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

Nickolay Gantchev, Oleg R. Gredil and Chotibhak Jotikasthira[§]

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ABSTRACT

Hedge fund activism is associated with improvements in the governance and performance of targeted firms. In this paper, we show that these positive effects of activism reach beyond the targets, as non-targeted peers make similar improvements under the threat of activism. Peers with higher threat perception, as measured by director connections to past targets, are more likely to increase leverage and payout, decrease capital expenditures and cash, and improve return on assets and asset turnover. As a result, their valuations improve, and their probability of being targeted declines. Our results are not explained by time-varying industry conditions or competition effects whereby improved targets force their product market rivals to become more competitive.

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

JEL classification: G12, G23, G32, G34

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[§]Gantchev (ngantchev@smu.edu) and Jotikasthira (cjotikasthira@smu.edu) are at the Edwin L. Cox School of Business at Southern Methodist University. Gredil (ogredil@tulane.edu) is at the A. B. Freeman School of Business at Tulane University.

1. Introduction

Hedge fund activism is an important governance device associated with significant improvements in the performance and governance of targeted firms (see Brav et al., 2008; Becht et al., 2008; Clifford, 2008). These positive effects often come at the expense of managers and directors who see a sharp drop in compensation and a higher likelihood of being replaced (see, for example, Brav, Jiang, and Kim, 2010). Ample anecdotes suggest that executives of yet-to-be-targeted firms feel threatened and proactively work with advisers to evaluate firm policies and minimize vulnerabilities to activist attacks. This "activist fire drill" leads to real policy changes such as "spinning off divisions or instituting return of capital programs to quell dissent before it begins".[1]

Our goal in this paper is to investigate the role of activism threat in inducing policy changes at non-targeted firms and examine whether such responses are effective at fending off activists. Previous work has focused on the targets, and documented significant increases in payout and leverage, decreases in capital expenditures, and improvements in return on assets and asset utilization. We provide novel large-scale evidence that activism threat prompts non-targeted peers to reduce agency costs and improve performance in a similar manner, and as a result, experience an increase in their valuations. Our evidence of these spillover effects contributes to a better understanding of the economy-wide effects of shareholder activism.

Despite abundant anecdotes, formally establishing that activism threat induces changes in firm policies is challenging. The ideal experiment entails randomly assigning different threat levels to otherwise similar firms and studying the ensuing policy changes. In the absence of such an experiment, we adopt an empirical framework in the spirit of a difference-in-differences design and exploit the interaction between two sources of variation. The first source, to which we refer as *Threat*, is the variation in activism intensity *across industries*. A non-target firm that observes high activism intensity in its industry is likely to feel pressured to improve its policies to avoid becoming the next target. However, industry-level *Threat* alone is insufficient to identify the threat effects of activism, as firms in the same industry may change policies in a similar way for other reasons,

[1] For example, see "Boardrooms Rethink Tactics to Defang Activist Investors", *The New York Times*, November 11, 2013. Additional anecdotal evidence is presented in Section 2.2.

such as changes in technology or product market competition. Hence, we introduce a second source of variation across firms *within an industry* – a firm's *Threat perception*. Not all firms feel equally threatened by activist targeting in their industry. Our identifying assumption is that the difference in policy changes between firms with high and low *Threat perception* does not systematically vary across industries with different levels of *Threat*, except through the activism threat channel.

Industry conditions may drive activism intensity and directly affect firm policies. To mitigate these confounding effects, we measure industry-level *Threat* using the amount of new capital available to hedge funds to target firms in an industry, a metric often used by practitioners to track activism intensity. The idea is that following large investor inflows, a hedge fund will be pressured to quickly deploy new capital in industries with which it is already familiar (see Coval and Stafford, 2007). We use individual hedge funds' past industry holdings to mechanically allocate their inflows (as in Edmans, Goldstein, and Jiang, 2012), and hence *Threat* should reflect the circumstances and skills of individual funds rather than possibly confounding industry conditions. Importantly, our measure of *Threat* is significantly predictive of the actual target frequency.

In addition, activist targeting may affect non-targeted firms in the same industry through channels other than activism threat. To isolate the threat channel, we measure a firm's *Threat perception* based on the idea that the firm's directors are more likely to appreciate the "personal costs" of being targeted if they are connected to other directors involved in recent activism (outside the firm's own industry). We define connected directors using educational links (as in Cohen, Frazzini, and Malloy, 2008). We argue that most effects of other spillover channels should be differenced out in the cross section of *Threat perception* as it is tied to activist targets outside the firm's industry.

Our results show positive spillover effects of activism – as activism threat increases, non-targeted firms with high threat perception are more likely to undertake policy changes mirroring those implemented at the targets. Specifically, an interquartile increase in *Threat* increases leverage (payout) by 0.8% (0.4%) and decreases capital expenditures (cash holdings) by 0.4% (0.6%) among non-targets with high threat perception, relative to those with low threat perception. The magnitudes of these changes, which occur over a two-year period, are about 35-80% of those observed at the targets. Unlike the targets, threatened peers significantly reduce cash holdings but do not lower CEO pay.

As for operating performance, firms with high threat perception significantly improve their return on assets and asset turnover, compared to those with low threat perception. The magnitudes are about a quarter to half of those observed at the targets. For example, for an interquartile increase in *Threat*, the increase in return on assets (asset turnover) over the two subsequent years is about 0.6% (0.8%) higher among firms with high threat perception. In addition, high threat perception peers also increase their return on sales, although this effect is not statistically significant.

Intuitively, activism threat should only affect firms that are vulnerable to activist targeting, given their policies and characteristics. In terms of policies, activists typically benchmark a firm against its peers to uncover potential shortcomings. Firms that underperform with respect to a given policy (e.g., pay lower dividends relative to industry peers) are therefore more likely to change that specific policy when faced with activism threat. We show that this is indeed the case; for example, dividend payout only increases in threatened firms that previously paid lower dividends than the industry median. We also find consistent results when we divide firms by liquidity and institutional ownership, two characteristics often positively associated with activist targeting (Edmans, Fang, and Zur, 2013). For example, activism threat induces significant policy changes only among firms with higher than median stock liquidity.

Next, we show that the policy changes that we document (or the expectation that they will occur) appear to be reflected in the valuation of non-targeted peers. An interquartile increase in industry-level *Threat* raises valuations, calculated over the current and next two years, by roughly 2.4% more among firms with high threat perception. These valuation effects are slightly less than one third of those observed at activist targets and occur one to two years after activism threat, with abnormal returns of 1.4-1.6% (0.8-1.5%) in the first (second) post-threat year. In addition, we find that these valuation effects are stronger and show up sooner among threatened firms with higher stock liquidity, corroborating our earlier results on policy improvements.

Finally, we close the loop by showing that the demonstrated policy improvements are effective at fending off activists. As *Threat* increases in an industry, firms generally experience an increased probability of being targeted but such effects are significantly mitigated among the firms that proactively correct their policy shortcomings. Our estimates indicate that it takes about two standard deviations of improvements in average policies or stock valuation to fully offset the increase in targeting probability. We also show that this feedback effect is significant only in more liquid firms, which as discussed, are vulnerable to activist targeting.

We conduct various robustness tests to address specific identification concerns that our difference-in-differences approach cannot completely rule out. First, *Threat* may still be correlated with some time-varying industry shocks or reflect available institutional capital in the economy, which may have different effects on the policies of firms with different threat perception. We argue that these explanations are unlikely. Falsification tests and a matched-sample analysis show that our results are not explained by (i) industry shocks that trigger widespread policy changes, (ii) waves of other capital-driven transactions, such as mergers, or (iii) other observable firm characteristics that may be correlated with both our measure of threat perception and a time-varying propensity to institute policy changes.

Second, non-target firms may change their policies as a result of the improved competitive position of activist targets in the product market (see Aslan and Kumar, 2016). If *Threat perception* is correlated with how close a given firm's products are as substitutes or complements to the targets' products, then our approach may potentially pick up the product market effects. Using the Hoberg and Phillips (2010, 2016) text-based similarity scores, we verify that this is not the case; the products of firms with high and low threat perception are, on average, equally similar to those of activist targets. Most importantly, we also show that the non-core segments of a diversified firm change policies in the same way as its core segment, suggesting that our results are not driven by product market effects, or more generally by shocks in the core industry.

We make two important contributions. 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 on the threat of hostile takeovers (Song and Walkling, 2000;

Servaes and Tamayo, 2014). However, Fos (2016) presents evidence of a substantial decline in hostile takeovers and a simultaneous surge in shareholder activism in the past twenty years. Our findings thus suggest that the threat of activism may have become a primary external disciplining force. The threat of activism has the same effects as the threat of hostile takeovers but works differently – non-target peers learn from the (perceived) mistakes and corrective actions of activist targets and, to avoid becoming the next target, proactively assess and correct policy vulnerabilities.

In addition, our results demonstrate *positive* real externalities of hedge fund activism, establishing that its impact reaches beyond the firms being targeted. These externalities have been an important but missing ingredient in the hotly contested debate about whether activism is good or bad for the economy. Our study significantly differs from Aslan and Kumar (2016), who focus on the product market effects – *negative* externalities of activism arising from the improved positions of target firms in the product market. First, the threat effects are more general in scope, relying primarily on a firm's perception that it might be on an activist's radar screen, whereas the product market channel is inherently dependent on the industry structure (e.g., barriers to entry) and the nature of competition among targets and non-targeted rivals (e.g., quality vs. price). Second, the threat effects are unequivocally positive while the product market effects are largely negative[2], except in the case where the products of peers and targets are complements. Aslan and Kumar (2016) use our threat measure from an earlier draft (predicted likelihood of being targeted) to isolate firms that due to threat, adapt to compete on the basis of strategic complements. By comparing peer firms with similar likelihoods of being targeted and generally identical products, our difference-in-differences approach isolates the effects of activism threat from those of product market complementarity.

[2] The estimates in Aslan and Kumar (2016) imply that the net negative spillover effects of activism are over half a trillion dollars over their sample period (55,928 peers x $804.8M average peer market cap x –1.37% average CAR = –$616.6B). We estimate that the positive direct effects of activism in the same sample are about $72.6B (1,332 targets x $681.5M average target market cap x 8% average CAR), assuming a generous CAR estimate from the literature. The negative spillover effects far outweigh the positive direct effects, implying that activism is more than twice as value-destructive as large firm acquisitions over the 20-year period from 1980 to 2001 (Moeller, Schlingemann, and Stulz, 2004). Our return analysis is very different but if we were to also use CAR[–5,+5] around a 13D filing, the net spillover effects in our sample would be +0.3-0.6% per event, in line with the estimated spillover effects of acquisitions and hostile takeovers (Song and Walkling, 2000, and Servaes and Tamayo, 2014). Therefore, we find it difficult to reconcile the results of Aslan and Kumar (2016) with well-known findings in both the activism and M&A literatures.

2. Data and Empirical Framework

2.1 Sample Construction and Description

Our activism sample consists of hand-collected data on hedge fund activist campaigns between 1997 and 2011. We combine data from regulatory filings and SharkRepellent.net, following the procedure described in Gantchev (2013). The main data source is Schedule 13D, which must be filed with the US Securities and Exchange Commission (SEC) by any investor who acquires more than 5% of the voting stock of a public firm with the intention of influencing its operations or management. We retain only the first instance of targeting within a firm-year and require that targets be matched to CRSP, Compustat, and Thomson Reuters 13F. In addition, our tests use director information from BoardEx, which further limits the final sample to 905 unique target-years.

As seen in Figure 1, the numbers of both targeted firms and targeted industries vary substantially over the sample period, peaking in 2005-2008. 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 an industry. Our measure for activism threat explores the role of hedge fund capital in predicting this variation in activism over time.

[Insert Figure 1]

Our main sample is a firm-year panel, which we create by merging the activism sample to the CRSP-Compustat-BoardEx sample of public firms. Table 1 reports important characteristics of the full panel (45,357 firm-years), and Appendix A provides variable definitions. At this point, we simply note that our variables are standard and have typical distributional properties.

[Insert Table 1]

2.2 Anecdotal Evidence

To motivate our study, we start with a few anecdotes that highlight how the growing influence of activism has transformed the way in which firms conduct their businesses. In their 2017 bulletin *Dealing with Activist Hedge Funds*, Wachtell, Lipton, Rosen & Katz, a premier law firm, touts the importance of "a periodic fire drill" as "the best way to maintain a state of preparedness" before an activist emerges. This preparation focuses on tracking activists that "have approached other companies in the same industry", "monitoring peer activity and the changes peers are making to their businesses" and "address[ing] reasons for any shortfall versus peer benchmarks".[3] Advisers, including both big-league investment banks such as Deutsche Bank, Barclays, Goldman Sachs and JPMorgan Chase, and smaller firms such as Moelis & Company, Evercore Partners, and Lazard, are steering their clients "to anticipate and thwart such vocal investors before they even show up".[4]

The above prescriptions have been translated into actions. Directors now regularly "review areas of weakness in company strategy that could be targeted by activists", and correcting potential vulnerabilities "is steadily becoming part of regular activities within boardrooms". The National Association of Corporate Directors (NACD) finds that "two-thirds of [survey] respondents reported taking action to prepare for a potential activist challenge".[5]

Concrete examples abound. EMC started paying a dividend in part to distract activist attention from its large cash balance. Yahoo! lined up advisers to explore strategic alternatives before activists agitate for a sale. IBM hired two investment banks to "formulate a defense plan" against potential activists. Novartis explored selling three peripheral businesses "to reduce the likelihood of an activist intervention".[6] As a Fortune 500 director states, "Activism is part of corporate life today. It should be expected and anticipated by every company."[7]

2.3 Empirical Strategy

Despite plentiful anecdotes, it is challenging to formally establish that the threat of activism induces changes in firm policies. Ideally, we would like to compare policy changes at two

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[3] See https://corpgov.law.harvard.edu/2017/01/26/dealing-with-activist-hedge-funds-and-other-activist-investors/ for a summary.

[4] See "Bankers Pitching Avoidance Advice as Activists Amass Record Cash", *Bloomberg*, January 6, 2014.

[5] See "The Governance Divide: Boards and Investors in a Shifting World", PwC, 2017; "Proactive Boards Take on Shareholder Activists", Morgan Stanley, June 2017; "2018 NACD Public Company Governance Survey".

[6] See "Boardrooms Rethink Tactics to Defang Activist Investors", *The New York Times*, November 11, 2013; "Yahoo Lines Up Advisers to Help Fend Off Activist Investor", *The New York Post*, February 21, 2016; "IBM Hires Advisers to Deal with Restless Investors", Reuters, April 2, 2015; "How to Outsmart Activist Investors", *Harvard Business Review*, May 2014.

[7] See "Engaging the Activists", Russel Reynolds Associates.

otherwise similar firms, one perceiving a higher level of threat than the other. If the threat level is randomly assigned, or at least conditionally exogenous (i.e., uncorrelated with unobserved but relevant variables), then the difference in policy changes between the two firms could be attributed to activism threat.

Because hedge funds' targeting decisions are not random and reflect a comprehensive set of firm and industry characteristics, such an ideal experiment does not exist. Our strategy to identify the effects of activism threat is to exploit the interaction between two sources of variation, in the spirit of a difference-in-differences design. The first source is the variation in activism intensity across industries, as suggested by the above anecdotes as well as the patterns depicted in Figure 1. Firms whose industry peers are more frequently targeted by hedge funds are more likely to feel threatened and take preemptive actions, because hedge funds may leverage their industry knowledge to rapidly expand their scale within the industry. We refer to the variable that captures the industry-year variation in activism intensity as *Threat*.

The industry-level *Threat* alone is insufficient to identify the effects of activism threat as firms in the same industry may change policies in a similar way for other reasons, which may be correlated with or even caused by activism. For example, activists may go after firms in an industry that undergoes some structural changes, and such changes themselves may also affect firms' optimal policies. Or, target firms may improve and erode the competitive positions of their peers, forcing the latter to also improve (Aslan and Kumar, 2016). Such improvements may be associated with *Threat* but may not occur through the threat channel. Therefore, we introduce a second source of variation across firms within an industry and refer to the variable that captures this variation as a firm's *Threat perception*. For a given level of activism intensity in the industry, firms that perceive a higher level of threat are more likely to make preemptive policy changes than others.

Together, we identify the threat effects as the coefficient β_3 of the interaction term, $Threat_{j,t} \times ThreatPerception_{i,j,t}$, in the following regression:

$$\Delta y_{i,j,t-1,t+n} = \beta_1 Threat_{j,t} + \beta_2 ThreatPerception_{i,j,t} + \beta_3 Threat_{j,t} \times ThreatPerception_{i,j,t} + Controls_{i,j,t} + \alpha_j + \tau_t + \varepsilon_{i,j,t-1,t+n} \qquad \text{Eq. (1)}$$

where $\Delta y_{i,j,t-1,t+n}$ is the change in policy y of firm i in industry j from year $t-1$ to year $t+n$, and α_j and τ_t are industry and time fixed effects.[8] Just like in a difference-in-differences design, our identifying assumption is that the difference in policy changes between firms with high and low *Threat perception* does not systematically vary across industries with different levels of *Threat*, except through the threat channel. Below, we describe how we construct measures of *Threat* and *Threat perception* that are relevant and plausibly fulfill the identifying assumption.

2.3.1 Industry-Level *Threat*

A natural way to capture activism intensity at the industry level is to count the number of activist campaigns in an industry, to which we refer as target frequency (number of campaigns divided by number of firms). However, activists do not randomly choose their targets, and therefore, target frequency may be correlated with unobserved industry factors that unevenly affect firms in the industry. These differential effects may be correlated with *Threat perception*, and picked up by our regressions as threat effects. There are too many (possibly unobservable) industry forces for us to reasonably argue the validity of target frequency. Hence, we seek another relevant measure of *Threat* that is, at the minimum, unrelated to unobserved industry forces.

Our chosen *Threat* variable is a transformation of *Flow-induced buys* (*FIB*), the amount of new capital available to activist hedge funds to target firms in an industry. We assume that following large investor inflows, a hedge fund will be pressured to quickly deploy new capital, and due to information costs and familiarity considerations, is likely to do so in industries in which it already owns stakes in some firms (see Coval and Stafford, 2007, and others).[9] Hence, we focus on hedge funds that experience inflows of at least 5% of their total assets, and assume that new capital is allocated across industries in proportion to their past representation in the funds' portfolios. We use each fund's industry holdings across both activism- and non-activism-related investments to

[8] Our empirical approach can also be presented in the social effects model of Manski (1993). In this framework, "being an activist target" is viewed as a peer characteristic, and hence, activism threat could be considered as a type of peer effect (specifically, contextual effect). See the Internet Appendix for details.

[9] Edmans, Goldstein, and Jiang (2012) use a similar measure as an instrument for stock price changes of potential takeover targets. Similarly, Gantchev and Jotikasthira (2018) study the impact of uninformed trading on activism, using institutional sell and buy fractions across a set of unrelated stocks to extract uninformed trading in a given stock.

minimize the possibility that unobserved activism-related industry forces enter our construction.[10] However, to give more importance to hedge funds that are primarily activism-focused, we also assume that each fund maintains its past ratio of activist- to non-activist holdings as it allocates new capital. The allocated new capital of each individual activist hedge fund is then aggregated across all funds, and normalized by the industry's market capitalization to obtain *FIB*. *Threat* is the cross industry-year percentile rank of *FIB*, which takes values from 0 to 1, with 1 being the highest *FIB*. Appendix B describes the technical details about the construction of *Threat*.

An important feature of our *Threat* variable (and *FIB*) is that it is constructed using hedge funds' hypothetical capital allocations, as opposed to their actual campaigns. As such, it primarily reflects the characteristics and circumstances of individual funds, and hence, is unlikely to be correlated with firm characteristics or industry forces. However, it is still possible that investor inflows to activist hedge funds may affect firm policies through channels other than activism threat. We defer the discussion of this concern and other specific identification issues until Section 6.

We argue that *Threat* is both practically and statistically relevant. Anecdotes suggest that advisers often track the amount of activist capital to gauge campaign intensity and advise firms on the need to prepare a defense strategy.[11] In Figure 2, we plot the average annual value of *Threat* against the number of industries in which at least one firm is targeted, and show that *Threat* tracks broad campaign activities well in the time series (correlation of 0.77). Table 2 reports panel regressions of target frequency on *FIB* (columns (1)-(3)) and *Threat* (columns (4)-(6)). The results show that both measures are statistically and economically significant in explaining the variation in targeting at the industry-year level. For example, in column (4), an interquartile increase in *Threat* raises the target frequency by 2% (=0.040 x 0.5), or 100% increase from the unconditional probability of 2% in our sample. Importantly, even after controlling for lagged target frequency in column (5) and, additionally, average firm characteristics in column (6), the coefficients of *Threat* remain significant, suggesting that capital availability plays a critical and distinct role in driving the scale

[10] Hedge funds are likely to be similarly informed about both their activism and non-activism holdings.
[11] See, for example, "Review of Shareholder Activism – 1H 2018" by Lazard's Shareholder Advisory Group and "Review and Analysis of 2017 U.S. Shareholder Activism" by Sullivan & Cromwell LLP.

of activism.

[Insert Figure 2 and Table 2]

2.3.2 Firm-Level *Threat Perception*

Naturally, non-target firms whose fundamentals are similar to those of recent targets in the industry are likely to perceive a high level of activism threat. One could therefore measure the perception of threat using a propensity model that captures the combined influence of firm fundamentals on targeting (see Brav et al., 2008, for example) or simply focusing on a specific determinant such as stock liquidity (see Edmans, Fang, and Zur, 2013) or institutional ownership. However, these fundamentals should not directly be used to identify the threat effects, as they may affect non-target firms' responses to activism through channels other than threat. For example, firms whose stocks are more liquid or more broadly owned by institutions may have greater incentives to improve governance and operations to attract new capital. Or, firms may have characteristics that are similar to past targets because they compete directly in the same product market. Hence, these firms are under competitive pressure when a large number of their rivals are targeted and experience policy improvements (see Aslan and Kumar, 2016). We need to capture the variation in the perception of threat that is, at least, orthogonal to these confounding effects.

We construct *Threat perception* based on the idea that even though activism events are fairly public, a firm's directors are more likely to appreciate the "personal costs" of being targeted by activists if they are connected to directors involved in recent activism events.[12] We conjecture that connected directors would be more inclined to discuss their experiences in dealing with activists; for example, beyond public events such as losing a director seat in a proxy battle, they may share the time, effort, and cost to respond to an activist demand. Therefore, for each firm, we define *Threat perception* as the number of target connections averaged across all of its directors, where a target connection is a school tie to a director at another firm that was targeted by an activist in the prior

[12] Our measure is motivated by the literature on saliency which shows that shocks hitting 'close to home' have strong effects on belief formation (e.g., Malmendier and Nagel, 2011; Knupfer, Rantapuska, and Sarvimaki, 2016). Directors with recent activism experience in their social network are more likely to undertake pre-emptive actions, just as farmers are more likely to get weather insurance after their friends do (Cai, De Janvry, and Sadoulet, 2015) and smokers are more likely to quit after their friends receive a cancer diagnosis (Patterson et al., 2010).

two years. Following Cohen, Frazzini, and Malloy (2008), two directors have a school tie if they receive the same educational degree from the same school within one year of each other. We exclude ties in the same industry to ensure that our measure is unrelated to industry-specific information. Since the information flow is likely non-linear in the number of connections, we use in our regression an indicator variable – *HTP*, or *High Threat Perception* – that equals one if *Threat perception* for a firm-year observation is above the industry-year median.

An important feature of *HTP* is that it is intended to capture individual directors' perception of the costs and challenges in dealing with activists, rather than firm fundamentals that may be correlated with differential firm policies in periods with low vs. high *Threat*. While firms in the two *HTP* groups differ significantly along several dimensions (Table IA.1 in the Internet Appendix), they have about the same likelihood of being targeted, both unconditionally and across periods with high and low *Threat* (Table IA.2 in the Internet Appendix). While these statistics do not prove that we fulfill our identification assumption, they raise the bar for alternative stories of the type in which activism intensity or other variables that are correlated with *Threat* (e.g., capital availability) differentially affect firms in the two *HTP* groups.

To summarize, we identify the effects of activism threat using a combination of industry-level *Threat* and firm-level *HTP* in the spirit of a difference-in-differences design. Our key assumption is that the difference in policy changes between firms with *HTP* = 0 and *HTP* = 1 does not systematically vary across industries with different levels of *Threat*, except through the threat channel. We construct *Threat* and *HTP* with the objective to minimize room for (i) endogeneity coming from time-varying industry shocks, and (ii) alternative channels through which firms may be affected by activism. We acknowledge that our empirical strategy cannot completely rule out all sources of endogeneity, and tackle some remaining specific concerns using a combination of counterfactual and subsample analyses in Section 6.

3. Policy Changes at Threatened Peers

To begin, we confirm prior findings that targeted firms reduce agency costs and improve operating performance following the activist campaigns.[13] Figure IA.1 in the Internet Appendix plots mean and median policy levels at activist targets in the years around the campaign in year *t*. To capture the long-term effects of activism, we examine policy changes up to five years after the campaign (i.e., from *t*-2 to *t+5*). Two findings deserve mention. First, targets increase leverage and payout, and decrease capital expenditures and CEO pay, suggesting a reduction in agency costs. These changes seem widespread as seen in both the mean and median levels, although some policies, such as leverage and CEO pay, appear to drift back to their pre-activism levels in the long run. Second, targets generally experience a worsening operating performance before activism, followed by a sizeable improvement in return on assets, return on sales, and asset turnover that slowly but steadily increase over the five years post-activism.

We confirm these findings in Table IA.3 in the Internet Appendix, where we regress policy levels on event-year dummies (from *t-2* to *t+2*). Consistent with the univariate evidence, we find that leverage, payout, capital expenditures, and CEO pay change relatively quickly after the start of the campaign; the change in all four policies is statistically significant between years *t*-1 and *t*+1, as seen in the last two rows. In contrast, improvements in return on assets and asset turnover appear to take longer to implement, and hence, are statistically significant between years *t* and *t*+2. Based on these findings, we choose a two-year horizon to investigate the peers' policy changes due to threat in year *t*; we focus on the period from *t*-1 to *t*+1 for financial and investment policies and from *t* to *t*+2 for operating performance.

We next turn to the central question in the paper and examine policy and performance changes at peers in threatened three-digit SIC industries. Figure 3 plots the mean and median differences in policy levels between non-targeted firms with high and low threat perception (*HTP* = 1 vs. 0) when the industry-level threat is in the top quartile of the sample (*Threat* > 0.75). On average, firms with high threat perception increase book leverage and payout yield, and decrease capital expenditures, cash holdings and CEO compensation, relative to non-targets with low threat

[13] Clifford (2008) and Klein and Zur (2009) find increases in leverage and dividend yield, which they interpret as evidence of lower agency costs. Brav, Jiang, and Kim (2015) show that activist targets raise output, asset utilization, and productivity. Clifford (2008) also finds a significant improvement in industry-adjusted return on assets, which he attributes to better asset utilization.

perception. We also observe an increase in the mean levels of return on assets, return on sales, and asset turnover. These results are in line with the improvements observed at the targets. We note also that the median changes for capital expenditures, cash holdings, and return on sales are largely flat. Our further investigation shows that the changes in mean differences appear to track the changes in differences of firms whose policies are at the 75th percentile and above.

[Insert Figure 3]

Table 3 reports OLS regressions of changes in firm policy and performance variables on industry-level *Threat*, firm-level *HTP*, and their interaction (equation (1)). The explanatory variable of interest is the interaction between *Threat* and *HTP*, which captures the difference in policy changes between firms with high and low threat perception across different levels of activism threat. Our regressions include dummies for being a past, current, or future target to control for changes in policies that may be driven by the firm being targeted at some point around the threat year. At the industry level, we control for industry target frequency in the past two years to absorb persistent time-varying industry conditions that may determine both targeting and policy changes. Finally, we include firm-level controls as in Leary and Roberts (2014), a dummy for whether the firm undergoes bankruptcy, policy quintile dummies to absorb the effects of hidden characteristics that may influence policies, as well as industry and calendar year fixed effects.[14]

[Insert Table 3]

Consistent with the univariate evidence, firms with high threat perception significantly increase their book leverage and payout, and decrease their capital expenditures and cash holdings when their industries are under threat. In economic terms, an interquartile increase in *Threat* (i.e., 0.5) increases leverage (payout) by 0.8% (0.4%) and decreases capital expenditures (cash holdings) by 0.4% (0.6%) among firms with high threat perception, relative to those with low threat perception. Our results are directionally similar to the changes observed at actual targets.[15] In addition, while the magnitudes may appear small relative to the mean levels, they are economically significant,

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[14] All control variables are measured as of year *t*-1 except the bankruptcy dummy, which is as of year *t*.
[15] The exceptions are cash holdings, which peers significantly reduce (unlike the targets), and CEO pay, where the decrease for threatened peers is far from being statistically significant.

representing about 35-80% of the respective changes at the targets.[16] For example, the targets' leverage increases by 1-1.4%, depending on the measurement window (based on the coefficients of *Year t* and *Year t*+1 under *Activist target event controls*), while the difference in leverage at non-targets with high vs. low threat perception increases by 0.8% in response to an interquartile increase in *Threat*.

As for performance variables, firms with high threat perception significantly improve their return on assets and asset turnover, relative to firms with low threat perception. Their return on sales also increases but this effect is not statistically significant. In economic terms, the increase in return on assets (asset turnover) is about 0.6% (0.8%) higher among firms with high threat perception for an interquartile increase in *Threat*. These magnitudes are about a quarter to half of those observed at the targets. Note that past industry target frequency does not significantly affect current policy changes, but many of the firm-level controls do. The effects of firm characteristics are as expected; for example, firms with higher market-to-book and EBITDA-to-asset ratios tend to decrease leverage while the opposite is true for firms with higher asset tangibility.

The anecdotal evidence presented earlier indicates that yet-to-be-targeted firms frequently hire advisers to assess policy vulnerabilities by benchmarking against peers. Such vulnerabilities are firm-specific, and hence, different firms, facing the same perceived threat, may change different policies depending on their perceived shortcomings. To test this conjecture, we divide firms at the industry median for each policy, and refer to the half with higher agency costs (e.g., below-median leverage) or worse performance as vulnerable. We then run our baseline regressions separately for the subsamples of vulnerable and non-vulnerable threatened firms.

The results in Panel A of Table 4 show that the magnitude of the policy response varies with the magnitude of the perceived shortcoming; that is, firms that are vulnerable with respect to a given policy are more likely to change that policy, when faced with activism threat. For example, an

[16] Some may think that the documented magnitudes at peers seem large, given the average target probability of 2% in normal times and about 4% when *Threat* is in the top quartile (0.75 or greater). We argue that risk-averse CEOs and directors may be willing to sacrifice some private benefits from specific policies (e.g., not returning cash to shareholders) to preserve their direct benefits from employment (e.g., compensation and reputation), consistent with the small and insignificant decrease in CEO pay despite significant changes in financial policies.

interquartile increase in industry-level *Threat* increases leverage by about 1.2% at vulnerable firms versus an increase of only 0.3% (not statistically significant) at non-vulnerable firms. The magnitudes of the changes at vulnerable firms are larger than those obtained from the full sample for most policies (although statistical significance varies due to the smaller sample size). In addition, none of the policy changes in the sample of non-vulnerable firms are significant.

[Insert Table 4]

To further validate that activism threat drives our results, we explore a sample split based on firm characteristics that are associated with activist targeting. The idea is that the effects of activism threat should be stronger among non-target firms that look more similar to past targets. Besides firm size, two important characteristics have been consistently shown to raise the likelihood of targeting – stock liquidity (Edmans, Fang, and Zur, 2013, and Norli, Ostergaard, and Schindele, 2015) and institutional ownership (Brav et al., 2008).[17] In Panel B of Table 4, we report estimates of our baseline regressions separately for the subsamples of more and less liquid firms, split by the industry median of prior-year Amihud ratio.

Our results show that the effects of activism threat are economically and statistically significant only among more liquid firms, which are more susceptible to activist targeting. For example, an interquartile increase in *Threat* increases leverage (return on assets) by 1.5% (0.6%) for liquid firms versus an increase of less than 0.1% (about 0.3%) for illiquid firms. We find similar results for the institutional ownership split which, for brevity, we report in Table IA.4 of the Internet Appendix.

Together, the results in Tables 3 and 4 demonstrate that activism threat has a positive effect on non-target peers, which respond by reducing agency costs and improving operating performance. In Section 6, we provide additional robustness tests.

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[17] In general, activists reap the benefits of their campaigns through an increase in firm valuation, and thus need to accumulate target shares without fully revealing their activist intentions (Maug, 1998). Both liquidity and institutional trading help in that regard (see Gantchev and Jotikasthira, 2018). Once a campaign has been launched, the targeting activist often relies on support from other institutional shareholders to implement specific policy changes.

4. Returns of Threatened Firms

We continue our investigation of the effects of activism threat by examining changes in threatened firms' valuations. Activism threat may impact the returns of non-targets through two channels – (i) *anticipatory*, whereby market participants update their beliefs about the likelihood of activist targeting and/or future policy and performance improvements at non-targets, and (ii) *policy*, whereby returns capture the realized improvements. In theory, the anticipatory channel should be detectable earlier whereas the policy channel could manifest itself later on (e.g., only after policy changes are implemented).

Empirically, the two channels are difficult to distinguish. From the lens of our analysis, firms with high and low threat perception have similar likelihoods of being targeted, and therefore, their returns associated with the anticipation of future targeting should not materially differ. We are left with the anticipatory and policy effects that both capture the market's update about firm policy changes and are thus intertwined. Since policy changes are not detectable as sharp events and often take a few years to implement, there is no clear temporal cutoff point between anticipation and realization.[18] As a result, we can only show the number of years it takes for the threat effects to be reflected in firm valuation, which is at best suggestive of the relative importance of the anticipatory versus policy channels.

To study the returns of threatened firms, we slightly modify our regression in equation (1). The dependent variable is now abnormal return, calculated as each firm's annual stock return minus a relevant benchmark return. The key explanatory variables are now the interactions between the lead/lag values of *Threat* and *HTP*, which allow us to decompose the abnormal return for each firm-year observation into components associated with the past, current, and future values of *Threat*. We include up to two years before and after the current year, as denoted by *Threat(t-2)* to *Threat(t+2)*, with the lags measuring the *post*-threat effects and the leads measuring the *pre*-threat effects. As before, we control for targeting and bankruptcy, which may confound the effects of

[18] In addition, the market may be slow to form beliefs at the firm level, as threat perception and general vulnerabilities are not easily ascertainable. Our framework cannot detect the threat effects until the market's anticipation starts to diverge for firms with high and low threat perception.

activism threat. Finally, we include industry-by-year fixed effects to absorb other time-varying industry effects that may be correlated with both activism intensity and firm returns.

Table 5 reports the regression results. In column (1), we use the CRSP value-weighted index as the benchmark. Consistent with the policy improvements we show earlier, the estimates here suggest that activism threat also generates positive long-term valuation effects. An interquartile increase in *Threat* raises firm valuation by about 2.4% (= (-0.012 + 0.029 + 0.030) x 0.5) over three years (the current and next two years), as captured by the difference in cumulative abnormal returns between firms with high and low threat perception in the post-threat period. These effects are about 28% of those observed at the targets over the same three-year horizon (8.5% = 0.017 + 0.047 + 0.021). However, unlike the targets which experience significantly negative returns in the year leading up to targeting, non-target firms with high and low threat perception do not see any significant differences in returns in the pre-threat period. This evidence confirms from a valuation perspective that our identifying assumption is plausible, as firms in the two threat perception groups do not appear to differ systematically in the absence of threat.

[Insert Table 5]

One obvious concern is that our results may be driven by differences in risk exposure, as firms in the two threat perception groups differ in several respects. We mitigate this concern in columns (2) and (3), in which we calculate abnormal returns with respect to the matched equally- and value-weighted Fama-French 25 size and style portfolios, respectively. Our results remain robust, suggesting that they are not driven by differential risk exposures (and their interaction with activism threat or other industry forces).

In terms of timing, the valuation effects occur one to two years after activism threat, with abnormal returns of 1.4-1.6% in the first post-threat year and 0.8-1.5% in the second (0.5 multiplied by the corresponding coefficients across the first three columns). As noted, these effects are related to policy changes, as the increased likelihood of targeting is differenced out. Even though we cannot distinguish between the anticipation vs. realization of policy improvements, the fact that the market continually updates the threatened firms' valuation over the span of two years suggests the interplay of both channels.

Finally, to better connect with the evidence on policies and performance, in the last two columns of Table 5, we examine the valuation effects in the subsamples of firms with low and high Amihud ratios. If the abnormal returns are indeed reflective of threat-induced policy changes, we should observe that the valuation effects are more pronounced where the policy changes are more likely, i.e., among liquid firms. The results show that this is indeed the case; an interquartile increase in *Threat* raises firm valuation by about 3.0% (= (-0.011 + 0.048 + 0.023) x 0.5) over three years in the sample of liquid firms but only by about 0.9% (= (-0.023 + 0.010 + 0.031) x 0.5) in the sample of illiquid firms. None of the coefficients are statistically significant in the latter sample. In addition, the valuation effects appear to show up slightly sooner among liquid firms, mostly in the first year after threat, compared to mostly in the second post-threat year among illiquid firms.

Overall, the market seems to welcome the policy changes at threatened peers, confirming that the positive effects of activism indeed extend beyond the actual targets.

5. Feedback Effect of Activism Threat

In this section, we examine whether the improvements implemented by threatened firms reduce their probability of being targeted. This feedback effect could result from two related sources: (i) the policy improvements may alleviate the problems which would have attracted an activist, and/or (ii) these changes, or the expectation that they are about to occur, may raise the threatened firms' market valuations, making it less profitable for an activist to initiate a campaign.[19]

In Table 6, we estimate linear probability models of activist targeting where the dependent variable is a dummy equal to one if a hedge fund targets the firm during years t to t+2 (matching the horizon for policy changes). All the explanatory variables, except *Target frequency*, are as of the end of year t-1. Though denoted as a contemporaneous variable, *Threat* reflects hedge fund flows in year

[19] To the extent that stock prices are efficient, it is not the price per se that affects the activist's profit. Rather, the positive announcement return of a campaign is likely reduced as the market price already reflects, at least partially, any future improvements that the threatened firm may make. Similar feedback effects have been shown by Edmans, Goldstein, and Jiang (2012) and Bradley et al. (2012). Bond, Edmans, and Goldstein (2012) survey the theoretical literature on this topic.

t and hedge fund holdings at the end of year *t*-2, as noted in Section 2 and Appendix B.

[Insert Table 6]

Column (1) shows that the coefficient of *Threat* is positive and statistically significant, consistent with our industry-level evidence in Table 2. An interquartile increase in industry *Threat* increases a firm's probability of becoming a target by 1.15% (=0.023 x 0.5), about 20% of the unconditional probability (reported in Table IA.2 as 2% = 995/45,357, or 6% over a three-year period).

We estimate the effects of a firm's realized policy improvements by adding an *Avg. improvement z-score* to our regression. To compare policy changes on the same scale, we calculate *Improvement z-score* for a given policy as the difference between a firm's improvement (e.g., increase in leverage or decrease in cash holdings) from years *t*-1 to *t*+1 and the average industry improvement over the same period, divided by the (within-industry) cross-sectional standard deviation. For performance variables, we use the improvement from years *t* to *t*+2. Policy improvements (deteriorations) take positive (negative) values, and *Avg. improvement z-score* is the average of *Improvement z-score* across all eight policy and performance variables.

The results in column (2) of Table 6 show that policy changes have a negligible impact on the probability of being targeted when *Threat* is zero (insignificant coefficient of *Avg. improvement z-score*), but significantly reduce such probability as *Threat* increases (significantly negative coefficient of *Threat* x *Avg. improvement z-score*). In economic terms, the interquartile range of *Avg. improvement z-score* is 0.50, with a standard deviation of 0.45; thus, it takes a little more than two standard deviations of average policy improvements to fully offset the effect of activism threat on the probability of being targeted (i.e., 0.026/(0.026 x 0.45)).

In column (3), we investigate the effect of a firm's valuation increase on its probability of being targeted. We measure the firm's valuation by its annualized average monthly abnormal returns in years *t* and *t*+1, calculated with respect to the matched Fama-French 25 value-weighted size and style portfolios. The coefficient on *Abnormal return* is negative but not statistically significant, suggesting that activists do not simply pick targets based on past returns. However, a firm's increased valuation has a large negative effect when its industry is under threat, as evidenced by the significantly negative coefficient on the interaction between *Threat* and *Abnormal return*. These results are consistent with the idea that valuation should only matter when it reflects the expected policy improvements due to activism, which is more likely when *Threat* is high. The interquartile range of *Abnormal return* is 0.40 and the standard deviation is 0.37. Hence, keeping other variables at their mean values, it takes just less than two standard deviations of annualized abnormal returns to fully offset the effect of activism threat on the probability of being targeted (i.e., 0.030/(0.042 x 0.37)).

The last two columns split the sample of firms into those with low and high Amihud ratios. The results show that both the effect of threat on the probability of being targeted and the feedback effect are significant only in liquid firms. The results corroborate our earlier findings on policy changes and returns. Since activists tend to focus on liquid firms, these firms recognize the threat of activism and the impact that their policy actions may have in reducing such threat. As a result, they make significant policy improvements (Panel B of Table 4), which positively affect their valuations (Table 5). Illiquid firms, on the other hand, face less significant threat and their actions have insignificant impact on the likelihood that they will be targeted. As such, they are less likely to improve policies and experience higher valuations.

Overall, the feedback effects we show support the idea that activism plays a disciplinary role at non-target firms. Nevertheless, we urge caution in interpreting these results since the preemptive policy improvements, market valuation, and subsequent reductions in the probability of being targeted are simultaneously determined, even if *Threat* is plausibly exogenous. This is a fixed-point problem in which the equilibrium is reached when all three rationally reflect each other, given other forces, such as the costs and frictions associated with policy changes.

6. Robustness and Alternative Explanations

Our empirical framework is in the spirit of a difference-in-differences design, in which the first difference is (in the policy changes) between firms with high and low threat perception (*HTP* = 1 vs. 0) and the second difference is across industries with varying levels of *Threat*. Thus, for an alternative explanation to be plausible, it has to confront *both* differences; that is, it must explain why the difference in policy improvements between firms with *HTP* = 1 and *HTP* = 0 is greater in industries with higher levels of *Threat*. In this section, we discuss the robustness of our baseline results by arguing that some obvious alternative explanations are unlikely and present robustness tests and counterfactuals to address a few specific alternatives.

6.1 *Threat* May Be Correlated with Other Time-Varying Industry Conditions

To start with, activists may be skilled at picking industries that undergo certain changes, which affect optimal policies for all firms in the industry; some firms may change voluntarily while others may be resistant to change, and hence, targeted by activists. This scenario will generate a positive association between activist targeting and policy changes at non-target firms. It is also possible that firms with high threat perception are more likely to improve since they are better informed (about the industry dynamics) or better governed.

Recall that we construct our *Threat* variable using large capital inflows in the current year but *individual* hedge funds' industry allocations (including both activism- and non-activism-related investments) at the *beginning of the previous year*. Yet, it is still possible that *Threat* picks up some industry-specific shocks affecting optimal policies if such shocks are persistent and investors recognize the hedge funds that have benefited and may continue to benefit from these shocks. While we cannot completely rule out this possibility, we perform a few additional analyses to show that such shocks are unlikely to explain our baseline results.

First, industry shocks that affect optimal policies should manifest themselves as a wave of policy changes among firms in the industry. To capture this idea, we replace *Threat* with a *Policy wave* variable defined as the percentile score (across industry-year observations) of the fraction of firms that significantly improve a certain policy (e.g., leverage). A significant improvement is a top-quartile change in the firm's policy if all firm-year observations are ordered from the most to the least improved (e.g., from the largest increase to the largest decrease in leverage). If firms with high threat perception respond more strongly to policy-relevant industry shocks, then they should improve more on a particular policy dimension during a wave of that policy. Panel A of Table 7 shows that this is not the case—for each policy or performance variable, the differential change between firms with high and low threat perception is not significant during a policy wave.

[Insert Table 7]

Second, one may argue that industry conditions would not necessarily create policy waves if only sophisticated investors (e.g., hedge funds) and informed managers (e.g., directors with expansive networks) are able to respond. Our *Threat perception* variable is based on a firm's director connections with past targets, which may be correlated with the overall size and quality of the firm's director network, a plausible proxy of sophistication. We address this concern in Table IA.5 of the Internet Appendix, where we replace threat perception with a measure of director network size. *Large director network* (*LDN*) is an indicator that equals one if the firm's average number of connections per director is greater than the industry median, and zero otherwise. The coefficients of the interaction between *Threat* and *LDN* are small and not statistically significant, confirming that our results are not driven by differential manager sophistication.[20]

Third, *Threat perception* may proxy for being able to govern, or generally more skilled at crafting policies. This may not be reflected in the size and quality of a firm's director network but still affect the firm's responses to industry shocks. This concern is legitimate, as the summary statistics in Table IA.1 of the Internet Appendix show that firms with *HTP* = 1 are larger, and have higher analyst following and institutional ownership. To address such catch-all concerns, we perform a matched-sample analysis. We match a firm with *HTP* = 1 to its closest industry peer with *HTP* = 0 in the same deciles of market capitalization and institutional ownership, which eliminates most of the differences in firm observables between the two groups, as reported in Table IA.6 of the Internet Appendix.[21] Table IA.7 confirms our baseline results in the matched sample, suggesting that they are not driven by firms with different observable characteristics responding differentially to unobserved industry shocks. Still, we note that our matched-sample test is uninformative in the unlikely case that the relevant firm/management qualities, as proxied by *Threat perception*, are not at all reflected in observable characteristics.

[20] We also find that our baseline results in Table 3 are not simply driven by directors at target and non-target firms sharing the same institutional culture or background. Our results disappear if we counterfactually count as a connection two directors attending the same school *more than two years* apart.

[21] The only remaining differences are in leverage and capital expenditures, both marginally significant just in means.

6.2 *Threat* May Be Correlated with Capital Availability

Our flow-based *Threat* variable may reflect available institutional capital in the economy and drive our results: (i) through other capital-driven transactions, such as mergers, or (ii) through firms catering to the demands of institutional investors in an attempt to attract new capital.[22]

Activists often exit their campaigns through mergers, and may therefore choose industries that experience merger waves.[23] At the same time, firms in industries that undergo merger waves may make policy changes as a result of or in preparation for a merger. Thus, our baseline results may be due to firms with high threat perception being more likely to respond to or engage in merger deals. In Panel B of Table 7, we find that this is not the case. We conduct a falsification test by replacing *Threat* with a *Merger wave* dummy that equals one for industry-years in which the number of mergers is at least 20% of all mergers in the industry over the period 2000-2011 (following Harford, 2005). The regression coefficients on the interaction between *Merger wave* and *HTP* are not statistically significant in any specification, except cash holdings (marginally significant but with opposite sign).

A related concern is that firms may improve their policies to attract institutional investor capital, which may be correlated with activist capital and by extension our *Threat* variable. As discussed, firms with *HTP* = 1 have higher institutional ownership, and hence may have a greater propensity to cater to their institutional clientele. We argue that the catering hypothesis is unlikely to explain our baseline results either, as our results are similarly significant in a matched sample in which firms with *HTP* = 0 and *HTP* = 1 have the same size and institutional ownership (Table IA.7 in the Internet Appendix). In addition, using the counterfactual cross section of director network size (Table IA.5 in the Internet Appendix), we argue against the explanation that firms with high threat

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[22] We also recognize that flows could potentially result in industry overvaluation, which in turn could affect firm policies. This is, however, unlikely because *FIB* is calculated only from activist hedge fund holdings, which account for less than 5% of all hedge fund assets and are an order of magnitude smaller than those of mutual funds. We also allocate flows based on the ratio of activism- to non-activism-related investments, which brings the magnitude down even further. The mean (median) of annual flow-induced fund buying pressure is just 0.02% (0.01%) of industry shares outstanding. In addition, activists target undervalued, not overvalued, firms and we explicitly control for valuation using market-to-book ratios in all of our regressions.

[23] Greenwood and Schor (2009), Becht et al. (2017), and Boyson, Gantchev, and Shivdasani (2017) show that activist targets that get acquired yield the highest return.

perception are more informed about, and hence more sensitive to, capital market conditions.

6.3 *High Threat Perception* Firms May Be More Responsive to Product Market Competition

Activism can have negative spillover effects, as improvements at activist targets often erode the competitive position of their product market rivals (Aslan and Kumar, 2016). These rivals, depending on incentives and capabilities, may make changes to their policies and operations to combat the increased pressure. Recall that we build the cross section of *Threat perception*, using director connections with targeted firms outside a given firm's industry, specifically to difference out this type of spillover effect. That is, we assume that peers with high and low threat perception are, on average, under similar competitive pressure and equally responsive to such pressure.

While we cannot fully prove the above assumption, we argue below that the product market alternative is unlikely to drive our baseline results. First, firms with high threat perception do not compete more closely with activist targets within their network of peers. We use Hoberg and Phillips (2010, 2016) firm-centric definition of a peer network, which is based on textual analysis of product descriptions in firms' 10K filings. In our full sample, the average similarity with targets is 0.042 for both peers with high and low threat perception. Restricting the sample to peers in industries with *Threat* greater than the sample median, we again observe no significant differences in the average similarity score with targets across firms in the two threat perception groups.

Second, even if firms with high and low threat perception compete equally closely with the targets in their industry, those in the high group may still respond more promptly to changes in the competitive landscape. As we discussed earlier, the directors of these firms may be better connected and informed, or these firms may be better governed, as they are larger and have higher institutional ownership. To the extent that the differential responses to product market pressure (and unobserved industry factors) are related to observable firm characteristics, this alternative story seems inconsistent with our results in Tables IA.5 and IA.7 of the Internet Appendix. That is, our baseline findings are not driven by the size of a firm's director network, and remain robust in the matched sample in which firms are similar in most observable characteristics except their threat perception.

Finally, some unobserved forces or firm characteristics may explain the differential responses to competition of firms with high vs. low threat perception. We address this remaining possibility by examining whether the non-core segments of a diversified firm experience similar policy and performance changes as its core segment (segments are defined as three-digit SIC codes). If our documented policy changes are driven by product market effects (or more broadly, by any shocks to the core industry), we should not observe similar changes in the non-core segments. On the other hand, activism threat should apply to all segments as the entire diversified firm seeks to fend off activists.

In Table 8, we report the estimates of our baseline regressions for the segment-year panel, including only the non-core segments of diversified firms. *Threat* and *HTP* are determined at the firm level, with *Threat* defined by the firm's core industry. We use Compustat business segment data to calculate policy outcomes and other segment-level controls, which comes with two caveats. First, we can construct only four of our eight outcome variables at the segment level – capital expenditures, return on assets, return on sales, and asset turnover. Second, segment data are very noisy and most firms either do not report or do not have non-core segments, both of which reduce statistical power.

[Insert Table 8]

Focusing on the interaction between *Threat* and *HTP*, we observe that even non-core segments significantly improve return on assets and return on sales, and reduce capital expenditures. For asset turnover, the coefficient is not statistically significant but has the same sign and magnitude as our baseline results. This segment-level analysis confirms that the policy improvements we have demonstrated among industry peers of activist targets are likely not driven by product market effects, or more generally by shocks to the core industry.

Finally, we note that the product market alternative we discuss above is subtly different from that in Aslan and Kumar (2016). First, the product market effects they show are largely negative (e.g., an average CAR of –1.37% during [–5, +5] days around an activism announcement and a 0.018 decrease in return on assets), whereas the product market alternative that we are concerned with involves positive improvements induced by competitive pressure. As Aslan and Kumar (2016) argue, these negative effects are due to the average peer competing "on the basis of strategic substitutes" and suffering a deteriorated market position when the targets improve. Second, the only positive effects in Aslan and Kumar (2016) are in firms with high probability of being targeted, which they claim compete "on the basis of strategic complements". Note however that even in their interpretation, activism threat is still the *motive* for the improvements, and the peers' competitive strategy, geared towards product complementarity, is the *result* of such improvements. In addition, Aslan and Kumar (2016) do not show any specific policy changes in threatened peers, beyond an 11-day CAR of 1.14% and very small and likely insignificant increases in market shares (price-cost margins) of 0.004 (0.002); in contrast, we show threat-induced improvements in eight policies and performance variables.

7. Conclusion

This paper investigates the role of activism threat in inducing policy changes at non-target firms and examines whether such proactive responses are effective at fending off activists. As activism intensity increases, firms with high threat perception, as measured by director connections to past targets, are more likely to increase leverage and payout, decrease capital expenditures and cash, and improve return on assets and asset turnover. These policy improvements are reflected in the threatened firms' valuations and reduce their ex-post probability of being targeted. Our empirical design, in combination with a host of robustness tests, limits the confounding effects of (i) time-varying industry shocks that may drive both firm policies and activism intensity, and (ii) alternative channels through which firms may be affected by activism.

Our results provide novel large-scale evidence of positive externalities of shareholder activism, implying that its impact 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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Appendix A: Variable Definitions

Variable	Observation	Definition
Abnormal returns	Firm-year	Stock return minus contemporaneous benchmark return. Three benchmarks are used: (i) CRSP value-weighted returns for market adjustment, (ii) value-weighted returns of Fama-French 25 size and value portfolios for FF25VW adjustment, and (iii) equally-weighted returns of Fama-French 25 size and value portfolios for FF25EW adjustment. Source: CRSP and Ken French's website.
Amihud ratio	Firm-year	Prior-year average of Amihud ratio, calculated as [1000* SQRT(|Daily Return| /(Daily Dollar Trading Volume))]. Daily ratios are capped at 30% before averaging, as in Acharya and Pedersen (2005). Source: CRSP.
Asset turnover	Firm-year	Total sales divided by the average of the book values of assets at the beginning and end of the year. Source: Compustat.
Book leverage	Firm-year	Debt (long-term debt plus debt in current liabilities) divided by the sum of debt and common equity. Year-end values. Source: Compustat.
Capex/Assets	Firm-year	Sum of capital expenditures and R&D expenses divided by the book value of assets at the beginning of the year. Source: Compustat.
Cash/Assets	Firm-year	Cash and short-term investments divided by total assets. Year-end values. Source: Compustat.
Bankruptcy	Firm-year	Dummy variable equal to one if the firm files for bankruptcy during the year and zero otherwise. Source: Capital IQ.
EBITDA/Assets	Firm-year	Earnings before interest, taxes, depreciation, and amortization divided by the book value of assets at the beginning of the year. Source: Compustat.
High threat perception (HTP)	Firm-year	Dummy variable equal to one if the beginning-of-year average target connections per director exceed the industry-year median, and zero otherwise. Source: BoardEx.
Improvement z-score	Firm-year	Standardized policy and performance improvement equal to *(change - mean(industry, year))/ stddev(industry, year)* or *(mean(industry, year) - change)/ stddev(industry, year)* depending on whether an increase or a decrease in the policy is considered an improvement. Change is measured from years *t*-1 to *t*+1 for policies (Book leverage, Payout/Market cap, Capex/Assets, Cash/Assets, ln(CEO pay)) and from years *t* to *t*+2 for performance measures (Return on assets, Return on sales, Asset turnover). Avg. improvement z-score is the average across all policy and performance variables, ignoring missing values. Source: Compustat.
Inst. ownership	Firm-year	Total ownership (as % of shares outstanding) of institutional investors who file 13F reports. Year-end values. Source: Thomson Reuters.
ln(Analysts)	Firm-year	Natural log of (one plus) the number of analysts following the firm during the year. Source: I/B/E/S.
ln(CEO pay)	Firm-year	Natural log of total CEO compensation for the year. Source: Execucomp.
ln(Market cap)	Firm-year	Natural log of the firm's market capitalization at the end of the year. Source: CRSP and Compustat.
ln(Sales)	Firm-year	Natural log of the firm's total sales for the year. Source: Compustat.
ln(Stock turnover)	Firm-year	Natural log of the firm's average daily stock turnover during the year. Daily stock turnover is the ratio of the number of shares traded on each trading day to the number of shares outstanding at the end of the year. Source: CRSP.
ln(Tobin's Q)	Firm-year	Natural log of Tobin's Q, calculated as the market value of common equity plus the book value of debt (long-term debt plus debt in current liabilities) divided by the sum of the book values of common equity and debt. Year-end values. Source: CRSP and Compustat.
Market-to-book ratio	Firm-year	Ratio of the market value to book value of common equity at the end of the year. Source: CRSP and Compustat.
Net PPE/Assets	Firm-year	Book value (net of depreciation) of property, plant, and equipment divided by book value of assets. Year-end values. Source: Compustat.

Variable	Observation	Definition
Ongoing campaign	Firm-year	Dummy variable equal to one if an activist campaign is ongoing as of the beginning of the year, and zero otherwise. Source: Schedule 13D.
Payout/Market cap	Firm-year	Sum of dividends and share repurchases divided by market capitalization at the beginning of the year. Source: Compustat.
Past campaigns	Firm-year	Natural log of (one plus) the number of hedge fund activist campaigns targeting the firm in the preceding three years. Source: Schedule 13D.
Policy quintile dummies	Firm-year	Set of five dummy variables defining the quintile in which the firm's beginning-of-year policy lies relative to the policies of other firms in the same 3-digit SIC industry. Source: Compustat.
Return on assets	Firm-year	Operating cash flow divided by the average of the book values of assets at the beginning and end of the year. Source: Compustat.
Return on sales	Firm-year	Operating cash flow divided by annual sales. Source: Compustat.
Sales growth	Firm-year	Percentage change in total sales from the previous year to the current year. Source: Compustat.
Target connections per director	Firm-year	Average target connections per director. A target connection is a school tie to a director at a firm that was targeted by a hedge fund activist in the prior two years and is in a different 3-digit SIC industry. Two directors have a school tie if they receive the same educational degree from the same school within one year of each other. Source: BoardEx.
Target frequency	SIC3-year	Number of firms targeted by activist hedge funds during the year divided by the total number of firms at the beginning of the year. Both quantities are for each 3-digit SIC industry, based on firms with available CRSP/ Compustat data.
Threat	SIC3-year	Capital-based measure of activism intensity. See Appendix B for details.

Appendix B: Construction of *Threat*

i. Fund's Capital Flows

Denote the sum of dollar flows to hedge fund h in year t by $Flow(h,t)$. As in Edmans et al. (2012), we focus on large flows exceeding 5% of total net assets, $TNA(h,t\text{-}1)$, as they tend to force funds to invest quickly and in a mechanical manner (Coval and Stafford, 2007):

$$Flow5(h,t) = \left(Flow(h,t) \text{ if } \frac{Flow(h,t)}{TNA(h,t\text{-}1)} > 0.05;\ 0, \text{ otherwise} \right)$$

ii. Fund's Allocation of Flows to Activism in a Particular Industry

First, denote the market value weight of each industry j in hedge fund h's portfolio at the end of year $t\text{-}2$ by $W(h,j,t\text{-}2)$. We assume that when forced to invest quickly, the fund will allocate its large dollar flows across industries based on its past portfolio weights. We use the weights at the end of year t-2 as opposed to the latest weights to avoid the confounding effects of time-varying industry shocks that may drive the fund's latest industry positioning. In addition, we use both activism- and non-activism related investments in calculating the industry weights, as our focus is not on the continuation of the fund's targeting in the same industry but rather on its understanding of and familiarity with the industry.

Second, denote the market value weights of activism and non-activism related investments in hedge fund h's portfolio at the end of year $t\text{-}2$ by $W(h,A,t\text{-}2)$ and $W(h,P,t\text{-}2)$, respectively. We assume that hedge fund h only allocates $W(h,A,t\text{-}2)$ of its large dollar flows, towards targeting. We use the weight of activism-related investments in combination with the industry weight to capture the fact that different hedge funds engage in activism to different degrees. For example, at the end of 2006, Farallon Capital had over \$10 billion in assets under management but only 5% was dedicated to activism. On the other hand, VA Partners (or ValueAct Capital) had less than \$4 billion but over 90% was dedicated to activism. As such, the flows to VA would have a greater contribution to activism threat than those to Farallon.

Finally, we define flow-induced fund buys, $FIFB(h,j,t)$, as the dollar flows that hedge fund h is expected to allocate to activism in industry j in year t:

$FIFB(h,j,t) = Flow5(h,t) \times W(h,A,t\text{-}2) \times W(h,j,t\text{-}2)$

iii. Aggregation across Hedge Funds to Obtain Industry-Level *Threat*

In the final few steps, we sum $FIFB(h,j,t)$ across all hedge funds for each industry j in year t, and divide the sum by the market capitalization of all firms in that industry, $MCAP(j,t\text{-}1)$, to obtain the percentage flow-induced buys, $FIB\%(j,t)$:

$$FIB\%(j,t) = \frac{\Sigma_h FIFB(h,j,t)}{MCAP(j,t)} \times 100.$$

$FIB\%(j,t)$ captures the additional capital received by all activists that need to launch campaigns quickly and, due to information costs and familiarity considerations, are likely to do so in industries in which they already own stakes in some companies. Finally, we calculate *Threat* as the cross industry-year percentile rank of $FIB\%(j,t)$, which takes values from 0 to 1, with 1 being the highest.

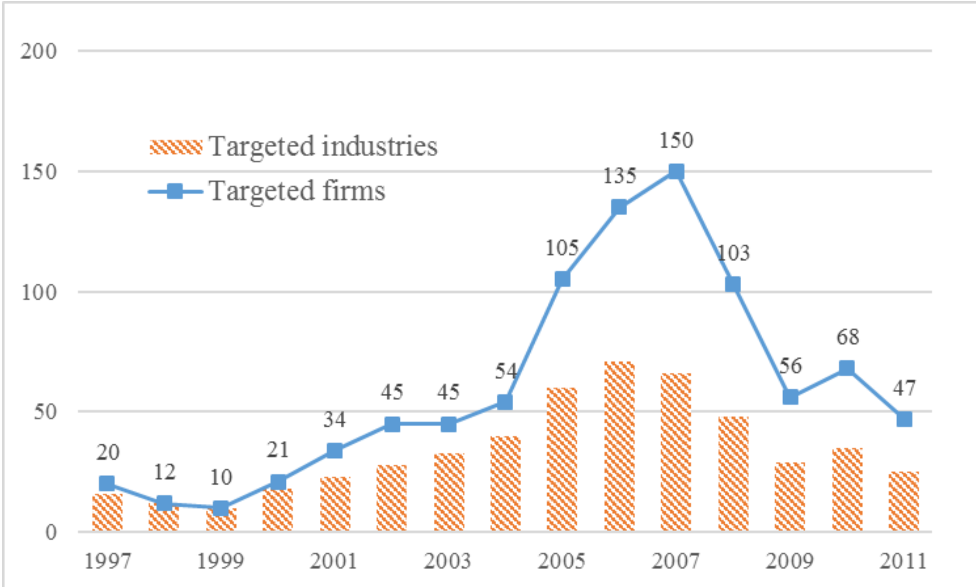

Figure 1: Numbers of Activist-Targeted Firms and Industries over Time. This figure plots frequency counts of firms (line with square markers) and three-digit SIC industries (patterned bars) targeted by hedge fund activists over the sample period from 1997 to 2011. Targeted industries are those with at least one firm targeted by an activist hedge fund in a given year. Included are targeted firms matched to CRSP, Compustat, Thomson Reuters 13F, and BoardEx data in three-digit SIC industries with at least 5 matched firms.

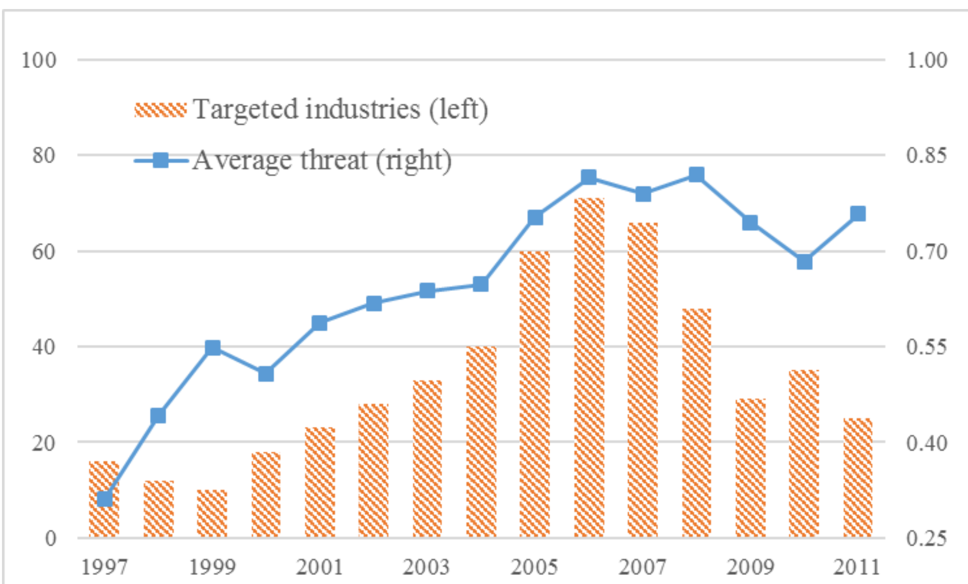

Figure 2: Numbers of Activist-Targeted and Threatened Industries over Time. This figure plots frequency counts of activist-targeted three-digit SIC industries (patterned bars, left scale) and average activism *Threat* (line with square markers, right scale) over the sample period from 1997 to 2011. Targeted industries are those with at least one firm targeted by an activist hedge fund in a given year. The construction of *Threat* is described in Appendix B. Included are only industries with *at least five firms* matched to CRSP, Compustat, Thomson Reuter 13F, and BoardEx data.

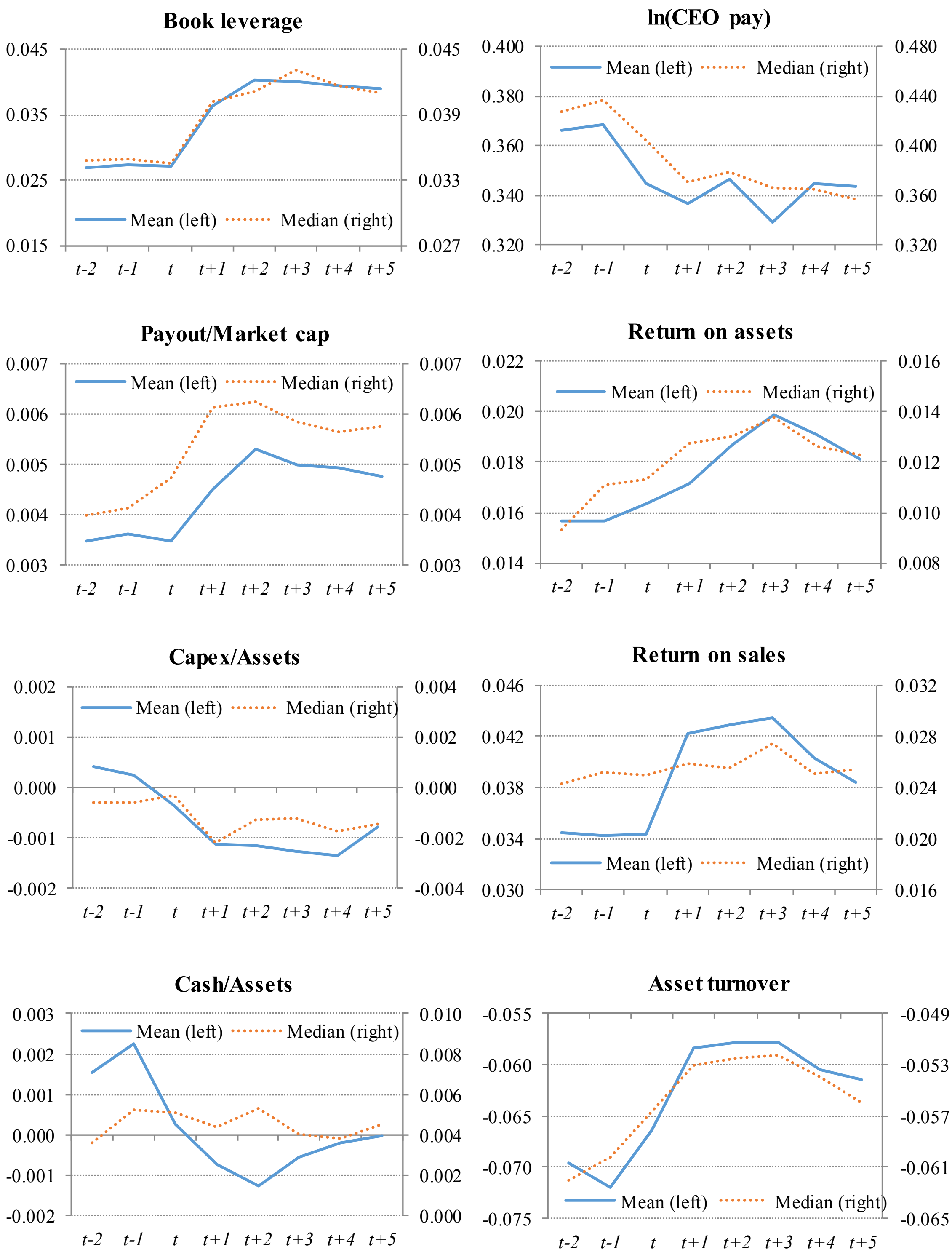

Figure 3: Policy Differences between Peer Firms with High vs. Low Threat Perception. This figure plots mean and median differences in financial, investment, and operating policies between non-targeted firms with high and low threat perception (*HTP* = 1 and *HTP* = 0, respectively). The sample period is 1997-2011. The statistics are calculated for event years *t-2* to *t+5*, where year *t* is the year in which industry *Threat* is in the top quartile of the sample (i.e., greater than 0.75). *HTP* and all policy variables are defined in Appendix A. The construction of *Threat* is described in Appendix B.

Table 1: Summary Statistics

This table reports summary statistics for select firm-level variables. The sample includes all firms that have non-missing CRSP, Compustat, Thomson Reuters 13F, and BoardEx data, and are in three-digit SIC industries with at least five firms. The observations are firm-year, and the sample period is 1997-2011. The number of observations is 45,357, with *CEO pay* available for 19,820 observations and *Analysts* available for 22,272 observations. The number of unique firms is 5,083, and the number of unique three-digit SIC industries is 187. All variables are winsorized at 2.5% and 97.5%, and are defined in Appendix A.

	Mean	Std. Dev.	5th PCT	25th PCT	Median	75th PCT	95th PCT
Market cap ($ million)	2,062	4,378	15	92	372	1,477	13,607
Book leverage	0.298	0.266	0.000	0.025	0.261	0.499	0.781
Payout/Market cap	0.023	0.033	0.000	0.000	0.006	0.035	0.097
Capex/Assets	0.086	0.110	0.000	0.004	0.047	0.121	0.323
Cash/Assets	0.193	0.222	0.005	0.028	0.094	0.290	0.705
CEO pay ($ million)	4.659	5.161	0.468	1.282	2.705	5.808	17.642
Return on assets	0.074	0.176	-0.281	0.024	0.101	0.169	0.297
Return on sales	-0.064	0.966	-1.019	0.044	0.122	0.224	0.436
Asset turnover	0.982	0.778	0.062	0.383	0.843	1.365	2.631
Tobin's Q	2.349	2.141	0.690	1.081	1.567	2.690	7.160
Stock turnover x 100	0.718	0.668	0.081	0.241	0.495	0.961	2.251
Sales growth	0.187	0.442	-0.287	-0.014	0.094	0.253	0.968
Analysts	9.105	9.040	1.000	3.000	6.000	12.000	28.000
Inst. ownership	0.513	0.302	0.032	0.243	0.530	0.783	0.951
Target connections per director	0.496	0.793	0.000	0.000	0.132	0.667	2.400

Table 2: Activism Threat and Target Frequency

This table reports OLS estimates from panel regressions of target frequency on (industry-level) percentage *Flow-induced buys* (*FIB%*) and *Threat*. The observations are three-digit SIC industry-year. Target frequency is calculated as the number of firms targeted by activist hedge funds during year *t* divided by the total number of firms in the industry at the beginning of year *t*. *FIB%* in year *t* is calculated using inferred flows to each hedge fund in year *t* and the fund's holdings at the end of year *t*-2. First, for each hedge fund, we aggregate the amount of dollar fund flows during year *t*. Second, we allocate the aggregate dollar flows across industries based on the fund's industry allocation at the end of year *t*-2, considering only the aggregate dollar flows that exceed 5% of the fund's total net assets at the end of year *t*-1. Third, we further scale the allocated dollar flows by the fund's allocation between activism- and non-activism-related investments, also as of the end of year *t*-2. Finally, to obtain *FIB%*, we sum the allocated flows to activism in each industry across all hedge funds, and divide the sum by the industry's total market capitalization at the end of year *t*-1 (scaling by 100, such that 1 = 1%). *FIB%* is positive for 2,395 of 2,856 (83%) industry-year observations and zero for the remaining. Of the positive values, the mean and median are 0.0213 and 0.0015, respectively. *Threat* is a percentile variable with values ranging from 0 to 1, reflecting the ordering of industry-year observations by *FIB%*. Additional details on the construction of *Threat* are in Appendix B. All columns include industry and year fixed effects. Columns (3) and (6) also include industry averages of *Book leverage*, *Payout/Market cap*, *Capex/Assets*, *Cash/Assets*, *ln(CEO pay)*, *Return on assets*, *Return on sales*, *Asset turnover*, *ln(Market cap)*, *ln(Sales)*, *Market-to-book ratio*, *EBITDA/Assets*, *Net PPE/Assets*. Standard errors, clustered by industry, are in parentheses. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
FIB%	0.140***	0.121***	0.117***			
	(0.028)	(0.031)	(0.031)			
Threat				0.040***	0.034***	0.034***
				(0.005)	(0.004)	(0.005)
Ownership		0.000	0.000		0.003*	0.004**
		(0.002)	(0.002)		(0.002)	(0.001)
Target frequency(*t*-1)		0.102*	0.061		0.093*	0.063*
		(0.052)	(0.038)		(0.050)	(0.038)
Average firm characteristics	NO	NO	YES	NO	NO	YES
Industry FE	YES	YES	YES	YES	YES	YES
Calendar year FE	YES	YES	YES	YES	YES	YES
Observations	2,856	2,856	2,481	2,856	2,856	2,481
R-squared (within industry)	0.090	0.099	0.113	0.099	0.108	0.112

Table 3: Policy Changes at Peer Firms Facing Activism Threat

This table reports OLS estimates from panel regressions of changes in policies and performance at peers of activist targets on (industry-level) *Threat*, (firm-level) *High threat perception (HTP)*, and their interaction. The observations are firm-year, and the sample period is 1997-2011. In columns (1) – (5), the dependent variables are changes in financial and investment policies from years *t*-1 to *t*+1, where year *t* is the current observation year. In columns (6) – (8), the dependent variables are changes in operating performance metrics from years *t* to *t*+2. Bankruptcy is as of year *t* while all other control variables are as of year *t*-1. All regressions include dummies for years around activist target events, industry and calendar year fixed effects, and policy quintile dummies. The construction of *Threat* is described in Appendix B. All other variables are defined in Appendix A. Standard errors, clustered by industry, are in parentheses. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	Policy Variables					Performance Variables		
	Δ Book leverage	Δ Payout/ Market cap	Δ Capex/ Assets	Δ Cash/ Assets	Δ ln(CEO pay)	Δ Return on assets	Δ Return on sales	Δ Asset turnover
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Main variables								
Threat	0.006	-0.005	-0.001	0.007	-0.015	-0.004	0.008	-0.006
	(0.007)	(0.003)	(0.004)	(0.005)	(0.064)	(0.004)	(0.014)	(0.007)
[HTP] High threat perception	-0.006	-0.002	0.003	0.007	0.074	-0.005*	0.001	0.003
	(0.006)	(0.002)	(0.003)	(0.005)	(0.048)	(0.003)	(0.011)	(0.006)
Threat x HTP	0.016**	0.008***	-0.007*	-0.011*	-0.087	0.011***	0.012	0.016*
	(0.008)	(0.003)	(0.004)	(0.006)	(0.069)	(0.004)	(0.015)	(0.008)
Activist target event controls								
Year *t*-1	-0.002	-0.000	-0.008*	-0.002	-0.015	0.008	-0.011	0.010
	(0.007)	(0.002)	(0.005)	(0.003)	(0.049)	(0.006)	(0.009)	(0.008)
Year *t*	0.010	0.014*	-0.009***	0.002	0.061	0.010**	0.039*	0.029***
	(0.007)	(0.007)	(0.003)	(0.006)	(0.042)	(0.004)	(0.022)	(0.010)
Year *t*+1	0.014***	0.000	-0.009**	0.005	-0.095***	-0.004	-0.010	-0.008
	(0.005)	(0.002)	(0.004)	(0.003)	(0.035)	(0.006)	(0.010)	(0.010)
Firm and industry controls								
Bankruptcy	-0.149***	-0.003	0.016	-0.003	0.374	0.018	0.047**	-0.013
	(0.034)	(0.010)	(0.014)	(0.028)	(0.430)	(0.014)	(0.020)	(0.083)
ln(Market cap)	0.011***	0.002***	0.002	-0.006***	0.053***	-0.007***	0.025***	-0.017***
	(0.002)	(0.000)	(0.001)	(0.001)	(0.011)	(0.002)	(0.005)	(0.004)

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	Policy Variables					Performance Variables		
	Δ Book leverage	Δ Payout/ Market cap	Δ Capex/ Assets	Δ Cash/ Assets	Δ ln(CEO pay)	Δ Return on assets	Δ Return on sales	Δ Asset turnover
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Sales)	-0.005**	-0.000	-0.004***	0.005***	0.066***	0.011***	-0.020***	0.017***
	(0.002)	(0.000)	(0.001)	(0.001)	(0.007)	(0.002)	(0.004)	(0.004)
Market-to-book ratio	-0.004***	-0.001***	-0.002***	0.001**	0.006***	-0.001	-0.003**	-0.008***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)
EBITDA/Assets	-0.039***	0.009***	0.013	-0.003	-0.313***	-0.135***	-0.321***	-0.205***
	(0.008)	(0.001)	(0.011)	(0.008)	(0.057)	(0.014)	(0.021)	(0.030)
Net PPE/Assets	0.068***	-0.010***	-0.031***	-0.035***	0.035	0.014***	0.036**	-0.063***
	(0.008)	(0.001)	(0.006)	(0.006)	(0.040)	(0.005)	(0.017)	(0.012)
Target frequency during *t*-2 and *t*-1	0.024	-0.005	-0.006	-0.000	0.059	-0.013	-0.045	0.008
	(0.019)	(0.005)	(0.008)	(0.013)	(0.122)	(0.015)	(0.030)	(0.041)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Calendar year FE	YES	YES	YES	YES	YES	YES	YES	YES
Policy quintile dummies	YES	YES	YES	YES	YES	YES	YES	YES
Observations	38,849	38,849	38,849	38,837	17,463	38,819	38,819	38,819
R-squared (within)	0.094	0.160	0.139	0.112	0.156	0.070	0.065	0.094

Table 4: Policy Changes at Threatened Firms Conditional on Their Vulnerability to Activist Targeting

This table reports OLS estimates from panel regressions of changes in policies and performance at peers of activist targets on (industry-level) *Threat*, (firm-level) *High threat perception* (*HTP*), and their interaction for the subsamples of firms that are vulnerable vs. not vulnerable to activist targeting, given their current policies (Panel A) and their stock liquidity (Panel B). The observations are firm-year, and the sample period is 1997-2011. In Panel A, for each specific policy (e.g., leverage), a firm is considered vulnerable if its policy at the end of *t*-1 is worse from the activists' perspective (e.g., lower leverage) than the industry median. In Panel B, a firm is considered vulnerable if its stock liquidity, as measured by its prior-year Amihud ratio, is lower than or equal to the industry median. In columns (1) – (5), the dependent variables are changes in policies from years *t*-1 to *t*+1. In columns (6) – (8), the dependent variables are changes in performance metrics from years *t* to *t*+2. As in Table 3, all regressions include dummies for years around activist target events, firm- and industry-level controls, industry and calendar year fixed effects, and policy quintile dummies. The construction of *Threat* is described in Appendix B. All other variables are defined in Appendix A. Standard errors, clustered by industry, are in parentheses. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

Table 4, Cont'd: Policy Changes at Threatened Firms Conditional on Their Vulnerability to Activist Targeting

Panel A: Policy-specific vulnerability

	Policy Variables					Performance Variables		
	Δ Book leverage	Δ Payout/ Market cap	Δ Capex/ Assets	Δ Cash/ Assets	Δ ln(CEO pay)	Δ Return on assets	Δ Return on sales	Δ Asset turnover
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A1: Vulnerable firms with regard to each policy								
Threat	0.004	0.004	-0.006	0.013	-0.121	-0.008	-0.003	-0.006
	(0.009)	(0.004)	(0.006)	(0.010)	(0.088)	(0.009)	(0.022)	(0.015)
[HTP] High threat perception	-0.009	0.008*	0.002	0.007	-0.001	-0.003	0.015	-0.019
	(0.008)	(0.004)	(0.003)	(0.008)	(0.070)	(0.004)	(0.015)	(0.013)
Threat x HTP	0.023*	0.012**	-0.008**	-0.011	-0.166*	0.013**	0.015	0.027*
	(0.012)	(0.006)	(0.003)	(0.011)	(0.095)	(0.006)	(0.020)	(0.016)
Observations	19,649	19,996	18,783	19,523	9,268	16,722	16,548	18,672
R-squared (within)	0.044	0.010	0.117	0.068	0.118	0.039	0.063	0.076
A2: Non-vulnerable firms with regard to each policy								
Threat	0.008	-0.013	0.004	0.008	0.084	0.002	0.009	-0.013
	(0.010)	(0.008)	(0.003)	(0.006)	(0.076)	(0.008)	(0.012)	(0.015)
[HTP] High threat perception	-0.008	-0.006	0.003	0.005	0.144*	-0.007	-0.012	-0.009
	(0.008)	(0.004)	(0.002)	(0.007)	(0.075)	(0.005)	(0.011)	(0.019)
Threat x HTP	0.006	-0.002	-0.005	-0.010	-0.001	0.006	0.005	0.009
	(0.012)	(0.007)	(0.003)	(0.009)	(0.102)	(0.007)	(0.017)	(0.020)
Observations	19,200	18,853	20,066	19,314	8,195	22,097	22,271	20,147
R-squared (within)	0.080	0.042	0.067	0.050	0.074	0.089	0.036	0.075
Controls and FEs as in Table 3	YES	YES	YES	YES	YES	YES	YES	YES

Table 4, Cont'd: Policy Changes at Threatened Firms Conditional on Their Vulnerability to Activist Targeting

Panel B: Vulnerability associated with stock liquidity

	Policy Variables					Performance Variables		
	Δ Book leverage	Δ Payout/ Market cap	Δ Capex/ Assets	Δ Cash/ Assets	Δ ln(CEO pay)	Δ Return on assets	Δ Return on sales	Δ Asset turnover
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
B1: Vulnerable firms = Liquid firms								
Threat	0.008	0.004	-0.004	-0.005	-0.065	0.005	0.027	0.003
	(0.012)	(0.003)	(0.004)	(0.009)	(0.072)	(0.008)	(0.017)	(0.015)
[HTP] High threat perception	-0.012	0.001	0.003	0.005	0.034	-0.008**	-0.005	-0.017
	(0.008)	(0.002)	(0.004)	(0.004)	(0.048)	(0.003)	(0.008)	(0.011)
Threat x HTP	0.029**	0.008*	-0.009*	-0.012*	-0.092	0.012**	0.006	0.026*
	(0.012)	(0.004)	(0.005)	(0.007)	(0.071)	(0.006)	(0.014)	(0.015)
Observations	21,845	21,845	21,845	21,845	14,779	21,832	21,832	21,832
R-squared (within)	0.093	0.164	0.170	0.130	0.168	0.108	0.100	0.118
B2: Non-vulnerable firms = Illiquid firms								
Threat	0.005	-0.002	0.003	0.016**	0.121	-0.012	-0.012	-0.021
	(0.008)	(0.002)	(0.006)	(0.007)	(0.116)	(0.009)	(0.021)	(0.020)
[HTP] High threat perception	-0.002	0.001	0.000	0.003	0.045	-0.000	0.011	0.008
	(0.008)	(0.002)	(0.004)	(0.006)	(0.098)	(0.005)	(0.022)	(0.016)
Threat x HTP	0.001	0.002	-0.002	-0.008	-0.054	0.006	0.001	0.010
	(0.011)	(0.003)	(0.006)	(0.009)	(0.139)	(0.007)	(0.027)	(0.021)
Observations	17,004	17,004	17,004	16,992	2,684	16,987	16,987	16,987
R-squared (within)	0.103	0.167	0.114	0.104	0.133	0.052	0.049	0.078
Controls and FEs as in Table 3	YES	YES	YES	YES	YES	YES	YES	YES

Table 5: Abnormal Returns of Peer Firms Facing Activism Threat

This table reports OLS estimates from panel regressions of abnormal stock returns on lead and lag values of (industry-level) *Threat*, (firm-level) *High threat perception* (*HTP*), and their interaction. Observations are firm-year, and the sample period is 1997-2011. Columns (1) – (3) include the full sample. Columns (4) and (5) are for the subsamples of firms with prior-year Amihud ratio lower than/equal to or greater than the industry median, respectively. In column (1), abnormal returns are stock returns minus CRSP value-weighted returns. In column (2) (columns (3) – (5)), abnormal returns are stock returns minus equally-weighted (value-weighted) returns of the Fama-French 25 size and style matched portfolios. All regressions include a control for *Bankruptcy*, and industry-by-year fixed effects. The construction of *Threat* is described in Appendix B. All other variables are defined in Appendix A. Standard errors, clustered by industry, are in parentheses. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	Market	FF25EW	FF25VW		
	Full Sample	Full Sample	Full Sample	Amihud ≤ Median	Amihud > Median
	(1)	(2)	(3)	(4)	(5)
Main variables					
[HTP] High threat perception	0.014	0.015	0.015	0.013	0.019
	(0.016)	(0.015)	(0.016)	(0.018)	(0.024)
Threat(*t*+2) x HTP	0.011	0.016	0.018	0.015	0.024
	(0.020)	(0.020)	(0.016)	(0.026)	(0.037)
Threat(*t*+1) x HTP	0.018	0.015	0.013	0.009	0.020
	(0.019)	(0.016)	(0.015)	(0.019)	(0.033)
Threat(*t*) x HTP	-0.012	-0.017	-0.017	-0.011	-0.023
	(0.019)	(0.018)	(0.018)	(0.024)	(0.028)
Threat(*t*-1) x HTP	0.029*	0.032*	0.027*	0.048**	0.010
	(0.017)	(0.017)	(0.016)	(0.021)	(0.031)
Threat(*t*-2) x HTP	0.030*	0.015	0.029*	0.023	0.031
	(0.018)	(0.020)	(0.017)	(0.025)	(0.036)
Activist target event controls					
Year *t*-2	-0.021	-0.020	-0.031**	-0.034*	-0.048**
	(0.012)	(0.015)	(0.014)	(0.017)	(0.022)
Year *t*-1	-0.068***	-0.075***	-0.073***	-0.083***	-0.054**
	(0.016)	(0.014)	(0.015)	(0.019)	(0.018)
Year *t*	0.017	0.020	0.017	0.020	0.003
	(0.020)	(0.019)	(0.018)	(0.025)	(0.018)
Year t+1	0.047**	0.043**	0.045**	0.022	0.065*
	(0.023)	(0.021)	(0.019)	(0.037)	(0.038)
Year t+2	0.021	0.023	0.020	0.009	0.041
	(0.020)	(0.017)	(0.018)	(0.024)	(0.025)
Other events					
Bankruptcy	-0.027	0.005	-0.000	-0.007	-0.011
	(0.092)	(0.040)	(0.052)	(0.066)	(0.110)
Industry x Calendar year FE	YES	YES	YES	YES	YES
Observations	32,959	32,959	32,959	19,278	13,681
R-squared (within)	0.002	0.002	0.002	0.005	0.002

Table 6: Feedback Effects of Policy Changes and Returns at Threatened Firms

This table reports OLS estimates for linear probability models of activist targeting. Observations are firm-year, and the sample period is 1997-2011. The dependent variable is an indicator variable that equals one if a firm is targeted by activist hedge funds during years t to t+2. The explanatory variables of interest are *Threat*, *Avg. improvement z-score*, *Abnormal return*, and the interactions between *Threat* and the latter two variables. *Avg. improvement z-score* is the average of normalized policy and performance changes, where as in Table 3, the changes are measured from years t-1 to t+1 for financial and investment policies and from years t to t+2 for performance metrics. *Abnormal return* is the annualized average monthly abnormal return in years t and t+1, calculated with respect to the matched Fama-French 25 value-weighted size and style portfolios. The construction of *Threat* is described in Appendix B. All other variables are defined in Appendix A. Columns (1) – (3) are for the full sample. Columns (4) and (5) are for the subsamples of firms with prior-year Amihud ratio lower than/equal to or greater than the industry median, respectively. All regressions include industry and calendar year fixed effects. Standard errors, clustered by industry, are in parentheses. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	Full Sample			Amihud ≤ Median	Amihud > Median
	(1)	(2)	(3)	(4)	(5)
Main variables					
Threat	0.023**	0.026**	0.030***	0.047***	0.012
	(0.009)	(0.010)	(0.011)	(0.017)	(0.013)
Avg. improvement z-score		-0.002	0.000	0.010	-0.001
		(0.011)	(0.012)	(0.014)	(0.014)
Threat x Avg. improvement z-score		-0.026**	-0.029**	-0.032**	-0.018
		(0.012)	(0.013)	(0.016)	(0.015)
Abnormal return			-0.005	0.002	-0.009
			(0.013)	(0.018)	(0.018)
Threat x Abnormal return			-0.042**	-0.068**	-0.027
			(0.020)	(0.028)	(0.028)
Firm and industry controls					
[HTP] High threat perception	-0.000	-0.001	-0.000	-0.004	0.006
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
ln(Market cap)	-0.010***	-0.010***	-0.011***	-0.009***	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
ln(Tobin's Q)	-0.020***	-0.024***	-0.016***	-0.016***	-0.012*
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Book leverage	0.007	0.009	0.014	0.017	-0.002
	(0.008)	(0.009)	(0.009)	(0.011)	(0.013)
Payout/Market cap	-0.019	-0.007	-0.021	-0.029	-0.029
	(0.051)	(0.055)	(0.055)	(0.062)	(0.091)
Sales growth	0.006*	0.005	0.002	0.003	0.000
	(0.004)	(0.005)	(0.004)	(0.007)	(0.004)

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	Full Sample			Amihud ≤ Median	Amihud > Median
	(1)	(2)	(3)	(4)	(5)
Return on assets	-0.011	-0.020*	-0.014	-0.033*	0.005
	(0.012)	(0.012)	(0.013)	(0.018)	(0.020)
ln(Stock turnover)	0.166	0.212	0.351	0.501	0.490
	(0.251)	(0.284)	(0.291)	(0.349)	(0.454)
ln(Analysts)	0.000	0.001	-0.000	-0.002	0.001
	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)
Inst. ownership	0.072***	0.073***	0.072***	0.067***	0.089***
	(0.008)	(0.009)	(0.009)	(0.011)	(0.015)
Past campaigns	0.498***	0.521***	0.512***	0.523***	0.490***
	(0.070)	(0.073)	(0.076)	(0.099)	(0.110)
Ongoing campaign	0.002	0.009	0.014	0.019	0.005
	(0.023)	(0.024)	(0.024)	(0.034)	(0.032)
Target frequency during *t*-2 and *t*-1	0.001	0.002	0.000	0.000	0.001
	(0.021)	(0.023)	(0.024)	(0.037)	(0.034)
Industry FE	YES	YES	YES	YES	YES
Calendar year FE	YES	YES	YES	YES	YES
Observations	34,277	34,277	33,077	18,881	14,196
R-squared (within)	0.031	0.030	0.032	0.038	0.028

Table 7: Policy Changes at Peer Firms Facing Time-Varying Industry Shocks (Falsification Tests)

This table reports OLS estimates from regressions of changes in policies and performance at peers of activist targets on time-varying industry shocks, (firm-level) *High threat perception* (*HTP*), and their interaction. The observations are firm-year, and the sample period is 1997-2011. Two specific types of shocks are studied: *Policy wave* (Panel A) and *Merger wave* (Panel B). For each specific policy (e.g., leverage), *Policy wave* is a percentile variable with values ranging from 0 to 1, reflecting the ordering of industry-year observations by the fraction of significantly improving firms in the industry. A significant improvement is defined as a policy change that is in the top quartile if all firm-year observations are ordered from the most to the least improved (e.g., from largest increase to largest decrease in leverage). Changes are measured from years *t*-1 to *t*+1 for financial and investment policies in columns (1) – (5) or from *t* to *t*+2 for operating performance metrics in columns (6) – (8). *Merger wave* is an indicator variable that equals one if the number of mergers in the industry during year *t* is at least 20% of the total number of mergers in the industry over the period 2000-2011 (when the merger data are available to us) and the total number of mergers in the industry is greater than five. As in Table 3, all regressions include dummies for years around activist target events, firm- and industry-level controls, industry and calendar year fixed effects, and policy quintile dummies. All variables are defined in Appendix A. Standard errors, clustered by industry, are in parentheses. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Policy waves

	Policy Variables					Performance Variables		
	Δ Book leverage	Δ Payout/ Market cap	Δ Capex/ Assets	Δ Cash/ Assets	Δ ln(CEO pay)	Δ Return on assets	Δ Return on sales	Δ Asset turnover
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Policy wave	0.119***	0.030***	-0.018***	-0.047***	-0.479***	0.052***	0.044***	0.186***
	(0.010)	(0.003)	(0.005)	(0.005)	(0.035)	(0.011)	(0.008)	(0.029)
[HTP] High threat perception	0.002	-0.001	-0.001	0.007*	0.001	0.000	-0.002	-0.004
	(0.006)	(0.002)	(0.001)	(0.004)	(0.030)	(0.003)	(0.005)	(0.005)
Policy wave x HTP	-0.004	0.003	0.002	-0.004	0.012	0.001	0.004	0.001
	(0.007)	(0.003)	(0.001)	(0.005)	(0.033)	(0.003)	(0.008)	(0.006)
Controls and FEs as in Table 3	YES	YES	YES	YES	YES	YES	YES	YES
Observations	38,849	38,849	38,849	38,837	17,463	38,819	38,819	38,819
R-squared (within)	0.108	0.044	0.141	0.120	0.189	0.080	0.067	0.114

Table 7, Cont'd: Policy Changes at Peer Firms Facing Time-Varying Industry Shocks (Falsification Tests)

Panel B: Merger waves (2000-2011)

	Policy Variables					Performance Variables		
	Δ Book leverage	Δ Payout/ Market cap	Δ Capex/ Assets	Δ Cash/ Assets	Δ ln(CEO pay)	Δ Return on assets	Δ Return on sales	Δ Asset turnover
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Merger wave	0.013*	-0.004	0.001	-0.003	0.055	-0.002	0.001	-0.021
	(0.006)	(0.005)	(0.003)	(0.003)	(0.044)	(0.006)	(0.010)	(0.013)
[HTP] High threat perception	-0.002	0.001	0.000	0.000	0.017	0.002	0.003	-0.003
	(0.002)	(0.001)	(0.001)	(0.001)	(0.011)	(0.001)	(0.003)	(0.003)
Merger wave x HTP	-0.006	0.003	0.001	0.007*	-0.067	0.000	-0.004	-0.001
	(0.007)	(0.005)	(0.003)	(0.004)	(0.057)	(0.005)	(0.010)	(0.010)
Controls and FEs as in Table 3	YES	YES	YES	YES	YES	YES	YES	YES
Observations	32,520	32,520	32,520	32,520	14,951	32,492	32,492	32,492
R-squared (within)	0.089	0.045	0.126	0.108	0.164	0.071	0.069	0.093

Table 8: Policy Changes at Non-Primary Segments of Threatened Firms

This table reports OLS estimates from regressions of changes in policies and performance at non-primary segments of peers of activist targets on (industry-level) *Threat*, (firm-level) *High threat perception* (*HTP*), and their interaction. The observations are segment-firm-year, and the sample period is 1997-2011. Non-primary segments are distinct parts of the firm with three-digit SICs that differ from the firm's main three-digit SIC. *Threat* is assigned to all segments of the firm based on its main three-digit SIC. Segment-level data are from Compustat Segment files. In column (1), the dependent variable is the change in segment-level *Capex*/*Assets* from years *t*-1 to *t*+1. In columns (2) – (4), the dependent variables are changes in segment-level *Return on assets*, *Return on sales*, and *Asset turnover*, respectively, from years *t* to *t*+2. Segment-level controls, given the availability of segment data, include *ln*(*Sales*) and *EBITDA*/*Assets*. All regressions include dummies for years around activist target events, firm- and (primary) industry-level controls, (segment) industry and calendar year fixed effects, and policy quintile dummies. The construction of *Threat* is described in Appendix B. All other variables are defined in Appendix A. Standard errors, clustered by firm, are in parentheses. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	Δ Capex/ Assets (1)	Δ Return on assets (2)	Δ Return on sales (3)	Δ Asset turnover (4)
Main variables				
Threat	0.000	0.005	0.004	0.007
	(0.003)	(0.008)	(0.009)	(0.026)
[HTP] High threat perception	0.004	0.003	0.006	0.006
	(0.003)	(0.009)	(0.011)	(0.029)
Threat x HTP	-0.010**	0.015*	0.022*	0.032
	(0.005)	(0.009)	(0.012)	(0.039)
Activist target event controls				
Year *t*-1	-0.003	0.007	0.001	0.015
	(0.002)	(0.006)	(0.007)	(0.017)
Year *t*	-0.010***	0.015**	0.028**	0.026
	(0.003)	(0.008)	(0.012)	(0.019)
Year *t*+1	-0.002	0.001	-0.004	0.032**
	(0.003)	(0.006)	(0.006)	(0.014)
Segment controls				
ln(Sales)	-0.002***	0.002*	-0.001	0.003
	(0.000)	(0.001)	(0.002)	(0.003)
EBITDA/Assets	-0.001	-0.120***	-0.108***	-0.252***
	(0.003)	(0.010)	(0.013)	(0.027)
Controls as in Table 3	YES	YES	YES	YES
(Segment) Industry FE	YES	YES	YES	YES
Calendar year FE	YES	YES	YES	YES
Policy quintile dummies	YES	YES	YES	YES
Observations	16,529	16,922	17,188	17,139
R-squared (within)	0.054	0.057	0.046	0.044

Internet Appendix for

Governance under the Gun: Spillover Effects of Hedge Fund Activism

Presentation of the Effects of Activism Threat in the Peer Effects Framework of Manski (1993)

We argue that the effects of activism threat can be interpreted as peer effects in the social effects framework of Manski (1993). Such an interpretation helps highlight the challenges in distinguishing activism threat from other forces that may affect both activist targeting and firm policies.

Following Leary and Roberts (2014), we model a firm's policy, y_{ijt}, as

$$y_{ijt} = \alpha + \beta\bar{y}_{-ijt} + \gamma'\bar{X}_{-ijt} + \lambda'X_{ijt} + U_{jt} + \varepsilon_{ijt}, \tag{1}$$

where the subscripts i, j, and t correspond to firm, industry, and year, respectively. The covariate $\bar{y}_{-ijt}$ denotes peer-firm average policy (excluding firm i), and the vectors $\bar{X}_{-ijt}$ and X_{ijt} are peer-firm average characteristics and own-firm characteristics, respectively. We define a peer group as firms in the same three-digit SIC industry. The vector U_{jt} contains time-varying industry factors that affect the outcome variable, and is usually assumed to contain a time-invariant industry component and a common time component that can be absorbed through industry and time fixed effects, i.e., $U_{jt} = \delta'\mu_j + \phi'v_t + \kappa'u_{jt}$.

Manski (1993) refers to $\beta\bar{y}_{-ijt}$ as the endogenous effects, $\gamma'\bar{X}_{-ijt}$ as the contextual (or exogenous) effects, and U_{jt} as the correlated effects. The first two are different manifestations of peer effects; the former represent group behavior affecting individual behavior, whereas the latter represent group characteristics affecting individual behavior. We view the effects of activism threat as *contextual effects* as policy changes are induced by the *peers' average characteristic of "being targeted"*. Consider an indicator equal to one if a firm is targeted as an element of X. Then, the corresponding element of $\bar{X}_{-ijt}$ is simply the number of activist targets divided by the number of firms in the industry, to which we refer as target frequency. Thus, proving the existence of activism threat boils down to proving that the element of γ associated with target frequency is non-zero and that it embeds among other things the effects of threat on policy actions.

Leary and Roberts (2014) show that the structural model (1) translates to the following reduced-form regression (ignoring the industry and time fixed effects for convenience):

$$E(y|X,u_j) = \alpha^* + \gamma^*{}'E(X|u_j) + \lambda^*{}'X + \kappa^*{}'u_j, \tag{2}$$

where $\alpha^* = \frac{\alpha}{1-\beta}$; $\gamma^{*'} = \left(\frac{\beta\lambda+\gamma}{1-\beta}\right)'$; $\lambda^{*'} = \lambda'$; $\kappa^{*'} = \left(\frac{\kappa}{1-\beta}\right)'$

Peer vs. Correlated Effects

The first challenge is to identify the effects of activism threat as peer effects. If activism has externalities on industry peers, then the coefficient γ^* in equation (2) should be non-zero (i.e., either endogenous or contextual effects or both are present). Hence, identifying the peer effects in a broad sense would only require that we include all relevant determinants of policies, both at the firm and industry levels, such that the regression residual is conditionally orthogonal to the included variables. Here, the orthogonality condition is likely violated since hedge funds carefully choose targets that would benefit the most from their policy prescriptions, and we do not observe the hedge funds' full information set. For instance, an industry may undergo some regulatory or technological changes that increase the optimal leverage for all firms in the industry. Some firms voluntarily change whereas others do not and get targeted. As a result, we would observe a positive association between target frequency and policy changes at non-targeted peers. This problem of unobserved industry shocks, or correlated effects in the language of Manski (1993), is common in studies like ours. To identify the peer effects from these unobserved correlated effects, we replace the likely endogenous peer vs. target outcomes comprising $E\left(X|u_j\right)$ with a plausibly exogenous variable, $\overline{Z}_j$, that is related to industry j's target frequency but should not affect a firm's policies, except through some peer effects mechanisms. If $E\left(X|u_j\right)$ is linear in $\overline{Z}_j$, then the coefficient of $\overline{Z}_j$ in the reduced-form regression (2) will be proportional to γ^*. As detailed in the paper, we use as $\overline{Z}_j$ the variable *Threat*, a proxy of flow-based capital available to hedge funds to target industry j in a given year.

Threat vs. Other Peer Effects

The second challenge is to differentiate the effects of activism threat from other peer effects such as product market competition and pure mimicking. To address this challenge, we rely on the cross-sectional variation of threat perception among industry peers. Specifically, we assume that the contextual effects in (1) take the form: $\gamma = \gamma_0 + \gamma_1 D_{ijt}$, where D_{ijt} proxies for the threat perceived by the managers and directors of firm i in industry j. Thus, γ_1 captures the effects of activism threat which, by our assumption, vary with D_{ijt}, and γ_0 captures other contextual effects, including those of product market competition. Assuming that $D = 1(0)$ indicates a high (low) threat perception (which may have a direct impact on policy y as captured by φ below) and X_{ijt} is a scalar indicator for being targeted, the reduced-form difference in the conditional expectation of y between firms with high and low threat perception is:

$$E\big(y\big|X,\, u_j, D = 1\big) - E\big(y\big|X,\, u_j, D = 0\big) = \gamma_1^* E\big(X\big|u_j\big) + \varphi, \quad \text{where} \quad \gamma_1^* = \frac{\gamma_1}{1 - \beta} \tag{3}$$

If the target frequency, $E\big(X\big|u_j\big)$, is exogenous, then we can estimate γ_1^*, a multiple of the threat effect, by adding D and $D \times E\big(X\big|u_j, D\big)$ to the regression (2). The coefficient of $D \times E\big(X\big|u_j, D\big)$ would be γ_1^*, the coefficient of D would be φ, and the coefficient of $E\big(X\big|u_j, D\big)$ would be $\frac{\beta\lambda + \gamma_0}{1 - \beta}$. By replacing $E\big(X\big|u_j, D\big)$ with $\overline{Z}_j$ as discussed above, our estimates will be proportional to these reduced-form parameters. As discussed in the paper, we use as D the variable *High threat perception* (*HTP*), a dummy that equals one if the average target connections per director are higher than the industry-year median, and zero otherwise.

Finally, we note that our use of *Threat* and *HTP* (as $\overline{Z}_j$ and D, respectively) to identify the effects of activism threat hinges on the assumption that the difference in policy changes between firms with *HTP* = 1 and *HTP* = 0 does not systematically vary across industries with different levels of *Threat*, except through the activism threat channel. Therefore, even if *Threat* might affect firm policies through channels that are unrelated to activism (e.g., capital availability), our identification strategy remains valid so long as the differences in such confounding effects experienced by firms with high and low threat perception are not greater in higher-*Threat* industries. We address specific alternative explanations using a combination of subsample analyses and falsification tests in Section 6 of the paper.

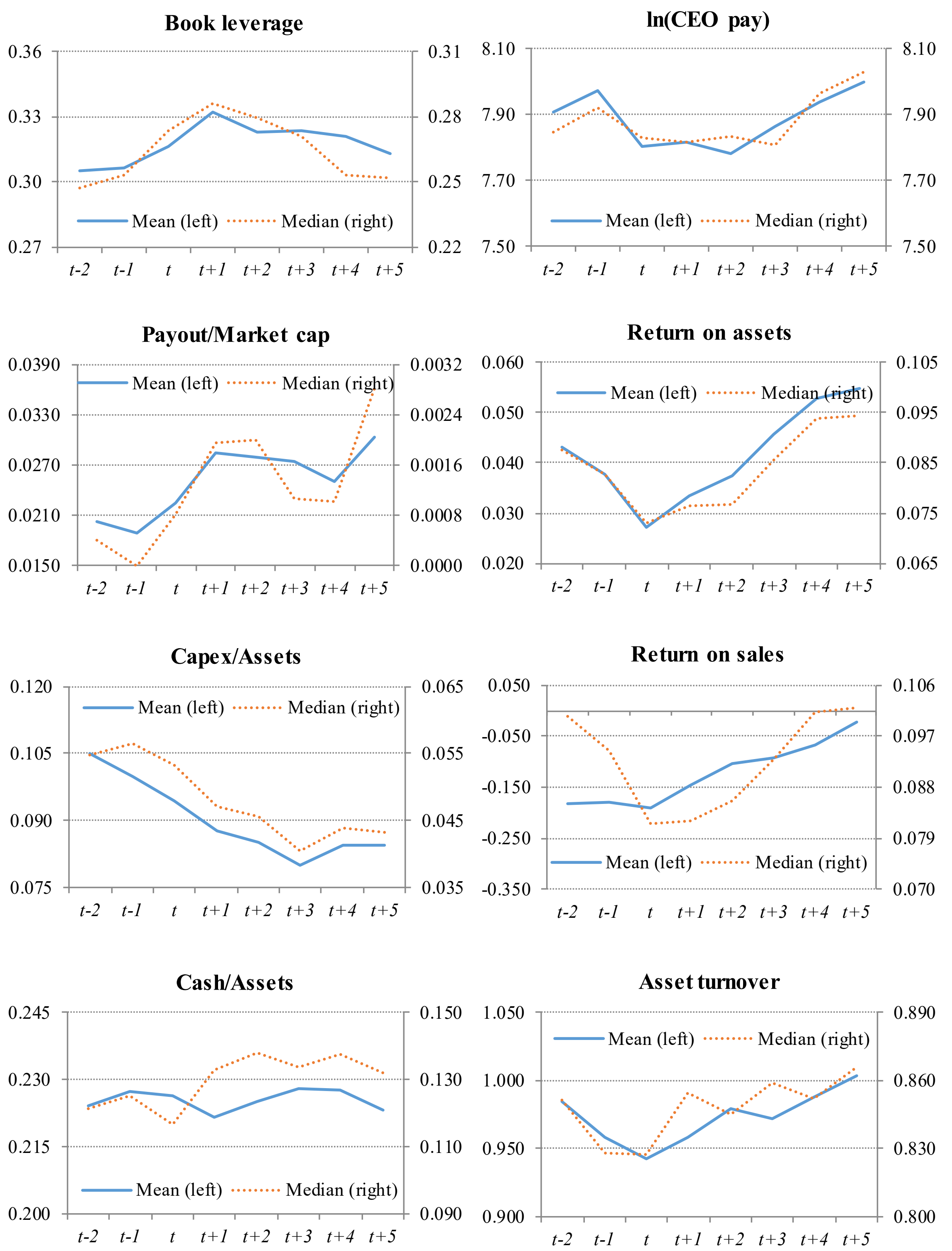

Figure IA.1: Policy Changes at Activist Targets. This figure plots mean and median levels of financial, investment, and operating policies at targets of hedge fund activism. The sample period is 1997-2011. The statistics are calculated for event years *t-2* to *t+5*, where year *t* contains the start of the activist campaign. All policy variables are defined in Appendix A of the paper.

Table IA.1: Summary Statistics for Activist Targets and Firms with High and Low Threat Perception

This table reports summary statistics of select firm-level variables for firms targeted by activist hedge funds (Panel A), firms with high threat perception (*HTP* = 1) (Panel B), and firms with low threat perception (*HTP* = 0) (Panel C). The full sample includes all firms that have non-missing CRSP, Compustat, Thomson Reuters 13F, and BoardEx data, and are in three-digit SIC industries with at least five firms. The observations are firm-year, and the sample period is 1997-2011. All variables are winsorized at 2.5% and 97.5%, and defined in Appendix A of the paper.

Panel A: Target firms

Number of observations: 905 (total), 349 (with available *CEO pay*), 559 (with available *Analysts*)

	Mean	Std. Dev.	5th PCT	25th PCT	Median	75th PCT	95th PCT
Market cap ($ million)	1,125	2,741	18	75	229	822	5,010
Book leverage	0.274	0.267	0.000	0.003	0.229	0.476	0.761
Payout/Market cap	0.020	0.033	0.000	0.000	0.000	0.029	0.099
Capex/Assets	0.095	0.114	0.000	0.011	0.057	0.132	0.326
Cash/Assets	0.226	0.232	0.006	0.039	0.133	0.342	0.726
CEO pay ($ million)	3.932	4.380	0.500	1.148	2.270	5.220	13.016
Return on assets	0.054	0.182	-0.330	0.015	0.088	0.149	0.275
Return on sales	-0.123	1.019	-1.106	0.019	0.094	0.186	0.397
Asset turnover	0.996	0.728	0.068	0.489	0.862	1.350	2.476
Tobin's Q	1.916	1.511	0.614	1.025	1.450	2.280	4.746
Stock turnover x 100	0.821	0.687	0.107	0.306	0.598	1.124	2.390
Sales growth	0.154	0.432	-0.267	-0.023	0.064	0.206	0.904
Analysts	8.945	8.175	1.000	3.000	6.000	13.000	24.000
Inst. ownership	0.596	0.289	0.094	0.356	0.647	0.857	0.951
Target connections per director	0.624	0.852	0.000	0.000	0.286	0.889	2.714

Table IA.1, Cont'd: Summary Statistics for Activist Targets and Firms with High and Low Threat Perception

Panel B: Firms with high threat perception (HTP = 1)
Number of observations: 19,047 (total), 9,571 (with available *CEO pay*), 10,482 (with available *Analysts*)

	Mean	Std. Dev.	5th PCT	25th PCT	Median	75th PCT	95th PCT
Market cap ($ million)	2,804	5,190	19	127	544	2,319	19,748
Book leverage	0.307	0.268	0.000	0.032	0.275	0.510	0.796
Payout/Market cap	0.025	0.034	0.000	0.000	0.009	0.038	0.102
Capex/Assets	0.084	0.109	0.000	0.003	0.045	0.119	0.318
Cash/Assets	0.197	0.223	0.006	0.032	0.100	0.293	0.715
CEO pay ($ million)	5.429	5.539	0.527	1.582	3.432	7.066	20.022
Return on assets	0.074	0.172	-0.270	0.024	0.099	0.166	0.290
Return on sales	-0.055	0.973	-0.958	0.049	0.131	0.236	0.447
Asset turnover	0.924	0.749	0.060	0.355	0.788	1.281	2.497
Tobin's Q	2.345	2.101	0.703	1.093	1.585	2.707	6.953
Stock turnover x 100	0.785	0.681	0.093	0.286	0.579	1.051	2.329
Sales growth	0.169	0.422	-0.290	-0.017	0.088	0.232	0.862
Analysts	10.599	9.997	1.000	3.000	7.000	15.000	31.000
Inst. ownership	0.564	0.299	0.047	0.311	0.612	0.835	0.951
Target connections per director	1.038	0.952	0.067	0.286	0.750	1.500	3.400

Panel C: Firms with low threat perception (HTP = 0)
Number of observations: 26,310 (total), 10,249 (with available *CEO pay*), 11,790 (with available *Analysts*)

	Mean	Std. Dev.	5th PCT	25th PCT	Median	75th PCT	95th PCT
Market cap ($ million)	1,525	3,586	14	76	292	1,067	8,138
Book leverage	0.291	0.264	0.000	0.021	0.250	0.493	0.770
Payout/Market cap	0.021	0.032	0.000	0.000	0.004	0.032	0.094
Capex/Assets	0.087	0.111	0.000	0.005	0.048	0.123	0.326
Cash/Assets	0.190	0.222	0.004	0.026	0.090	0.288	0.699
CEO pay ($ million)	3.941	4.667	0.429	1.115	2.172	4.691	14.776
Return on assets	0.074	0.179	-0.289	0.024	0.102	0.172	0.304
Return on sales	-0.070	0.961	-1.057	0.041	0.116	0.214	0.426
Asset turnover	1.024	0.795	0.064	0.405	0.886	1.426	2.705
Tobin's Q	2.351	2.169	0.682	1.072	1.555	2.679	7.276
Stock turnover x 100	0.669	0.653	0.074	0.214	0.439	0.885	2.163
Sales growth	0.201	0.455	-0.285	-0.012	0.099	0.271	1.046
Analysts	7.777	7.861	1.000	2.000	5.000	10.000	24.000
Inst. ownership	0.475	0.299	0.026	0.205	0.472	0.735	0.951
Target connections per director	0.104	0.246	0.000	0.000	0.000	0.071	0.600

Table IA.2: Target Frequencies among Firms with High and Low Threat Perception

This table reports counts of activist targets among firms with high and low threat perception (*HTP* = 1 and *HTP* = 0, respectively). The sample includes all firms that have non-missing CRSP, Compustat, Thomson Reuters 13F, and BoardEx data, and are in three-digit SIC industries with at least five firms. The observations are firm-year, and the sample period is 1997-2011. The first two columns are for the full sample. The middle two columns are for the firm-year observations with (industry-level) *Threat* less than or equal to the sample median. The last two columns are for the firm-year observations with (industry-level) *Threat* greater than the sample median. The construction of *Threat* is described in Appendix B of the paper, while *HTP* is defined in Appendix A.

	Full Sample		Threat ≤ Median		Threat > Median	
	# Firms	# Targets	# Firms	# Targets	# Firms	# Targets
HTP = 0	26,310	518	14,727	164	11,583	354
HTP = 1	19,047	387	8,764	109	10,283	278
Total	45,357	905	23,491	273	21,866	632

Table IA.3: Policy Changes at Activist Targets

This table reports OLS estimates from regressions of policies and performance measures on targeting event year dummies, where *Year t* contains the start of an activist campaign. The observations are firm-year, and the sample period is 1997-2011. Bankruptcy is as of year *t* while all other control variables are as of year *t*-1. All regressions include industry and calendar year fixed effects, and policy quintile dummies. All variables are defined in Appendix A of the paper. Standard errors, clustered by industry, are in parentheses. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	Policy Variables					Performance Variables		
	Book leverage	Payout/ Market cap	Capex/ Assets	Cash/ Assets	ln(CEO pay)	Return on assets	Return on sales	Asset turnover
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Activist target event time								
Year *t*-2	0.002	-0.000	0.006**	0.000	0.036	0.002	0.005	-0.040***
	(0.004)	(0.001)	(0.002)	(0.004)	(0.035)	(0.002)	(0.019)	(0.016)
Year *t*-1	0.007	-0.001	0.006*	0.008*	0.068**	0.001	0.002	-0.062***
	(0.004)	(0.001)	(0.003)	(0.004)	(0.033)	(0.001)	(0.017)	(0.013)
Year *t*	0.010*	0.001	0.003	0.007**	0.028	-0.001	-0.013	-0.061***
	(0.006)	(0.001)	(0.003)	(0.003)	(0.031)	(0.001)	(0.011)	(0.013)
Year *t*+1	0.019***	0.004**	-0.002	0.002	-0.001	0.005*	0.008	-0.049***
	(0.006)	(0.001)	(0.003)	(0.006)	(0.029)	(0.003)	(0.011)	(0.014)
Year *t*+2	0.015**	0.003*	-0.002	0.001	-0.006	0.009**	0.019	-0.030***
	(0.006)	(0.002)	(0.003)	(0.005)	(0.024)	(0.004)	(0.016)	(0.015)
Firm controls								
Bankruptcy	0.037	-0.009	0.013	0.053	-0.141	-0.015**	-0.391***	-0.290***
	(0.030)	(0.009)	(0.016)	(0.036)	(0.241)	(0.007)	(0.117)	(0.095)
ln(Market cap)	-0.031***	-0.001***	0.013***	0.044***	0.108***	-0.003***	-0.262***	-0.173***
	(0.002)	(0.000)	(0.003)	(0.006)	(0.014)	(0.001)	(0.065)	(0.018)
ln(Sales)	0.041***	0.001***	-0.015***	-0.054***	0.063***	0.007***	0.298***	0.169***
	(0.002)	(0.000)	(0.003)	(0.007)	(0.018)	(0.002)	(0.069)	(0.020)
Market-to-book ratio	0.008***	0.000	0.003***	0.000	0.007**	-0.000	0.014	0.034***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.003)	(0.000)	(0.011)	(0.005)

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	Policy Variables					Performance Variables		
	Book leverage	Payout/ Market cap	Capex/ Assets	Cash/ Assets	ln(CEO pay)	Return on assets	Return on sales	Asset turnover
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EBITDA/Assets	-0.077***	-0.002	-0.125***	-0.120***	-0.019	0.764***	2.292***	0.376***
	(0.013)	(0.001)	(0.027)	(0.023)	(0.102)	(0.016)	(0.234)	(0.090)
Net PPE/Assets	0.104***	-0.000	0.017	-0.149***	-0.250***	0.016***	-0.004	-0.157**
	(0.024)	(0.001)	(0.011)	(0.031)	(0.060)	(0.003)	(0.068)	(0.067)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Calendar year FE	YES	YES	YES	YES	YES	YES	YES	YES
Policy quintile dummies	YES	YES	YES	YES	YES	YES	YES	YES
Observations	39,259	39,259	39,259	39,256	17,874	39,229	39,229	39,229
R-squared (within)	0.730	0.575	0.582	0.668	0.782	0.945	0.576	0.629
Year *t+1* - Year *t-1*	0.012**	0.005***	-0.008*	-0.006	-0.069*	0.004	0.006	0.013
Year *t+2* - Year *t*	0.005	0.002	-0.005	-0.006	-0.034	0.010**	0.032	0.031*

Table IA.4: Policy Changes at Threatened Firms Conditional on Institutional Ownership

This table reports OLS estimates from panel regressions of changes in policies and performance at peers of activist targets on (industry-level) *Threat*, (firm-level) *High threat perception* (*HTP*), and their interaction for the subsamples of firms that are vulnerable vs. not vulnerable to activist targeting, given their institutional ownership. The observations are firm-year, and the sample period is 1997-2011. A firm is considered vulnerable if its institutional ownership is greater than or equal to the industry median. In columns (1) – (5), the dependent variables are changes in policies from years t-1 to t+1. In columns (6) – (8), the dependent variables are changes in performance metrics from years t to t+2. All regressions include dummies for years around activist target events, firm- and industry-level controls, industry and calendar year fixed effects, and policy quintile dummies. The construction of *Threat* is described in Appendix B of the paper, while all other variables are defined in Appendix A. Standard errors, clustered by industry, are in parentheses. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	Policy Variables					Performance Variables		
	Δ Book leverage	Δ Payout/ Market cap	Δ Capex/ Assets	Δ Cash/ Assets	Δ ln(CEO pay)	Δ Return on assets	Δ Return on sales	Δ Asset turnover
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Group 1: Vulnerable firms = Firms with high institutional ownership								
Threat	0.008	0.004	-0.004	-0.005	-0.065	0.005	0.027	0.003
	(0.012)	(0.003)	(0.004)	(0.009)	(0.072)	(0.008)	(0.017)	(0.015)
[HTP] High threat perception	-0.012	0.001	0.003	0.005	0.034	-0.008**	-0.005	-0.017
	(0.008)	(0.002)	(0.004)	(0.004)	(0.048)	(0.003)	(0.008)	(0.011)
Threat x HTP	0.029**	0.008*	-0.009*	-0.012*	-0.092	0.012**	0.006	0.026*
	(0.012)	(0.004)	(0.005)	(0.007)	(0.071)	(0.006)	(0.014)	(0.015)
Observations	21,845	21,845	21,845	21,845	14,779	21,832	21,832	21,832
R-squared (within)	0.093	0.164	0.170	0.130	0.168	0.108	0.100	0.118
Group 2: Non-vulnerable firms = Firms with low institutional ownership								
Threat	0.005	-0.002	0.003	0.016**	0.121	-0.012	-0.012	-0.021
	(0.008)	(0.002)	(0.006)	(0.007)	(0.116)	(0.009)	(0.021)	(0.020)
[HTP] High threat perception	-0.002	0.001	0.000	0.003	0.045	-0.000	0.011	0.008
	(0.008)	(0.002)	(0.004)	(0.006)	(0.098)	(0.005)	(0.022)	(0.016)
Threat x HTP	0.001	0.002	-0.002	-0.008	-0.054	0.006	0.001	0.010
	(0.011)	(0.003)	(0.006)	(0.009)	(0.139)	(0.007)	(0.027)	(0.021)
Observations	17,004	17,004	17,004	16,992	2,684	16,987	16,987	16,987
R-squared (within)	0.103	0.167	0.114	0.104	0.133	0.052	0.049	0.078
Controls and FEs as in Table 3	YES	YES	YES	YES	YES	YES	YES	YES

Table IA.5: Policy Changes at Peer Firms with Large and Small Director Networks (Falsification Test)

This table reports OLS estimates from regressions of changes in policies and performance at peers of activist targets on (industry-level) *Threat*, (firm-level) *Large director network* (*LDN*), and their interaction. The observations are firm-year, and the sample period is 1997-2011. In columns (1) – (5), the dependent variables are changes in financial and investment policies from years *t*-1 to *t*+1, where year *t* is the current observation year. In columns (6) – (8), the dependent variables are changes in operating performance metrics from years *t* to *t*+2. *LDN* equals one if the beginning-of-year average connections per director exceed the industry median and zero otherwise. A connection is a school tie to a director at another firm. Two directors have a school tie if they receive the same educational degree from the same school within one year of each other. Bankruptcy is as of year *t* while all other control variables are as of year *t*-1. All regressions include industry and calendar year fixed effects and policy quintile dummies. The construction of *Threat* is described in Appendix B of the paper, while all other variables are defined in Appendix A. Standard errors, clustered by industry, are in parentheses. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	Policy Variables					Performance Variables		
	Δ Book leverage (1)	Δ Payout/ Market cap (2)	Δ Capex/ Assets (3)	Δ Cash/ Assets (4)	Δ ln(CEO pay) (5)	Δ Return on assets (6)	Δ Return on sales (7)	Δ Asset turnover (8)
Main variables								
Threat	0.010	-0.003	-0.001	0.009	-0.025	-0.003	0.003	0.002
	(0.008)	(0.005)	(0.004)	(0.008)	(0.060)	(0.007)	(0.015)	(0.018)
[LDN] Large director network	-0.004	0.003	0.003	0.001	0.071*	-0.001	-0.003	0.005
	(0.008)	(0.003)	(0.003)	(0.005)	(0.037)	(0.003)	(0.010)	(0.011)
Threat x LDN	0.003	-0.004	-0.004	-0.000	-0.031	0.005	0.013	-0.010
	(0.010)	(0.005)	(0.004)	(0.007)	(0.055)	(0.005)	(0.015)	(0.016)
Activist target event controls								
Year *t*-1	-0.003	-0.001	-0.008*	-0.002	-0.014	0.008	-0.011	0.010
	(0.007)	(0.003)	(0.005)	(0.003)	(0.049)	(0.006)	(0.009)	(0.008)
Year *t*	0.010	0.014*	-0.009***	0.002	0.063	0.010**	0.039*	0.030***
	(0.007)	(0.007)	(0.003)	(0.006)	(0.042)	(0.004)	(0.022)	(0.010)
Year *t*+1	0.014***	0.003	-0.009**	0.005	-0.095***	-0.004	-0.010	-0.008
	(0.005)	(0.003)	(0.004)	(0.003)	(0.035)	(0.006)	(0.010)	(0.010)
Firm and industry controls								
Bankruptcy	-0.148***	-0.000	0.016	-0.003	0.350	0.018	0.046**	-0.012
	(0.034)	(0.014)	(0.014)	(0.028)	(0.432)	(0.014)	(0.020)	(0.084)

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	Policy Variables					Performance Variables		
	Δ Book leverage (1)	Δ Payout/ Market cap (2)	Δ Capex/ Assets (3)	Δ Cash/ Assets (4)	Δ ln(CEO pay) (5)	Δ Return on assets (6)	Δ Return on sales (7)	Δ Asset turnover (8)
ln(Market cap)	0.011***	0.002***	0.002	-0.006***	0.051***	-0.007***	0.025***	-0.017***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.011)	(0.002)	(0.005)	(0.004)
ln(Sales)	-0.005**	0.001**	-0.004***	0.005***	0.066***	0.011***	-0.020***	0.017***
	(0.002)	(0.000)	(0.001)	(0.001)	(0.007)	(0.002)	(0.004)	(0.004)
Market-to-book ratio	-0.004***	-0.001***	-0.002***	0.001**	0.006***	-0.001	-0.003**	-0.008***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)
EBITDA/Assets	-0.039***	0.008***	0.014	-0.003	-0.310***	-0.135***	-0.320***	-0.205***
	(0.008)	(0.003)	(0.011)	(0.008)	(0.056)	(0.014)	(0.021)	(0.030)
Net PPE/Assets	0.068***	-0.007	-0.031***	-0.035***	0.036	0.014***	0.036**	-0.063***
	(0.008)	(0.006)	(0.006)	(0.006)	(0.040)	(0.005)	(0.017)	(0.012)
Target frequency during *t*-2 and *t*-1	0.024	-0.008	-0.006	-0.001	0.053	-0.013	-0.045	0.009
	(0.019)	(0.008)	(0.008)	(0.013)	(0.121)	(0.014)	(0.030)	(0.042)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Calendar year FE	YES	YES	YES	YES	YES	YES	YES	YES
Policy quintile dummies	YES	YES	YES	YES	YES	YES	YES	YES
Observations	38,849	38,849	38,849	38,849	17,463	38,819	38,819	38,819
R-squared (within)	0.093	0.041	0.139	0.112	0.157	0.070	0.065	0.094

Table IA.6: Summary Statistics for Firms with High and Low Threat Perception Matched by Industry, Size, and Institutional Ownership

This table reports summary statistics of select firm-level variables for firms with high threat perception (*HTP* = 1) (Panel A) and firms with low threat perception (*HTP* = 0) (Panel B), matched by industry, market capitalization, and institutional ownership. The observations are firm-year, and the sample period is 1997-2011. For each firm-year observation with *HTP* = 1, matched firm-year observations with *HTP* = 0 are picked, with replacement, from the same industry, market capitalization decile, and institutional ownership decile. In case of no matches, the observation is dropped. In case of multiple matches, only one matched firm with the closest market capitalization is kept. The only variables that remain significantly different between the two groups are book leverage and number of target connections per director (the latter by construction). All variables are defined in Appendix A of the paper.

Panel A: Firms with high threat perception (HTP = 1)
Number of observations: 10,632 (total), 4,901 (with available *CEO pay*), 5,866 (with available *Analysts*)

	Mean	Std. Dev.	5th PCT	25th PCT	Median	75th PCT	95th PCT
Market cap ($ million)	2,416	4,711	12	77	433	1,977	16,176
Book leverage	0.287	0.273	0.000	0.006	0.232	0.509	0.775
Payout/Market cap	0.022	0.033	0.000	0.000	0.004	0.035	0.097
Capex/Assets	0.110	0.126	0.000	0.003	0.071	0.167	0.386
Cash/Assets	0.246	0.247	0.008	0.040	0.151	0.405	0.781
CEO pay ($ million)	5.423	5.534	0.506	1.681	3.418	6.978	20.460
Return on assets	0.040	0.198	-0.397	0.009	0.072	0.152	0.284
Return on sales	-0.167	1.219	-2.455	0.020	0.139	0.265	0.449
Asset turnover	0.753	0.661	0.055	0.216	0.615	1.080	1.995
Tobin's Q	2.630	2.357	0.739	1.136	1.731	3.129	8.371
Stock turnover x 100	0.824	0.734	0.083	0.271	0.583	1.153	2.544
Sales growth	0.193	0.465	-0.314	-0.024	0.102	0.265	1.020
Analysts	11.412	10.523	1.000	3.000	8.000	16.000	33.000
Inst. ownership	0.522	0.330	0.024	0.203	0.537	0.854	0.951
Target connections per director	0.937	0.903	0.061	0.250	0.600	1.333	3.125

Table IA.6, Cont'd: Summary Statistics for Firms with High and Low Threat Perception Matched by Industry, Size, and Institutional Ownership

Panel B: Firms with low threat perception (HTP = 0)
Number of observations: 10,632 (total), 4,793 (with available *CEO pay*), 5,928 (with available *Analysts*)

	Mean	Std. Dev.	5th PCT	25th PCT	Median	75th PCT	95th PCT
Market cap ($ million)	2,336	4,570	13	76	428	1,979	15,075
Book leverage	0.275	0.266	0.000	0.003	0.216	0.494	0.747
Payout/Market cap	0.022	0.033	0.000	0.000	0.004	0.035	0.096
Capex/Assets	0.104	0.122	0.000	0.003	0.066	0.154	0.366
Cash/Assets	0.246	0.246	0.008	0.038	0.154	0.403	0.761
CEO pay ($ million)	5.093	5.329	0.476	1.425	3.132	6.617	18.332
Return on assets	0.047	0.191	-0.365	0.012	0.074	0.156	0.290
Return on sales	-0.115	1.106	-1.512	0.027	0.142	0.266	0.452
Asset turnover	0.758	0.666	0.057	0.239	0.627	1.075	2.087
Tobin's Q	2.670	2.411	0.741	1.139	1.724	3.166	8.499
Stock turnover x 100	0.832	0.741	0.077	0.259	0.594	1.199	2.557
Sales growth	0.203	0.464	-0.312	-0.021	0.105	0.285	1.063
Analysts	11.448	10.460	1.000	4.000	8.000	16.000	33.000
Inst. ownership	0.522	0.331	0.023	0.197	0.540	0.855	0.951
Target connections per director	0.121	0.240	0.000	0.000	0.000	0.154	0.636

Table IA.7: Policy Changes at Peer Firms with High and Low Threat Perception Matched by Industry, Size, and Institutional Ownership

This table reports OLS estimates from regressions of changes in policies and performance at peers of activist targets on (industry-level) *Threat*, (firm-level) *High threat perception* (*HTP*), and their interaction. The sample includes firms with *HTP* = 1 and *HTP* = 0 matched by industry, market capitalization, and institutional ownership. The observations are firm-year, and the sample period is 1997-2011. For each firm-year observation with *HTP* = 1, matched firm-year observations with *HTP* = 0 are picked, with replacement, from the same industry, market capitalization decile, and institutional ownership decile. In case of no matches, the observation is dropped. In case of multiple matches, only one match with the closest market capitalization is kept. In columns (1) – (5), the dependent variables are changes in financial and investment policies from years *t*-1 to *t*+1, where year *t* is the current year. In columns (6) – (8), the dependent variables are changes in operating performance metrics from years *t* to *t*+2. Bankruptcy is as of year *t* while all other control variables are as of year *t*-1. All regressions include industry and calendar year fixed effects, and policy quintile dummies. The construction of *Threat* is described in Appendix B of the paper, while all other variables are defined in Appendix A. Standard errors, clustered by industry, are in parentheses. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	Policy Variables					Performance Variables		
	Δ Book leverage (1)	Δ Payout/ Market cap (2)	Δ Capex/ Assets (3)	Δ Cash/ Assets (4)	Δ ln(CEO pay) (5)	Δ Return on assets (6)	Δ Return on sales (7)	Δ Asset turnover (8)
Main variables								
Threat	0.008	-0.002	-0.004	0.016	-0.096	0.014	0.024	0.021
	(0.008)	(0.003)	(0.007)	(0.010)	(0.119)	(0.009)	(0.019)	(0.017)
[HTP] High threat perception	0.004	-0.005	0.006	0.013	0.006	-0.010	0.011	-0.013
	(0.009)	(0.004)	(0.006)	(0.008)	(0.088)	(0.008)	(0.013)	(0.016)
Threat x HTP	0.016*	0.014**	-0.012*	-0.020*	-0.155	0.019*	0.032	0.033*
	(0.009)	(0.006)	(0.007)	(0.011)	(0.112)	(0.010)	(0.021)	(0.019)
Activist target event controls								
Year *t*-1	-0.012	0.003	-0.011	-0.012	0.054	0.011	-0.025	-0.002
	(0.010)	(0.003)	(0.002)	(0.008)	(0.106)	(0.013)	(0.020)	(0.022)
Year *t*	0.026**	0.014***	-0.016**	-0.023*	-0.048	0.033**	0.100*	0.072***
	(0.012)	(0.004)	(0.008)	(0.012)	(0.055)	(0.015)	(0.056)	(0.018)
Year *t*+1	0.014	0.000	-0.001	0.002	-0.107**	0.006	-0.001	0.003
	(0.012)	(0.002)	(0.008)	(0.013)	(0.051)	(0.006)	(0.015)	(0.009)
Firm and industry controls								
Bankruptcy	-0.014	0.011**	-0.011	0.016	-0.456	0.028	0.090**	0.035*
	(0.048)	(0.005)	(0.009)	(0.038)	(0.458)	(0.027)	(0.035)	(0.020)

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	Policy Variables					Performance Variables		
	Δ Book leverage (1)	Δ Payout/ Market cap (2)	Δ Capex/ Assets (3)	Δ Cash/ Assets (4)	Δ ln(CEO pay) (5)	Δ Return on assets (6)	Δ Return on sales (7)	Δ Asset turnover (8)
ln(Market cap)	0.013***	0.002***	0.003	-0.006**	0.098***	-0.006**	0.039**	-0.014
	(0.004)	(0.000)	(0.002)	(0.003)	(0.024)	(0.002)	(0.016)	(0.009)
ln(Sales)	-0.007	0.001**	-0.005**	0.005**	0.077***	0.012***	-0.035**	0.016*
	(0.004)	(0.000)	(0.003)	(0.003)	(0.015)	(0.003)	(0.015)	(0.009)
Market-to-book ratio	-0.004***	-0.001***	-0.002***	0.001	0.004*	-0.001	-0.007***	-0.009***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)
EBITDA/Assets	-0.021*	0.006***	0.010	-0.023*	-0.384***	-0.139***	-0.288***	-0.160***
	(0.011)	(0.002)	(0.015)	(0.014)	(0.119)	(0.011)	(0.034)	(0.037)
Net PPE/Assets	0.051***	-0.008***	-0.040***	-0.048***	-0.036	0.008	0.030	-0.086***
	(0.017)	(0.003)	(0.012)	(0.014)	(0.051)	(0.009)	(0.027)	(0.024)
Target frequency during *t*-2 and *t*-1	0.033	0.001	-0.013	-0.010	0.306	-0.026	-0.135	-0.045
	(0.038)	(0.011)	(0.023)	(0.022)	(0.288)	(0.034)	(0.111)	(0.101)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Calendar year FE	YES	YES	YES	YES	YES	YES	YES	YES
Policy quintile dummies	YES	YES	YES	YES	YES	YES	YES	YES
Observations	18,144	18,144	18,144	18,144	8,634	18,134	18,134	18,134
R-squared (within)	0.103	0.165	0.149	0.134	0.252	0.078	0.074	0.107