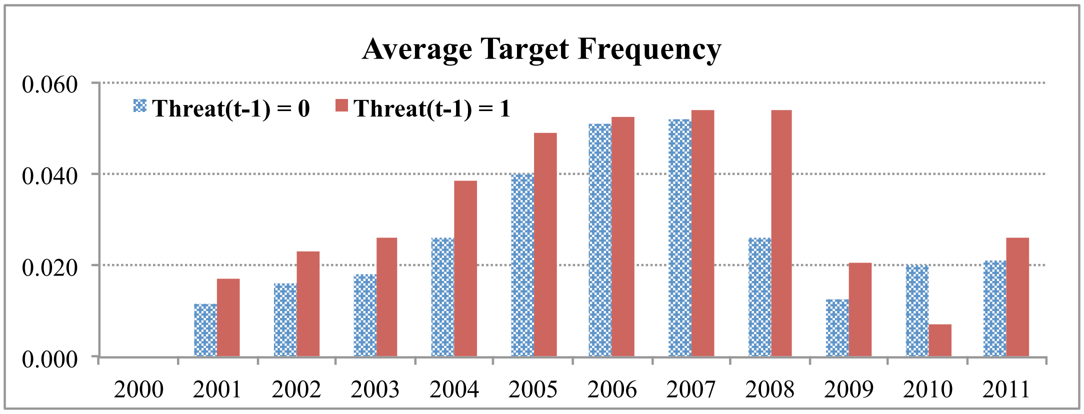

Figure 2: Policy Changes at Activist Targets

This figure plots mean and median levels of financial, investment, and operating policies at targets of hedge fund activism. The observations are firm-year and the sample period is 2000-2011. The statistics are calculated for event years *t-2* to *t+2*, where year *t* contains the start of the activist campaign. *Book leverage* is debt (long-term debt and debt in current liabilities) divided by the sum of debt and common equity. *Payout/Market cap* is the sum of dividends and share repurchases divided by stock market capitalization. *Capex/Assets* is the sum of capital expenditures and R&D expense divided by assets. *Return on assets* is operating cash flow divided by total assets. *Return on sales* is operating cash flow divided by total sales. *Asset turnover* is sales divided by total assets.

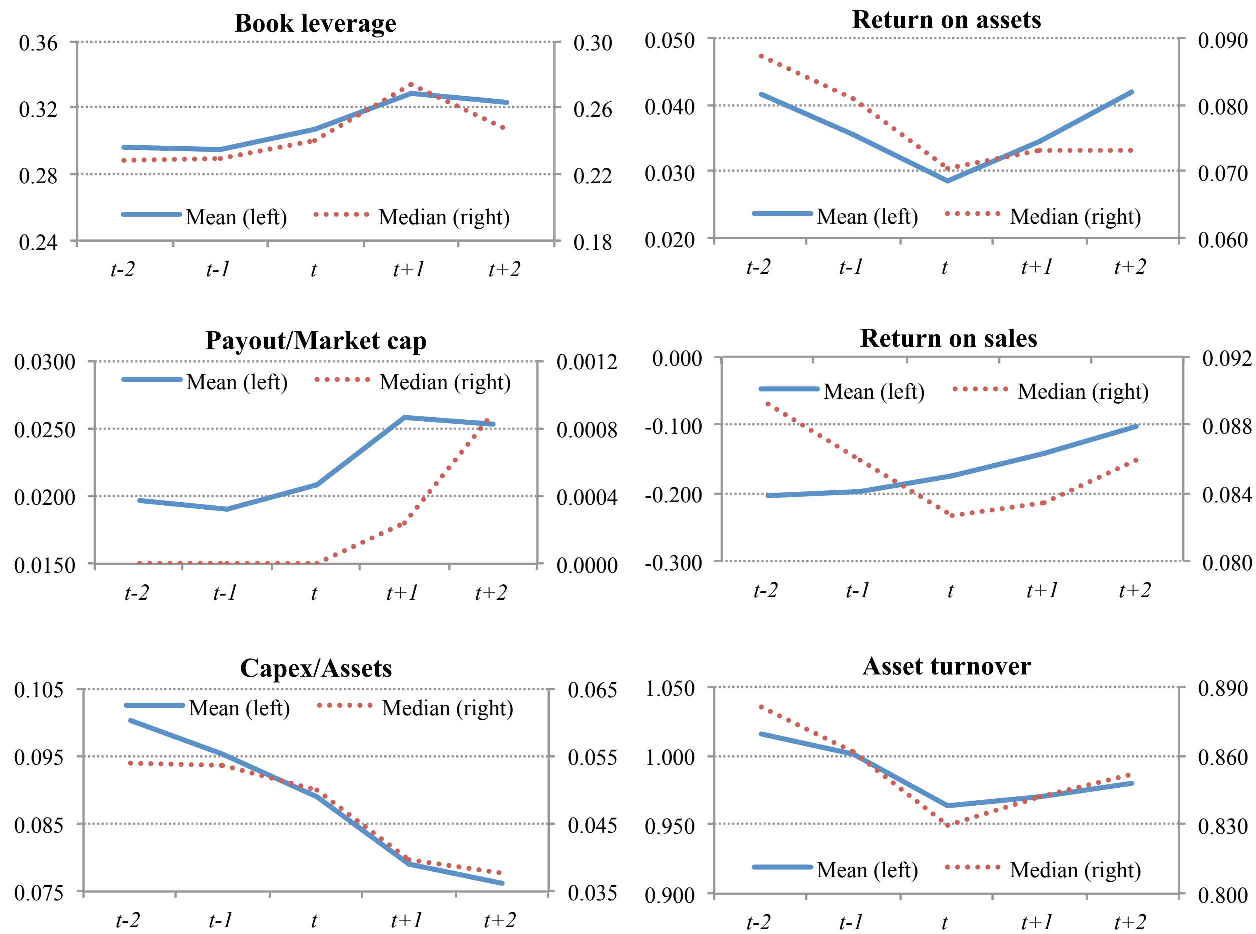

Figure 3: Policy Changes at Peer Firms

This figure plots mean and median levels of financial, investment, and operating policies at the industry peers of firms targeted by hedge fund activists. The observations are firm-year and the sample period is 2000-2011. The statistics are calculated for event years *t-2* to *t+2*, where year *t* is the threat year. For each industry, a given year is the threat year if the industry's target frequency (i) exceeds the sample average of 2.5% for the first time in the preceding three years, or (ii) has increased for two consecutive years leading up to the current year. For each policy or performance metric, the threat definition also requires that the majority of activist targets in the threatened industry change the policy or performance metric in the desired direction. *Book leverage* is debt (long-term debt and debt in current liabilities) divided by the sum of debt and common equity. *Payout/Market cap* is the sum of dividends and share repurchases divided by stock market capitalization. *Capex/Assets* is the sum of capital expenditures and R&D expense divided by assets. *Return on assets* is operating cash flow divided by total assets. *Return on sales* is operating cash flow divided by total sales. *Asset turnover* is sales divided by total assets. Only industries with at least 5 firms are included.

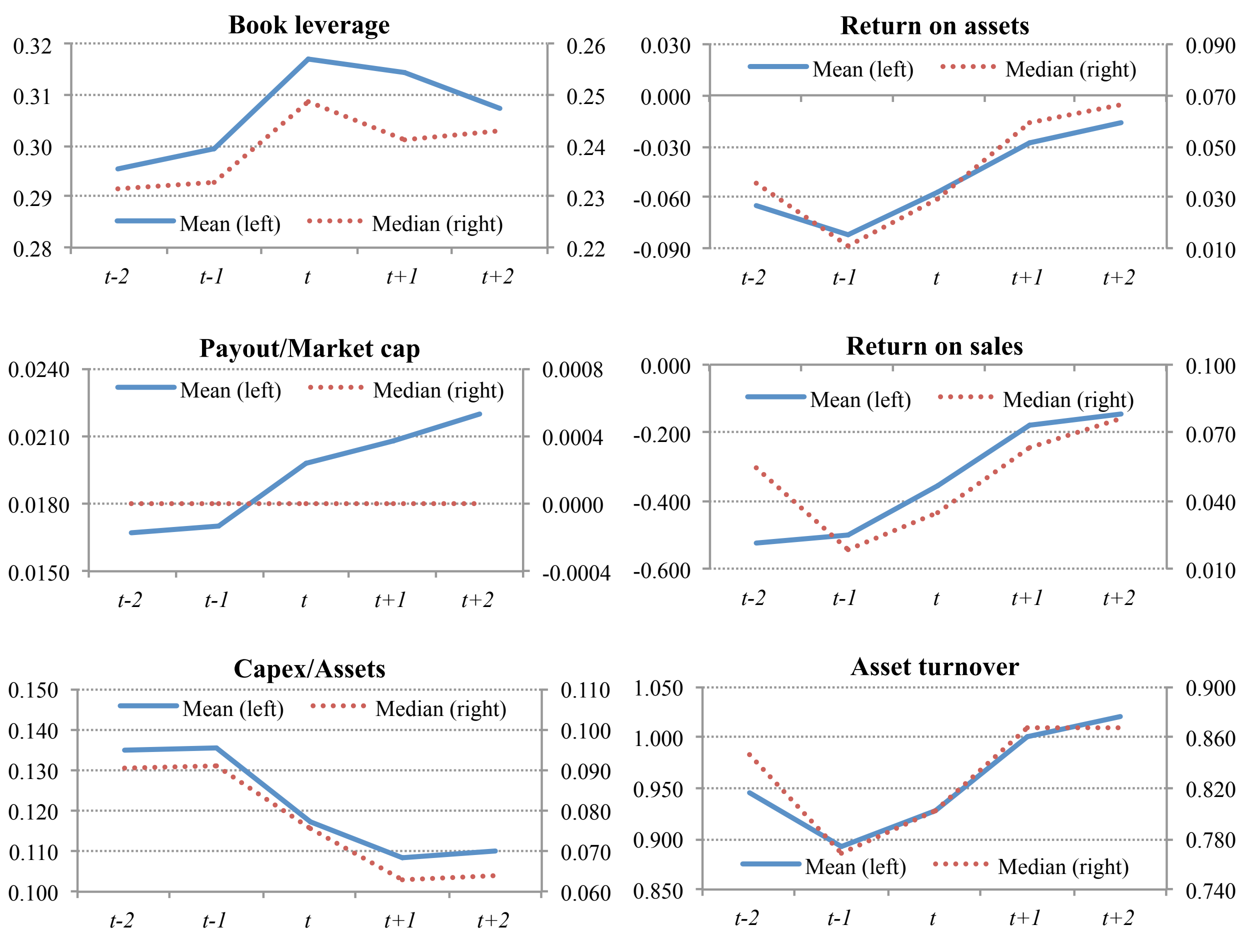

Figure 4: Differences between Improving and Non-improving Threatened Peers

These figures plot the policy gaps between improving and non-improving peer firms (Panel A) and the cumulative difference in the peers' annual average target frequencies (Panel B). Peers are classified as threatened in years 2000 and 2001 if the industry's target frequency in these years (i) exceeds the sample average of 2.5% for the first time in the preceding three years, or (ii) increases for two consecutive years leading up to the current year. For each policy, the samples of improving and non-improving peers are fixed based on whether firms improve that policy by at least one industry quintile in the two-year period following threat. In Panel B, improving firms must improve at least two, out of six, policies. All policy variables are defined in Figure 2.

Panel A: Differences in Policies between Improving and Non-Improving Threatened Peers

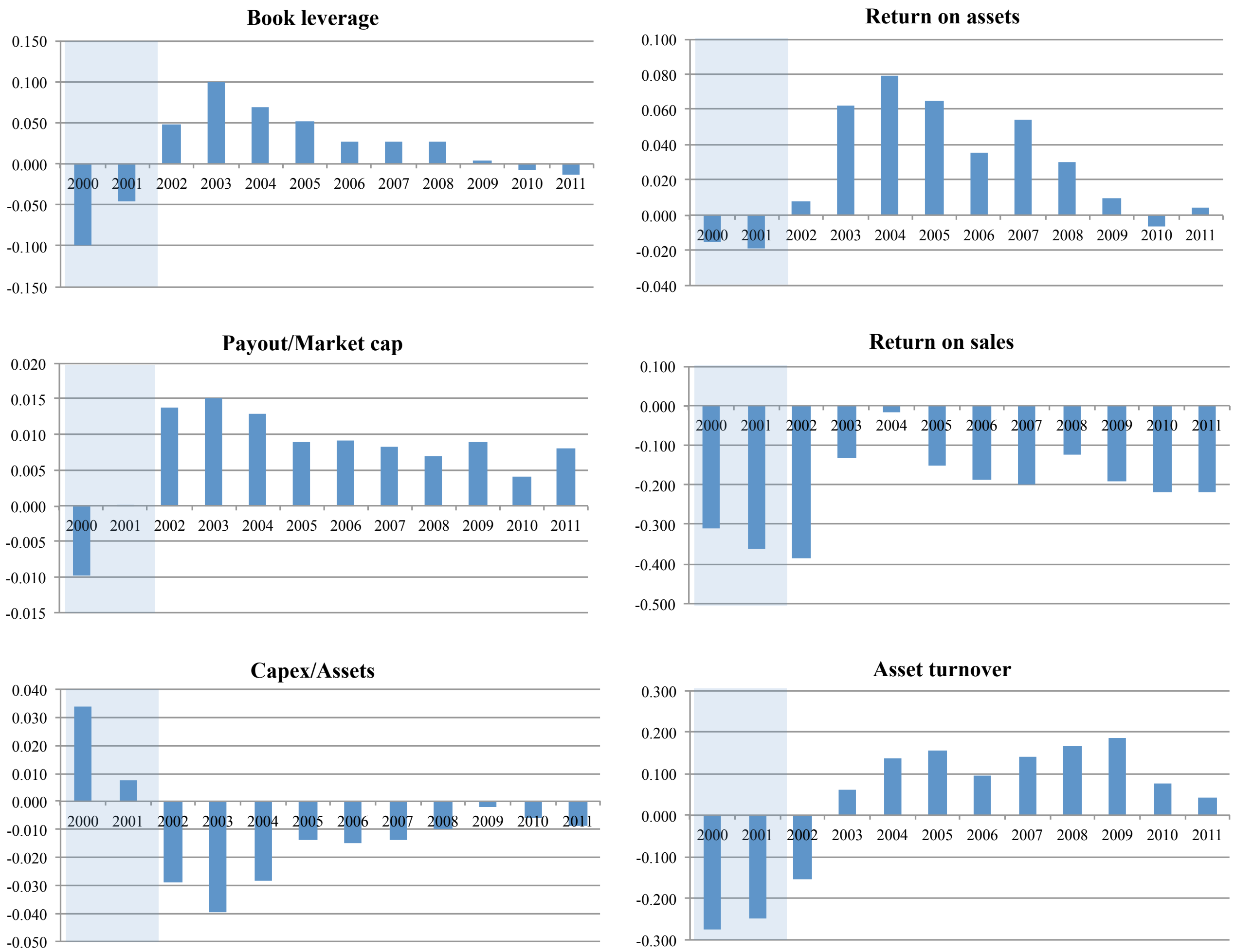

Figure 4, cont'd: Differences between Improving and Non-improving Threatened Peers

Panel B: Annual Target Frequencies for Improving and Non-Improving Threatened Peers

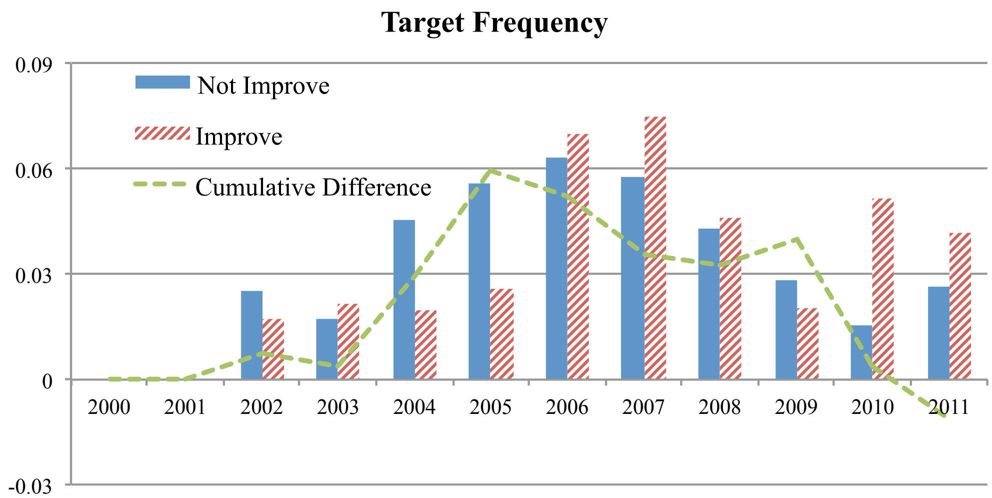

Table 1: Characteristics of Target and Non-Target Firms

This table reports the characteristics of firms targeted by hedge fund activists (Panel A) and of other CRSP-Compustat firms with available data (Panel B). The observations are firm-year and the sample period is 2000-2011. All variables are as of the end of the prior year. *Market cap* is the stock market capitalization in $ million (ME). *Tobin's Q* is the ratio of market value of assets (ME plus book value of debt) to book value of assets (the sum of book values of debt and common equity). *Stock return* is the total yearly stock return. *Stock turnover* is the ratio of average daily shares traded to shares outstanding. *Book leverage* is debt (long-term debt and debt in current liabilities) divided by the sum of debt and common equity. *Distance to default* is the ratio of the market value of assets to default threshold (max[0.1ME, book value of debt]), normalized by the firm's equity volatility. *Payout* is the sum of dividends and share repurchases. *Capex/Assets* is sum of capital expenditures and R&D expense divided by assets. *Return on assets* is the ratio of operating cash flow to assets. *Return on sales* is operating cash flow divided by sales. *Asset turnover* is sales divided by assets. *Sales growth* is the yearly growth in sales from the prior year. *Inst. ownership* is the proportion of shares held by 13-F institutional investors.

Panel A: Target Firms (N = 1,034)

Variable	Mean	Std. Dev.	5th Pct	25th Pct	Median	75th Pct	95th Pct
Market cap. ($ million)	946	2,743	12	50	146	477	4,691
Tobin's Q	1.868	1.615	0.561	0.965	1.326	2.206	4.736
Stock return	0.013	0.584	-0.732	-0.366	-0.070	0.239	1.106
Stock turnover x 100	0.699	0.616	0.093	0.258	0.504	0.941	1.966
Book leverage	0.261	0.271	0.000	0.002	0.184	0.460	0.782
Distance to default	11.274	6.780	2.016	6.195	10.193	14.928	24.937
Payout/Market cap.	0.019	0.033	0.000	0.000	0.000	0.028	0.098
Payout/Cash flows	0.155	0.336	-0.030	0.000	0.000	0.166	1.082
Capex/Assets	0.097	0.115	0.000	0.013	0.057	0.142	0.358
Return on assets	0.036	0.194	-0.358	-0.007	0.077	0.145	0.263
Return on sales	-0.207	1.185	-1.898	-0.009	0.080	0.159	0.384
Asset turnover	1.006	0.744	0.061	0.458	0.878	1.333	2.575
Sales growth	0.123	0.417	-0.372	-0.047	0.047	0.180	0.859
Inst. ownership	0.514	0.276	0.065	0.276	0.521	0.764	0.921

Panel B: Non-Target Firms (N = 41,909)

Variable	Mean	Std. Dev.	5th Pct	25th Pct	Median	75th Pct	95th Pct
Market cap. ($ million)	1,957	4,631	10	60	254	1,149	13,112
Tobin's Q	2.264	2.171	0.614	1.015	1.457	2.559	7.177
Stock return	0.122	0.659	-0.746	-0.296	0.023	0.358	1.538
Stock turnover x 100	0.676	0.661	0.073	0.220	0.457	0.885	2.125
Book leverage	0.302	0.273	0.000	0.022	0.259	0.513	0.797
Distance to default	10.532	6.794	1.867	5.415	9.102	14.200	24.778
Payout/Market cap.	0.021	0.033	0.000	0.000	0.003	0.033	0.095
Payout/Cash flows	0.168	0.312	-0.011	0.000	0.000	0.229	0.880
Capex/Assets	0.087	0.112	0.000	0.004	0.045	0.123	0.334
Return on assets	0.046	0.195	-0.378	0.011	0.083	0.154	0.280
Return on sales	-0.148	1.148	-1.589	0.018	0.107	0.214	0.435
Asset turnover	0.941	0.766	0.060	0.345	0.793	1.317	2.595
Sales growth	0.177	0.458	-0.335	-0.035	0.082	0.244	1.056
Inst. ownership	0.450	0.294	0.017	0.176	0.444	0.714	0.907

Table 2: Composition of Firm and Industry Panels by Year

This table reports annual frequency counts of firms and industries that are targeted or under threat of being targeted by hedge fund activists. Columns "Total" report the total numbers of firms and industries in the sample. Columns "Targeted" report the numbers of firms and industries with at least one activist campaign in the industry-year. Columns "Threatened" report the numbers of firms and industries that are under threat of being targeted, defined as having the value of the threat variable equal to one. For each industry-year, threat equals one if the industry's target frequency (i) exceeds the sample average of 2.5% for the first time in the preceding three years, or (ii) increases for two consecutive years leading up to the current year; threat equals zero, otherwise. Only industries with at least 5 firms are included.

	Number of Firms			Number of Industries		
Year	Total	Targeted	Threatened	Total	Targeted	Threatened
2000	5,394	57	708	189	42	33
2001	5,234	69	1,819	179	44	30
2002	4,589	89	1,098	175	46	20
2003	4,201	82	751	173	49	16
2004	3,949	83	390	169	54	20
2005	4,309	148	1,384	167	72	35
2006	4,211	181	889	159	82	26
2007	4,173	209	435	160	80	21
2008	4,065	140	957	160	54	13
2009	3,825	69	41	158	35	3
2010	3,569	84	72	151	43	7
2011	3,451	72	169	155	38	10

Table 3: Firms with High and Low Propensity of Becoming a Target

This table reports the characteristics of firms with high (above-median) and low (below-median) propensity of being targeted by hedge fund activists (Panel A and B, respectively). The target propensity is estimated by a baseline probit model (Column 3 of Table A.1), which predicts a firm's propensity of becoming a target as a function of firm fundamental characteristics only. The observations are firm-year and the sample period is 2000-2011. All variables are defined in Table 1.

Panel A: High Target Probability Firms (N = 21,991)

Variable	Mean	Std. Dev.	5th Pct	25th Pct	Median	75th Pct	95th Pct
Market cap. ($ million)	573	1,382	6	34	144	506	2,537
Tobin's Q	1.595	1.287	0.520	0.886	1.204	1.829	3.849
Stock return	-0.039	0.560	-0.803	-0.419	-0.093	0.204	0.969
Stock turnover x 100	0.671	0.640	0.086	0.228	0.460	0.883	2.056
Book leverage	0.290	0.268	0.000	0.016	0.244	0.494	0.785
Distance to default	10.068	6.543	1.597	5.083	8.810	13.735	23.235
Payout/Market cap.	0.020	0.033	0.000	0.000	0.001	0.029	0.095
Payout/Cash flows	0.152	0.314	-0.057	0.000	0.000	0.186	0.897
Capex/Assets	0.082	0.106	0.000	0.004	0.043	0.117	0.307
Return on assets	0.034	0.183	-0.350	0.000	0.071	0.136	0.248
Return on sales	-0.153	1.096	-1.395	0.000	0.086	0.177	0.402
Asset turnover	0.966	0.766	0.060	0.371	0.824	1.352	2.600
Sales growth	0.096	0.383	-0.387	-0.069	0.049	0.169	0.671
Inst. ownership	0.493	0.299	0.018	0.220	0.516	0.765	0.925

Panel B: Low Target Probability Firms(N = 20,952)

Variable	Mean	Std. Dev.	5th Pct	25th Pct	Median	75th Pct	95th Pct
Market cap. ($ million)	3,359	6,110	23	110	492	2,899	22,052
Tobin's Q	2.945	2.625	0.802	1.208	1.906	3.582	10.122
Stock return	0.285	0.710	-0.615	-0.156	0.139	0.510	2.065
Stock turnover x 100	0.682	0.681	0.062	0.213	0.457	0.891	2.203
Book leverage	0.312	0.278	0.000	0.026	0.274	0.532	0.806
Distance to default	11.055	7.015	2.268	5.798	9.425	14.768	26.517
Payout/Market cap.	0.023	0.033	0.000	0.000	0.005	0.036	0.095
Payout/Cash flows	0.184	0.311	0.000	0.000	0.015	0.269	0.872
Capex/Assets	0.092	0.118	0.000	0.003	0.048	0.130	0.363
Return on assets	0.058	0.206	-0.412	0.019	0.097	0.173	0.306
Return on sales	-0.146	1.202	-1.839	0.038	0.130	0.246	0.461
Asset turnover	0.918	0.765	0.060	0.326	0.763	1.282	2.586
Sales growth	0.260	0.510	-0.273	0.004	0.125	0.336	1.478
Inst. ownership	0.408	0.282	0.017	0.147	0.379	0.654	0.874

Table 4: Policy Changes at Activist Targets

This table reports changes in financial, investment, and operating policies at targets of hedge fund activism in 2000-2011. Panel A presents OLS regressions of policy levels on event year dummies, where year *t* contains the start of the activist campaign. All variables are defined in Table 1. Panel B reports mean changes and proportion of targets that improve each policy (i.e., positive changes for all variables except for capital expenditures). The statistics are reported for all targets and for targets in two groups of industries: (i) industries in which the majority of targets improve each policy, and (ii) industries in which the majority of targets do not. Standard errors, clustered by firm, are in parentheses. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Multivariate Regression of Levels around Event

	Policy Variables			Performance Variables		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Book leverage	Payout/ Mkt. cap	Capex/ Assets	Return on assets	Return on sales	Asset turnover
Year *t*-2 dummy	0.001	0.001	0.002	0.015***	0.063**	-0.017
	(0.006)	(0.001)	(0.002)	(0.004)	(0.028)	(0.011)
Year *t*-1 dummy	-0.001	-0.001	0.002	0.002	0.034	-0.029***
	(0.007)	(0.001)	(0.002)	(0.004)	(0.027)	(0.010)
Year *t* dummy	0.001	0.002	-0.003*	0.003	0.038	-0.047***
	(0.006)	(0.001)	(0.002)	(0.005)	(0.036)	(0.013)
Year *t*+1 dummy	0.015**	0.005***	-0.007**	0.020***	0.080**	-0.015
	(0.007)	(0.002)	(0.003)	(0.006)	(0.035)	(0.012)
Year *t*+2 dummy	0.004	0.003*	-0.006***	0.024***	0.128***	-0.022
	(0.008)	(0.002)	(0.002)	(0.006)	(0.033)	(0.014)
Default dummy	0.125***	-0.005**	-0.011	0.013	0.116	-0.071***
	(0.025)	(0.002)	(0.007)	(0.015)	(0.119)	(0.024)
ln(Mkt. cap)	-0.002*	0.002***	-0.003**	0.016***	0.030***	-0.013***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.006)	(0.003)
Industry FE	YES	YES	YES	YES	YES	YES
Calendar year FE	YES	YES	YES	YES	YES	YES
Policy quintile FE	YES	YES	YES	YES	YES	YES
R-squared	37,464	37,464	37,464	36,992	36,992	36,992
Observations	0.527	0.216	0.345	0.402	0.180	0.531
Year *t*+1 - Year t-1	0.016*	0.006***	-0.009***	0.018**	0.046*	0.014
Year *t*+2 - Year t	0.003	0.001	-0.003	0.021***	0.090***	0.025*

Panel B: Univariate Statistics of Changes around Event

	Policy Variables			Performance Variables		
	(1)	(2)	(3)	(4)	(5)	(6)
	Book leverage	Payout/ Mkt. cap	Capex/ Assets	Return on assets	Return on sales	Asset turnover
Mean change						
All	0.022***	0.007***	-0.013***	0.008	0.041**	0.037***
Ind. - majority improved	0.120***	0.029***	-0.034***	0.048***	0.120***	0.147***
Ind. - majority not improved	-0.051***	-0.006*	0.020***	-0.067***	-0.112***	-0.174***
Proportion positive change						
All	0.494	0.546*	0.424***	0.546***	0.544**	0.549**
Ind. - majority improved	0.839***	0.867***	0.208***	0.806***	0.798***	0.800***
Ind. – majority not improved	0.159***	0.212***	0.880***	0.066***	0.057***	0.064***

Table 5: Policy Changes at Threatened Peer Firms

This table reports changes in financial, investment, and operating policies at peers of activist targets in 2000-2011. The sample includes only industries with at least 5 firms. All policy and performance variables are defined in Table 1. Panel A presents OLS regressions of policy changes on a *Threat* dummy, a *High target prob.* dummy and their interaction. *Threat* equals one if the firm is in an industry whose target frequency (i) exceeds the sample average of 2.5% for the first time in the preceding three years, or (ii) increases for two consecutive years leading up to the current year. For each policy or performance variable, the threat definition is further conditioned on the majority of activist targets in the threatened industry changing the policy or performance variable in the desired direction. *High target prob.* is a dummy equal to one if a firm has above-median probability of becoming a target, estimated as a function of firm fundamentals only (using the model in Column (3) of Table A.1 in the Appendix). *Target* is a dummy equal to one if a firm is targeted by an activist in the current year. For each policy or performance variable, *Improved ind. (Not improved ind.)* is a dummy equal to one if the majority of activist targets experience (do not experience) an improvement in that particular policy or performance variable. *Default* is a dummy equal to one if a firm defaults on its fixed income obligations from *t-2* to *t+2*, where year *t* is the current year (according to data from Mergent FISD). Industry, calendar year and policy quintile fixed effects are included in all regressions. Panel B also includes a *Slack* dummy, which equals one for firms in the worst two quintiles of a given policy, i.e. firms with the greatest flexibility to change that policy. Standard errors, clustered by firm, are in parentheses. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Multivariate Regression of Policy Changes at Peer Firms

	Policy Variables			Performance Variables		
	(1)	(2)	(3)	(4)	(5)	(6)
	Book leverage	Payout/ Mkt. cap	Capex/ Assets	Return on assets	Return on sales	Asset turnover
Main variables						
Threat dummy	-0.001	0.001	-0.003	0.002	0.045***	0.020
	(0.006)	(0.001)	(0.003)	(0.005)	(0.016)	(0.018)
High target prob. dummy	0.004**	0.002***	-0.001	0.003***	-0.007	0.022***
	(0.002)	(0.000)	(0.001)	(0.001)	(0.004)	(0.004)
Threat dummy	0.015***	0.003**	-0.005*	0.015***	0.019	0.017*
x High target prob. dummy	(0.006)	(0.002)	(0.003)	(0.005)	(0.012)	(0.010)
Target dummy	0.102***	0.022***	-0.029***	0.027***	0.046**	0.098***
x Improved ind. dummy	(0.008)	(0.002)	(0.005)	(0.009)	(0.023)	(0.014)
Target dummy	-0.055***	-0.012***	0.001	0.004	0.010	-0.014
x Not improved ind. dummy	(0.010)	(0.002)	(0.004)	(0.005)	(0.015)	(0.013)
Control variables						
Default dummy	-0.012	-0.007***	-0.017***	0.005	0.003	0.067***
	(0.021)	(0.002)	(0.005)	(0.007)	(0.017)	(0.016)
ln(MCAP)	0.004***	0.003***	-0.001***	0.002***	0.005***	-0.011***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)
Industry FE	YES	YES	YES	YES	YES	YES
Calendar year FE	YES	YES	YES	YES	YES	YES
Policy quintile FE	YES	YES	YES	YES	YES	YES
Observations	39,621	39,621	39,621	36,943	36,177	36,943
R-squared (within)	0.092	0.165	0.098	0.042	0.042	0.064

Table 5, cont'd: Policy Changes at Threatened Peer Firms

Panel B: Policy Changes at Peer Firms (Controlling for Policy Slack)

	Policy Variables			Performance Variables		
	(1)	(2)	(3)	(4)	(5)	(6)
	Book leverage	Payout/ Mkt. cap	Capex/ Assets	Return on assets	Return on sales	Asset turnover
Main variables						
Threat dummy	-0.008	0.003**	0.004*	-0.003	0.001	0.011
	(0.008)	(0.002)	(0.003)	(0.005)	(0.011)	(0.015)
High target prob. dummy	0.004**	0.002***	-0.001	0.004***	-0.006	0.022***
	(0.002)	(0.000)	(0.001)	(0.001)	(0.004)	(0.004)
Threat dummy	0.015***	0.004**	-0.006*	0.013**	0.007	0.018*
x High target prob. dummy	(0.006)	(0.002)	(0.003)	(0.005)	(0.011)	(0.011)
Threat dummy	0.017**	-0.004*	-0.019***	0.016*	0.136***	0.022
x Slack dummy	(0.008)	(0.002)	(0.006)	(0.009)	(0.043)	(0.020)
Target dummy	0.102***	0.022***	-0.029***	0.027***	0.047**	0.098***
x Improved ind. dummy	(0.008)	(0.002)	(0.005)	(0.009)	(0.023)	(0.014)
Target dummy	-0.055***	-0.012***	0.001	0.004	0.010	-0.014
x Not improved ind. dummy	(0.010)	(0.002)	(0.004)	(0.005)	(0.015)	(0.013)
Control variables						
Default dummy	-0.012	-0.007***	-0.017***	0.005	0.004	0.067***
	(0.021)	(0.002)	(0.005)	(0.007)	(0.017)	(0.016)
ln(MCAP)	0.004***	0.003***	-0.001***	0.002***	0.005***	-0.011***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)
Industry FE	YES	YES	YES	YES	YES	YES
Calendar year FE	YES	YES	YES	YES	YES	YES
Policy quintile FE	YES	YES	YES	YES	YES	YES
Observations	39,621	39,621	39,621	36,943	36,177	36,943
R-squared (within)	0.092	0.166	0.099	0.042	0.045	0.064

Table 6: Policy Feedback Effect of Activism Threat

This table reports estimates for linear probability models of activist targeting. Observations are firm-year and the sample period is 2000-2011. The dependent variable is a dummy that equals one if a firm is targeted in an activist campaign within the next two years. *Threat* equals one if the firm is in an industry whose target frequency (i) exceeds the sample average of 2.5% for the first time in the preceding three years, or (ii) increases for two consecutive years leading up to the current year. *High (low) prob.* denotes firms with above (below) median target propensity, estimated as a function of firm fundamentals only (using the model in Column (3) of Table A.1 in the Appendix). The same set of firm characteristics is also included as firm-level controls in all regressions. *Avg. improvement quintiles* denotes a firm's average improvement across all six policies, measured in terms of the number of quintiles. For each policy, improvement is $max(quintile_{t+1} - quintile_{t-1}, 0)$ or $\max(quintile_{t+2} - quintile_{t}, 0)$ for policies for which increase is good, and opposite for policies for which decrease is good. *Avg. improvement z-score* is the average improvement across all six policies in terms of *z*-score. For each policy, improvement is *max[(change - mean(industry, year))/ stddev(industry, year), 0]* for policies for which increase is good, and opposite for policies for which decrease is good. Standard errors, clustered by industry, are in parentheses. */**/*** denotes significance at 10/5/1%.

	(1) All	(2) Low Prob.	(3) High Prob.	(4) All	(5) Low Prob.	(6) High Prob.
Threat dummy	0.012**	0.004	0.020**	0.016**	0.009	0.024*
	(0.005)	(0.006)	(0.010)	(0.006)	(0.006)	(0.013)
Avg. improvement quintiles	-0.002	0.002	-0.007			
	(0.004)	(0.004)	(0.006)			
Threat dummy	-0.017*	-0.005	-0.030*			
x Avg. improvement quintiles	(0.010)	(0.017)	(0.015)			
Avg. improvement z-score				-0.003	0.001	-0.008
				(0.004)	(0.006)	(0.007)
Threat dummy				-0.031***	-0.023	-0.043**
x Avg. improvement z-score				(0.009)	(0.016)	(0.021)
Controls as in Table A.1	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Calendar year FE	YES	YES	YES	YES	YES	YES
Observations	27,274	14,011	13,263	27,274	14,011	13,263
R-squared (within)	0.013	0.014	0.010	0.013	0.015	0.010

Table 7: Effect of Activism Threat on the Returns of Peer Firms

This table reports estimates for regressions of monthly abnormal stock returns on threat quarter dummies. Observations are firm-month and the sample period is 2000-2011. For each firm, *Threat qtr t* equals one if (i) the firm's industry observes at least one new activist target in that quarter, (ii) the industry's four-quarter rolling target frequency lies between 1% and 5%, and (iii) that quarter lies in the *ex-post* threat year. For each industry, threat year is a year in which the industry's target frequency (a) exceeds the sample average of 2.5% for the first time in the preceding three years, or (b) increases for two consecutive years leading up to the current year. High *(low) prob.* denotes firms with above (below) median target propensity, estimated as a function of firm fundamentals only (using the model in Column (3) of Table A.1 in the Appendix). Market-adjusted returns are stock returns minus CRSP VW returns. FF25VW (EW)-adjusted returns are stock returns minus value-weighted (equally-weighted) returns of the Fama-French 25 size and style matched portfolios. Standard errors, clustered by industry, are in parentheses. */**/*** denotes significance at 10/5/1%.

	(1) Market	(2) Market	(3) FF25VW	(4) FF25EW
Threat qtr *t*-2 dummy	-0.0043	-0.0043	-0.0061	-0.0054
	(0.0054)	(0.0051)	(0.0046)	(0.0042)
Threat qtr *t*-1 dummy	0.0062	0.0065	0.0067	0.0059
	(0.0071)	(0.0073)	(0.0059)	(0.0049)
Threat qtr *t* dummy	0.0087*	0.0061	0.0052	0.0050
	(0.0050)	(0.0045)	(0.0040)	(0.0031)
Threat qtr *t*+1 dummy	0.0018	0.0021	0.0034	0.0032
	(0.0030)	(0.0024)	(0.0025)	(0.0022)
Threat qtr *t*+2 dummy	-0.0018	-0.0020	-0.0031	-0.0048*
	(0.0040)	(0.0042)	(0.0031)	(0.0025)
High target prob. dummy		0.0078***	0.0049***	0.0049***
		(0.0012)	(0.0011)	(0.0011)
Threat qtr *t*-2 dummy x High target prob. dummy		0.0000	0.0007	0.0009
		(0.0027)	(0.0026)	(0.0026)
Threat qtr *t*-1 dummy x High target prob. dummy		-0.0005	0.0009	0.0007
		(0.0041)	(0.0038)	(0.0039)
Threat qtr *t* dummy x High target prob. dummy		0.0055**	0.0060***	0.0058**
		(0.0027)	(0.0021)	(0.0024)
Threat qtr *t*+1 dummy x High target prob. dummy		-0.0003	-0.0010	-0.0009
		(0.0030)	(0.0028)	(0.0031)
Threat qtr *t*+2 dummy x High target prob. dummy		0.0008	0.0008	0.0003
		(0.0031)	(0.0026)	(0.0027)
Target qtr *t*-2	-0.0125***	-0.0138***	-0.0148***	-0.0145***
	(0.0032)	(0.0033)	(0.0033)	(0.0032)
Target qtr *t*-1	-0.0107***	-0.0122***	-0.0122***	-0.0127***
	(0.0029)	(0.0030)	(0.0032)	(0.0033)
Target qtr *t*	0.0177***	0.0161***	0.0178***	0.0163***
	(0.0029)	(0.0029)	(0.0028)	(0.0028)
Target qtr *t*+1	0.0000	-0.0012	-0.0014	-0.0025
	(0.0034)	(0.0034)	(0.0035)	(0.0033)
Target qtr *t*+2	0.0066	0.0056	0.0047	0.0039
	(0.0069)	(0.0068)	(0.0068)	(0.0068)
Default dummy, Industry FE, and Year FE	YES	YES	YES	YES
Observations	506,543	506,543	506,543	506,543
R-squared (within)	0.007	0.007	0.003	0.001

Table 8: Return Feedback Effect of Activism Threat

This table reports estimates for linear probability models of activist targeting. Observations are firm-year and the sample period is 2000-2011. The dependent variable is a dummy that equals one if a firm is targeted in an activist campaign within the next two years. *Threat* equals one if the firm is in an industry whose target frequency (i) exceeds the sample average of 2.5% for the first time in the preceding three years, or (ii) increases for two consecutive years leading up to the current year. *High (low) prob.* denotes firms with above (below) median target propensity, estimated as a function of firm fundamentals only (using the model in Column (3) of Table A.1 in the Appendix). The same set of firm characteristics is also included as firm-level controls in all regressions. *Avg. abnormal return* is a firm's average monthly abnormal return in the year, where monthly abnormal return is the firm's stock return minus value-weighted return of the Fama-French 25 size and style matched portfolio. *Avg. improvement z-score* is the average improvement across all six policies in terms of *z*-score. For each policy, improvement is *max[(change - mean(industry, year))/ stddev(industry, year), 0]* for policies for which increase is good, and opposite for policies for which decrease is good. Standard errors, clustered by industry, are in parentheses. */**/*** denotes significance at 10/5/1%.

	(1) All	(2) Low Prob.	(3) High Prob.	(4) All	(5) Low Prob.	(6) High Prob.
Threat dummy	0.008*	0.005	0.012	0.019***	0.013**	0.026**
	(0.004)	(0.005)	(0.008)	(0.007)	(0.006)	(0.013)
Avg. abnormal return	-0.416***	-0.339***	-0.478***	-0.416***	-0.339***	-0.478***
	(0.056)	(0.076)	(0.078)	(0.056)	(0.076)	(0.078)
Threat dummy	-0.311***	-0.315***	-0.351*	-0.301**	-0.312***	-0.328
x Avg. abnormal return	(0.114)	(0.111)	(0.206)	(0.117)	(0.110)	(0.217)
Avg. improvement z-score				-0.002	0.001	-0.004
				(0.005)	(0.007)	(0.007)
Threat dummy				-0.033***	-0.026*	-0.044*
x Avg. improvement z-score				(0.012)	(0.014)	(0.025)
Controls as in Table A.1	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Calendar year FE	YES	YES	YES	YES	YES	YES
Observations	25,764	13,282	12,482	25,764	13,282	12,482
R-squared (within)	0.018	0.019	0.015	0.018	0.020	0.015

Appendix. Baseline Activism Model

Table A.1: Baseline Target Probability

This table reports probit model estimates of activist targeting. Observations are firm-year and the sample period is 2000-2011. *Specification (3)*, with year and industry fixed effects set to zero, is used to compute each firm's baseline target probability. The dependent variable is a dummy equal to one if a firm experiences at least one activist campaign in year *t*, and zero otherwise. *Stock return* is a dummy equal to one if a firm's return exceeds the industry median. *Return on assets* is a dummy equal to one if the decrease in a firm's ratio of operating cash flow to book value of assets exceeds the industry median. *Payout* is a dummy if the sum of dividends and share repurchases divided by operating cash flow decreases from the prior year. *Sales growth* is a dummy equal to one if a firm's sales growth is in the top-quartile within the industry. *Past campaigns* is the logarithm of the number of hedge fund activist campaigns at the firm in the past 3 years. *Ongoing campaigns* is a dummy equal to one if a previous activist campaign at the firm is continuing in the current year. All other variables, except *Inst. ownership*, are in logarithms and defined in Table 1. *Mfx* denotes marginal effects evaluated at the mean for continuous variables and changes from 0 to 1 for dummies. Standard errors, clustered by firm, are in parentheses. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	(1)		(2)		(3)	
Variables	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx
Market cap. ($ million)	−0.176***	−0.009	−0.157***	−0.007	−0.141***	−0.006
	(0.011)		(0.012)		(0.012)	
Tobin's Q	−0.058*	−0.003	−0.165***	−0.007	−0.137***	−0.006
	(0.034)		(0.039)		(0.038)	
Distance to default	0.226***	0.012	0.111***	0.005	0.085***	0.004
	(0.024)		(0.027)		(0.026)	
Stock turnover	0.093***	0.005	0.077***	0.004	0.057***	0.002
	(0.018)		(0.019)		(0.018)	
Stock return (dummy)	−0.141***	−0.007	−0.110***	−0.005	−0.103***	−0.004
	(0.028)		(0.029)		(0.029)	
Return on assets (dummy)	0.078***	0.004	0.068**	0.003	0.058**	0.002
	(0.028)		(0.028)		(0.028)	
Payout (dummy)	0.088**	0.005	0.083**	0.004	0.067	0.003
	(0.041)		(0.041)		(0.041)	
Sales growth (dummy)	−0.112***	−0.006	−0.093**	−0.004	−0.074*	−0.003
	(0.041)		(0.041)		(0.041)	
Inst. ownership	0.877***	0.045	0.803***	0.036	0.714***	0.030
	(0.069)		(0.074)		(0.073)	
Past campaigns					2.833***	0.120
					(0.134)	
Ongoing campaigns					−1.403***	-0.060
					(0.285)	
Industry FE	No		Yes		Yes	
Year FE	No		Yes		Yes	
Observations	46372		46159		46159	
Pseudo R^2/Baseline prob.	0.053	0.027	0.083	0.027	0.148	0.027

Table A.2: Across- and Within-Industry Sorts by Baseline Target Probability

This table reports firm-year and industry-year sorts by baseline target probability, which reflects the likelihood that a firm will be targeted by an activist hedge fund conditional only on firm-specific characteristics (calculated using the model in Column (3) of Table A.1). The sample period is 2000-2011. Industries (defined by 3-digit SIC) with fewer than 5 firms are excluded. Columns "Total" report the total numbers of firm-years and industry-years in the sample. Columns "Targeted" report the numbers of firm-years and industry-years with at least one activism campaign. Columns "Threatened" report the number of firm-years and industry-years under threat of being targeted. *Threat* equals one if an industry's target frequency (i) exceeds the sample average of 2.5% for the first time in the preceding three years, or (ii) increases for two consecutive years leading up to the current year; threat equals zero, otherwise. Panel A splits firm-years (industry-years) into high (above-median) and low (below-median) probability groups based on their estimated target probabilities (average industry target probabilities). Panel B reports a within industry-year sort of firms based on their estimated target probabilities and compares this within industry-year sort with the pooled sort in Panel A. The column "Agreed" denotes the proportion of firms for which the within-industry classifications are consistent with the pooled classifications in Panel A.

Panel A: Pooled Sort

	Number of Firms			Number of Industries		
Target Prob. Group	Total	Targeted	Threatened	Total	Targeted	Threatened
Low	21,472	246	2,748	997	284	66
High	21,471	788	2,684	996	353	83

Panel B: Within SIC3-Year Sort

	Number of Firms			Pooled Target Prob. Group		
Target Prob. Group	Total	Targeted	Threatened	Low	High	Agreed
Low	20,952	268	2,774	18,195	2,757	86.841%
High	21,991	766	2,658	3,277	18,714	85.098%