INSTITUTE FOR PRIVATE CAPITAL WORKING PAPER

December, 2017

Governance under the Gun: Spillover Effects of Hedge Fund Activism

INSTITUTE FOR PRIVATE CAPITAL

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

Nickolay Gantchev, Oleg Gredil and Chotibhak Jotikasthira[§]

December 2017

ABSTRACT

Hedge fund activism is associated with improvements in the governance and performance of targeted firms. In this paper, we show that the positive effects of activism reach beyond the targets, as yet-to-be-targeted peers make similar improvements under the threat of activism. Peers with higher threat awareness, as measured by board 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. Time-varying industry conditions or product market effects do not explain our results.

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

JEL classification: G12, G23, G32, G34

[◆]We are grateful to Renee Adams, Vikas Agarwal, Nicole Boyson, Alon Brav, Chris Clifford, Martijn Cremers, Vicente Cunat, Andrew Ellul, Vivian Fang, Vyacheslav Fos, Paolo Fulghieri, Neal Galpin, Diego Garcia, Mariassunta Giannetti, Vincent Gregoire, Wei Jiang, Steven Kaplan, Jonathan Karpoff, April Klein, Camelia Kuhnen, Ulf von Lilienfeld-Toal, Fangzhou Liu, Spencer Martin, Ron Masulis, Daniel Metzger, Paige Ouimet, Frank Partnoy, Urs Peyer, Raghu Rau, Jacob Sagi, Francesco Sangiorgi, Merih Sevilir, Geoffrey Tate, Randall Thomas, Hannes Wagner, Jun Wu, and Stefan Zeume. We also thank seminar and conference participants at Drexel University, Fordham University, George Washington University, Georgia State University, Luxembourg School of Finance, North Carolina State University, Southern Methodist University, Stockholm School of Economics, University of Bristol, University of Cambridge, University of Colorado Boulder, University of Exeter, University of North Carolina at Chapel Hill, University of Melbourne, University of New South Wales, University of Oxford, University of Texas at Dallas, University of Warwick, American Finance Association Meeting (2015), China International Conference in Finance (2015), European Finance Association Meeting (2014), Financial Intermediation Research Society (2015), Midwest Finance Association Meeting (2015), SEC-University of Maryland Conference on Regulation of Financial Markets (2014), University of British Columbia's Summer Finance Conference (2015), and University of San Diego's Conference on Future Directions in Hedge Fund Activism (2015).

[§]Gantchev (ngantchev@smu.edu) and Jotikasthira (cjotikasthira@smu.edu) are at the Cox School of Business at Southern Methodist University. Gredil (ogredil@tulane.edu) is at the 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, Jiang, Partnoy, and Thomas, 2008; Becht, Franks, Mayer, and Rossi, 2008; Clifford, 2008).[1] These positive effects often come at the expense of managers and directors who see a sharp reduction in compensation and a higher likelihood of being replaced (see, for example, Brav, Jiang, and Kim, 2010). Anecdotes suggest that executives of yet-to-be-targeted firms feel threatened and proactively work with advisors and lawyers to evaluate firm policies "with a view toward minimizing vulnerabilities to attacks by activist hedge funds".[2] The press has shown that 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".[3]

Our goal is to investigate the role of activism threat in inducing policy changes at the peers of activist targets and examine whether such responses are effective at fending off activists.[4] Previous work has focused on the targeted firms, and documented significant increases in payout and leverage, decreases in capital expenditures, and improvements in return on assets and asset utilization. We provide novel evidence that peers preemptively take similar actions to reduce agency costs and improve performance, and as a result, experience an increase in their valuations. Our evidence of these spillover effects contributes to a better understanding of shareholder activism as a governance device. Absent these externalities, the literature does not fully capture the overall impact of activism.

We view activism threat as a peer effect – the directors and managers of a non-target firm observe that its peer firms are being targeted by activists and feel pressured to improve its policies and operations to avoid becoming the next target. A firm's policy choice can be affected not only by

[1] Recent academic work has shown that among activist investors, hedge funds achieve better success as monitors than mutual funds, pension funds, and labor unions (see Kahan and Rock, 2006; Gillan and Starks, 2007).
[2] See "Key Issues for Directors in 2014" by Martin Lipton of Wachtell, Lipton, Rosen and Katz, *The Harvard Law School Forum on Corporate Governance and Financial Regulation*, December 16, 2013.
[3] See "Boardrooms Rethink Tactics to Defang Activist Investors", *The New York Times*, November 11, 2013.
[4] We define peer firms naturally as companies that operate in the same three-digit SIC industry as previous activist targets. This is consistent with a large theoretical literature (e.g., Jensen, 1986; Shleifer and Vishny, 1988).

its peers' actions and characteristics but also by common industry forces. Thus, establishing the existence of activism threat requires that we differentiate it from time-varying industry conditions and other peer effects mechanisms.

First, peer firms may have similar policies because they are exposed to *common industry forces*. For instance, an industry may undergo (unobserved) changes that increase the optimal leverage for all firms in the industry. If some firms change voluntarily whereas others do not and get targeted, we would observe a positive association between the frequency of targeting and policy changes at non-targeted peers. Thus, our first challenge is to identify the peer effects of activism from common industry factors that may dictate a firm's policy choice. We do so by using, as a source of plausibly exogenous variation in activism, flow-based capital available to activist hedge funds to target an industry. We argue that our *industry-level* proxy of activism threat is likely uncorrelated with industry shocks because it captures time-varying characteristics of individual hedge funds, as opposed to firm or industry characteristics.[5] Most activist hedge funds are generalists and invest only about 10% of their assets in activist targets; hence, fund flows are unlikely to be directed towards activism in specific industries.

Second, firms may change certain policies in response to *peer actions or characteristics*. For example, Leary and Roberts (2014) show that firms mimic industry peers in choosing their leverage and suggest that product market competition is an explanation for such behavior.[6] Aslan and Kumar (2016) demonstrate that the peers of activist targets experience a decline in valuation due to their eroding positions in the product market, and change certain policies to improve their competitive standing. Thus, our second challenge is to establish the effects of activism threat as distinct from those of product market competition, the most plausible alternative peer mechanism. In this regard, our goal is to present evidence on the overall policy and operational changes induced

[5] We control for persistence in targeting at the industry level to isolate the additional variation induced by fund flows.
[6] Popadak (2014) and Shue (2013) provide evidence of peer effects in dividend policies and compensation, respectively.

by activism threat as opposed to product market competition, rather than to differentiate between changes due to the targets' characteristics and those due to the targets' actions.[7]

To accomplish our second goal, we rely on the cross-section of threatened peers and exploit the social networks of directors to identify possible information transfers (as in Cohen, Frazzini, and Malloy, 2008). We define a *firm-level* measure of threat awareness based on the idea that directors who attend the same university program around the same time would be more inclined to share with each other their experiences about activism. We only count directors' connections to *past targets outside the firm's industry* to isolate activism-related information from other information pertaining to the industry that may generally flow within the directors' social network. Therefore, our cross-sectional measure of threat awareness is unlikely to be related to product market competition or information transfers unrelated to hedge fund activism.

In sum, we employ a combination of industry-level *Threat* and firm-level *Threat awareness*, and compare policy changes between firms with different levels of threat awareness when their industry is under activism threat. Our results show positive spillover effects of activism – in periods of high threat, non-targeted peers with high threat awareness undertake real policy changes to reduce agency costs and improve operating performance in the same way as the targets.[8] Specifically, relative to peers with low threat awareness, those with high threat awareness increase leverage and payout, decrease cash holdings and capital expenditures, and improve return on assets and asset turnover. They also appear to reduce CEO compensation and increase return on sales although these changes lack statistical significance. Furthermore, we provide corroborating evidence that policy vulnerability determines the magnitude of the response. In periods of high threat, threatened peers with below-median leverage, payout, return on assets, return on sales, and

[7] The two types of peer effects cannot be separately identified. This is commonly known as the "reflection problem" (Manski, 1993).

[8] Brav et al. (2010) show that targets increase payout, CEO turnover, and pay-performance sensitivity. Both Clifford (2008) and Klein and Zur (2009) find increases in leverage and dividend yield, which they interpret as evidence of lower agency costs. Brav et al. (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.

asset turnover are more likely to increase these policies whereas peers with above-median capital expenditures and CEO compensation are more likely to decrease them.

We conduct various robustness tests to alleviate remaining concerns about the confounding effects of time-varying industry shocks and product market competition. First, we show that neither an industry policy wave nor a capital-driven merger wave leads to the same effects as those of activism threat. Second, we 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 likely not explained by shocks in the core industry. Third, we confirm that differences in observable characteristics across peers with high and low threat awareness do not explain our results. Fourth, we show that our findings are not driven by directors with larger networks being generally more informed and responsive to market conditions. Finally, we differentiate the effects of activism threat from those of product market competition by using reductions of import tariffs to proxy for a rise in competitive pressure (Fresard, 2010).

Next, we investigate the peers' stock returns around the time that their industry is threatened.[9] Activism threat may impact peer valuations because the market updates its beliefs about the peers' probability of being targeted or because peer firms implement real policy improvements. We find that an interquartile increase in threat raises valuations, calculated over a three-year period, by roughly 4% more among peers with high threat awareness than those with low threat awareness. Much of the valuation effects lag threat by 1-2 years, suggesting that they are driven by the policy improvements rather than the market's anticipation of a higher likelihood of activism.

Finally, we examine the effectiveness of this 'do-it-yourself' activism and demonstrate that firms, which proactively correct potential vulnerabilities, reduce their ex-post probability of becoming a target.[10] In general, activism threat raises the probability of being targeted but such effects are significantly weaker for firms that (i) improve their policies and/or (ii) experience an increase in valuation, suggesting the presence of a feedback effect. The positive policy changes that we show

[9] Activists generate significant abnormal returns at their targets, both in absolute terms and in comparison to non-activist investing (see Brav et al., 2008; Clifford, 2008; and Boyson and Mooradian, 2011).

[10] Empirically, similar feedback effects have been shown by Edmans, Goldstein, and Jiang (2012) and Bradley, Brav, Goldstein, and Jiang (2012). Bond, Edmans, and Goldstein (2012) survey the theoretical literature on this topic.

seem to alleviate the need for activist monitoring or raise market valuations, making it costlier for an activist to enter.

We make two important contributions to the literature. First, we contribute to the broad corporate governance literature by providing evidence of a new disciplining force in the marketplace – the threat of activism. Previous work has focused mainly on the threat of hostile takeovers (Song and Walkling, 2000; Servaes and Tamayo, 2014) and motivated the use of indexes of takeover defenses as measures of external governance (the G-index by Gompers, Ishii, and Metrick, 2003, and the E-index by Bebchuk, Cohen, and Ferrell, 2009).[11] However, Fos (2016) and Zhu (2013) present evidence of a substantial decline in hostile takeovers. Our findings suggest that the threat of hedge fund activism may have replaced the threat of hostile takeovers as an external disciplining force. Since many takeover defenses (e.g., poison pills) are not as effective in defending against activists, our findings also imply that the construction of governance indexes should be revisited (for recent work, see Karpoff, Schonlau, and Wehrly, 2017).

Second, our results demonstrate positive real externalities of hedge fund activism, establishing that its impact reaches beyond the firms being targeted and may have been underestimated in previous studies (Brav et al., 2008, and Clifford, 2008, for example). These externalities have been an important but missing ingredient in the hotly contested debate about whether hedge fund activism is good or bad for the economy.[12] We show that non-targeted peers respond to the threat of activism by reducing agency costs and improving operating performance, typical policy prescriptions of activists at targeted firms. This proactive mentality has positive real effects. For example, at the 75th percentile of industry-level threat, peers with high threat awareness experience a relative increase in valuation of roughly 6% over three years, in comparison to about 16% for an average target over the same three-year horizon.

Our findings complement those of Fos (2016) and Zhu (2013) who show that firms with certain characteristics, such as low leverage, payout, and market valuation, are likely to make policy and

---

[11] See also Karpoff and Wittry (2014) and Cremers and Ferrell (2014) for recent work in this literature.
[12] For example, see "Don't Run Away from the Evidence: A Reply to Wachtell Lipton" by Bebchuk, Brav, and Jiang, *The Harvard Law School Forum on Corporate Governance and Financial Regulation*, September 17, 2013.

operational improvements. Since these characteristics are determinants of being targeted in a proxy contest, an activist campaign, or a hostile takeover, Fos (2016) and Zhu (2013) interpret their findings as consistent with the idea that firms learn from their *own past mistakes*, and take corrective actions to avoid external interventions. In contrast, we focus on activism threat as a *peer effect* – not-yet-targeted firms learn from the mistakes and corrective actions of activist targets, and institute similar policy changes to address their own vulnerabilities to activism. Similarly, in a recent working paper, Feng, Zhu, and Zhu (2017) examine the effects of activism threat on the creditors of peer firms.

Our findings also complement those of Aslan and Kumar (2016), who study the product market effects of activism and show that peer firms fall behind the activist targets in terms of policies and operations, and hence, experience significantly *negative* abnormal returns upon the announcements of activism.[13] We isolate the spillover effects due to threat, and show that they are *positive and distinct* from other externalities of hedge fund activism.

2. Data and empirical framework

2.1 Sample 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 primary 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 cross-sectional tests use director information from BoardEx, which further limits the final sample to 905 unique target-years.

[13] Our back-of-the-envelope calculation using Aslan and Kumar (2016)'s estimated abnormal returns indicates that the net effect of hedge fund activism is negative (by about half a trillion dollars over our sample period) as the negative spillover effects on peer firms outweigh the positive direct effects on targeted firms (many more peers than targets). Aslan and Kumar (2016) borrow the identification strategy from our first draft but we cannot replicate their results.

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]

We create an annual firm-year panel by merging the activism sample to the CRSP-Compustat-BoardEx sample of public firms. Table 1 reports important characteristics of the full panel of 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 Empirical framework

Our empirical approach follows the social effects model of Manski (1993), in which a firm's policy choice (e.g., leverage) is influenced either by its peers' actions and characteristics or by common industry forces.[14] Thus, to identify the peer effects of activism threat, we need to differentiate them from the effects of (i) time-varying industry forces, and (ii) alternative peer effects mechanisms, such as product market competition. Below, we describe our identification strategies. Appendix B provides additional technical details.

2.2.1 Threat vs. industry factors

The first challenge is to establish the effects of activism threat as peer effects, rather than as responses to common industry conditions. We use lagged target frequency to control for these correlated effects, as we are mostly concerned with the extent to which they also relate to hedge

[14] In Manski (1993)'s model, there are two types of peer effects – endogenous (due to the peers' actions) and contextual (due to the peers' characteristics). Firms may also have similar policies due to their exposure to common industry factors, referred to as correlated effects.

fund targeting. Still, some relevant industry characteristics may not be observable, and therefore, our estimation may suffer from an omitted variable bias.

To address this issue, we proxy for the variation in activism at the industry level by the flow-based capital available to activist hedge funds to target an industry. As we argue below, this measure is driven largely by characteristics of individual activist funds, and hence, unlikely to be correlated with firm or industry characteristics. Edmans, Goldstein, and Jiang (2012) use a similar measure as an instrument for stock price changes in the context of corporate acquisitions. Similarly, Gantchev and Jotikasthira (2017) 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.[15]

Specifically, we calculate the flow-induced buying pressure in industry j and year t, $FIB(j,t)$, as:

$$FIB(j,t) = \frac{\sum_h FIFB(h,j,t)}{MCAP(j,t)}$$

where $FIFB(h,j,t) = Flow5(h,t) \times \frac{TNA(h,j,t\text{-}2)}{TNA(h,t\text{-}2)}$ and

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

$FIFB(h,j,t)$ is hedge fund h's flow-induced fund buys, defined as the expected allocation of its large dollar inflow, $Flow5(h,t)$, to industry j in year t. Following Edmans et al. (2012), we consider the inflow large if it exceeds 5% of total net assets, $TNA(h,t\text{-}1)$, and focus only on large flows since they tend to force funds to invest quickly and in a mechanical manner (Coval and Stafford, 2007). However, our allocation rule is not based on the latest industry allocation, as in Edmans et al. (2012), but rather on the allocation at the end of year t-2, calculated as the ratio of hedge fund h's

[15] More generally, our flow-based measure captures what the literature on institutional investing calls "push" effects, or cases in which institutions change their investment in an asset in response to their own circumstances (such as preferences or endowments), largely in the absence of any changes in asset fundamentals (see Coval and Stafford, 2007, for example). On the other hand, "pull" effects refer to observable and unobservable asset characteristics that draw institutions to a particular asset. In our setting, the omitted variable bias is likely caused by a pull effect in which time-varying industry conditions or shared firm characteristics simultaneously impact both activism scale and policy changes at non-targeted peers.

assets in industry *j*, *TNA*(*h*,*j*,*t*-2), to its total net assets at that time. The additional lag ensures that our measure picks up the persistent part of industry allocations, and is therefore clean from the effects of time-varying industry shocks on the fund's latest industry positioning. Once we have determined each hedge fund's flow-induced buys, we sum them across all hedge funds and divide the sum by the market capitalization of all firms in industry *j*, *MCAP*(*j*,*t*-1), to obtain *FIB(j,t)*.

To argue the relevance of *FIB* as a proxy of activism threat, we appeal to the literature on institutional investing, which finds that institutions with abundant capital are often under pressure to dispose of it quickly, and as a result, tend to invest in assets they currently hold. *FIB* captures the additional capital received by all activists that need to launch campaigns quickly and, due to cost and familiarity considerations, are likely to do so in industries in which they already own stakes in some companies.[16] For ease of interpretation in subsequent analyses, we calculate the cross industry-year percentile rank of *FIB*, which takes values from 0 to 1, with one being the highest *FIB*. We refer to it as *threat*, and show in Figure 2 that threat tracks targeting well, even though it is not conditioned on the occurrence of activism campaigns.[17]

[Insert Figure 2]

Table 2 provides additional evidence of the explanatory power of the two versions of our threat measure. In columns (1)-(3), we regress an industry's target frequency on *FIB*; in columns (4)-(6), we use *Threat*, the percentile rank of *FIB*. 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 probability of being targeted by 1.85% (=0.037 x 0.5, a 90% increase from the unconditional probability of 2%). Importantly, even after controlling for lagged target frequency in column (5) and, additionally, average firm characteristics in column (6), the coefficients of the threat measure are still highly statistically and economically significant, suggesting that capital availability plays a critical and distinct role in driving the scale

[16] Activist hedge funds accumulate most of their ownership in the target in the 60 days immediately preceding the Schedule 13D file date (Gantchev and Jotikasthira, 2017).

[17] Threat performs poorly in 2000-2001 as hedge funds receive large inflows but only target a handful of companies.

of activism. In our analysis of policy changes, we isolate the variation that comes from capital availability by similarly controlling for lagged target frequency and firm characteristics.

[Insert Table 2]

With respect to the exclusion restriction, we argue that our threat proxy is plausibly uncorrelated with common industry factors (after controlling for past targeting as well as industry and year fixed effects) because it is driven by time-varying characteristics (lagged holdings and contemporaneous flows) *of individual hedge fund companies*.[18] Most activists are generalists, and our flow data, inferred from 13F reports, are at the investment company level. On average, hedge fund companies invest just about 10% of their assets in activist campaigns[19] so fund flows are unlikely to be directed to activism in specific industries. Finally, we note that unobserved fund managers' information, which drives their current targeting decisions, does not affect our threat measures since we allocate flows mechanically across prospective industries based on (two-year) lagged holdings. To alleviate any remaining concerns, we conduct a host of robustness tests, described in Section 4.

2.2.2 Threat vs. other peer effects

The second challenge is to identify the effects of activism threat from other peer mechanisms, the most plausible of which is product market competition. Consider a target firm that enhances its competitive position as a result of an activist engagement. Such an improvement may prompt a policy response from industry peers even if they do not feel threatened by activism. To differentiate these two peer effects, we explore how the cross-section of non-targeted peers with different *threat awareness* respond to activism threat. We argue below that this cross-section is unlikely to be related to product market competition in the same way as it is to activism threat.

To measure a peer firm's awareness of activism threat, we rely on the social networks of its directors to identify plausible channels of information transfer. We conjecture that directors who

---

[18] In addition, as noted in Griffin and Xu (2009), who use the same 13F data, "hedge funds exhibit no ability to time sectors or pick better stock styles".
[19] The 75th (90th) percentile of asset allocation to activist targets is about 7% (34%). Even among the largest hedge fund companies (which drive most of the variation we capture), the corresponding statistics are 6% (26%).

attend the same university program around the same time would be more inclined to share with each other their experiences about activism. That is, directors involved in recent activism events would be more likely to alert their fellow alumni at non-targets to the "personal costs" of being involved in activism.[20] Specifically, for each firm-year observation, we calculate the average number of target connections per director where a target connection is a school tie to a director at another firm that was targeted by an activist in the prior 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 school ties in the same three-digit SIC industry to make sure that our measure is unrelated to industry-specific information. In our empirical analysis, we use a dummy variable – *HTA*, or High Threat Awareness – that equals one if the average number of target connections is above the industry-year median (see Appendix A for a detailed definition).

Recent work confirms that external director networks formed by educational ties provide a viable vehicle for information transfers which impact firm policies. Engelberg, Gao, and Parsons (2012) find evidence of better information flows when bank and lender executives attended the same university. Fracassi and Tate (2012) show that educational networks of directors affect the intensity of board monitoring. Shue (2013) documents the effects of the random assignment of MBA students to class sections on their subsequent decision making as managers.

Despite our careful construction, a firm's threat awareness is naturally correlated with the size and quality of its director network, and by extension, certain firm characteristics, such as size and leverage (as seen in Table IA.1 in the Internet Appendix). Firms with above-median threat awareness (*HTA* = 1) are generally larger and have higher leverage and payout, which sets them apart from a typical target and may potentially induce bias against finding our expected results. That is, firms with above-median threat awareness are less likely to pursue the policy changes that typical targets undertake. In addition, *HTA* status is not associated with the odds of becoming an

[20] Fos and Tsoutsoura (2014) show that directors replaced through a proxy contest are also likely to lose board seats at other firms.

activist target. The frequency of targeting is virtually identical across the two *HTA* groups regardless of the industry-wide threat level (as shown in Table IA.2 in the Internet Appendix).

Nevertheless, we recognize that threat awareness is not randomly assigned, and firms with high vs. low threat awareness may respond differently, for reasons other than threat, to the targets' actions or the resulting increase in product market competition. For example, directors of firms with high threat awareness may be generally better connected and more informed, and therefore respond more promptly to changes in the competitive landscape. To alleviate these types of concerns, we check the robustness of our results in Section 4. Specifically, we perform (i) a matched sample analysis to rule out the possibility that observable differences in firm characteristics drive our results, (ii) a counterfactual analysis that replaces threat awareness with the average number of connections per director to mitigate the concern that threat awareness simply picks up the size and quality of the directors' networks, and (iii) a counterfactual analysis that specifically addresses the product market alternative. In addition, we note that firms with high threat awareness do not appear to be closer product market competitors to activism targets based on the Hoberg and Philips (2009)'s firm-centric definition of a peer network.

3. Policy changes at peer firms

To begin, we confirm prior findings that targeted firms reduce agency costs and improve operating performance following the activist campaigns. Figure IA.1 in the Internet Appendix plots mean and median policy levels at activism targets in the five-year period around the campaign (year *t*). 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 to be widespread as seen in both the mean and median levels. Second, targets generally experience a worsening operating performance before activism, followed by a sizeable improvement in mean return on assets, return on sales, and asset turnover in the two years post-activism. These operational changes appear to take longer to implement and are not as widespread as seen by the smaller improvements in the median performance levels.

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 *Year t*-1 and *Year t*+1 as seen in the last two rows. In contrast, improvements in return on assets and asset turnover seem to take longer and are statistically significant between *Year t* and *Year t*+2. Based on these findings, we choose a two-year horizon to investigate policy changes at non-targeted peers as a result of threat in year *t*, but 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 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 peers with high and low threat awareness (*HTA* = 1 vs. 0) around the events in which the industry-level threat is in the top quartile of the sample (*Threat* > 0.75). In relative terms, peers with high threat awareness increase mean book leverage and payout yield, and decrease capital expenditures, cash holdings and CEO compensation. 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 actual targets. We note also that the median changes for capital expenditures, cash holdings, and return on sales are largely flat, suggesting that the changes in mean differences are driven by a few peers which exhibit large changes in these policies.

[Insert Figure 3]

Table 3 reports OLS regressions of changes in policy and performance variables on industry-level *Threat*, firm-level *HTA*, and their interaction. Unless otherwise noted, all models include firm-level controls as in Leary and Roberts (2014), a dummy for whether the firm undergoes bankruptcy (which may impact policy outcomes), policy quintile dummies to capture the flexibility of a firm to change a policy as well as industry and calendar year fixed effects.[21] In addition, we add dummies for being a past, current, or future target to control for changes in policies that may be

[21] All control variables are measured as of year *t*-1 except the bankruptcy dummy, which is as of year *t*.

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 time-varying industry conditions that may drive both future targeting and changes in firm policies.

[Insert Table 3]

The explanatory variable of interest is the interaction between *Threat* and *HTA*, which captures the difference in policy changes between firms with high and low threat awareness across different levels of activism threat. Consistent with the univariate evidence, peers with high threat awareness significantly increase their book leverage and payout, and decrease their capital expenditures and cash holdings (relative to peers with low threat awareness). In economic terms, an interquartile increase in *Threat* (i.e., 0.5) increases leverage (payout) by 0.6% (0.4%) and decreases capital expenditures (cash holdings) by 0.4% (0.6%) among peers with high threat awareness, relative to those with low threat awareness. Our results are again directionally similar to the changes observed at actual targets but the magnitudes are slightly less than half of those at the targets. The exceptions are cash holdings, which threatened peers significantly reduce (unlike the targets), and CEO pay, where the decrease for threatened peers is far from being statistically significant.[22]

As for performance variables, peers with high threat awareness significantly improve their return on assets and asset turnover, relative to their industry counterparts with low threat awareness. 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 0.5% (0.8%) higher among peers with high threat awareness for an interquartile increase in activism threat. These magnitudes are about a quarter to half of those observed at the targets. We also note here that past industry-level target frequency does not seem to significantly affect current policy changes, but many of the firm-level controls do. The effects of firm characteristics are generally as expected; for example, firms with

[22] The documented magnitudes at peers may seem large, given the average target probability of 2% in normal times and slightly less than 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 lack of observable decrease in CEO pay despite significant changes in financial policies.

higher market-to-book and EBITDA-to-assets ratios tend to decrease leverage while the opposite is true for firms with higher asset tangibility.

As suggested by the anecdotal evidence discussed earlier, the managers and directors of peer firms frequently hire advisors to assess policy vulnerabilities (e.g., excess cash that could be returned to shareholders). Such vulnerabilities are firm-specific, and hence, different firms 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 or worse performance as vulnerable. We then run our baseline regressions separately for the subsamples of vulnerable and non-vulnerable firms. Table 4 reports the results.

[Insert Table 4]

We show that peers that are vulnerable with respect to a given policy are more likely to change that policy. For example, an interquartile increase in industry-level *Threat* increases leverage by about 0.8% for vulnerable peers versus an increase of only 0.3% (not statistically significant) for non-vulnerable peers. The magnitudes of the changes at vulnerable peers are larger than those obtained from the full sample for most policies. In addition, none of the policy changes in the sample of non-vulnerable threatened peers are significant.

Together, the results in Tables 3 and 4 demonstrate that activism threat has a disciplining effect on peers, which respond by reducing agency costs and improving operating performance. These effects are similar to those documented by Fos (2016) who shows that firms exposed to potential proxy contests increase leverage, dividends and CEO turnover, and reduce capital expenditures. However, our results differ from the average peer effects shown in Aslan and Kumar (2016) who demonstrate negative product market effects of activism on peer cash flows and return on assets. Interestingly, when they divide peers into those that are more vs. less likely to be targeted in the future, they find results consistent with the threat hypothesis, i.e., peers in the former group, arguably more threatened, experience no negative performance effects while those in the latter group bear the brunt of the negative externality. In the next section, we further differentiate the effects of activism threat from those of product market competition.

4. Robustness tests

4.1 Can common industry factors or shared firm characteristics explain our results?

In our baseline analysis, we use *Threat* – percentile rank of flow-induced buys in each industry-year observation – as a plausibly exogenous source of variation in activism. The idea is to capture *time-varying hedge fund characteristics* (size, flows, and capital), which are arguably uncorrelated with time-varying industry conditions that may drive both firm policies and activist targeting. Nevertheless, it is impossible for us to show that our threat measure is fully exogenous. Therefore, we report several counterfactual/robustness tests to address alternative mechanisms that may confound our results.

In Table 5, we present two examples of counterfactual industry waves targeting two specific alternative explanations for our results. First, 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 peer firms. To test this hypothesis, we create a *Policy wave* variable for each specific policy that measures the fraction of significantly improving firms in an industry-year. We define a significant improvement 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 the largest increase to the largest decrease in leverage). To ensure similar distributional properties and comparability with *Threat*, we define *Policy wave* as a percentile score across industry-year observations. Panel A reports the results.

[Insert Table 5]

We first note that the coefficient on *Policy wave* is highly statistically and economically significant in all models, validating our construction of this variable. More importantly, the coefficient on the interaction between *Policy wave* and *HTA* is never statistically significant and has a *t*-statistic of less than one for every policy, except for *Capex* whose sign is opposite to our baseline results in Table 3. That is, peers with high threat awareness do not respond to the policy wave differently from peers with low threat awareness. It appears that changing industry conditions associated with significant policy changes at the majority of industry peers do not lead to the same effects as those of activism threat.

Another concern is that our flow-based proxy of activism threat broadly reflects available capital in the economy, which may be correlated with the scale of other capital-driven transactions, such as mergers. Activists often exit their campaigns through mergers and may therefore choose industries that experience merger waves.[23] Thus, the documented effects of activism threat may instead be due to the differential responses of peers to a capital-driven merger wave.

To test this alternative hypothesis, we follow Harford (2005) and define a *Merger wave* dummy as equal to 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. We use merger data from Thomson Reuters SDC Platinum, and manually verify key transaction details, as described in Boyson, Gantchev, and Shivdasani (2017). We also require that the total number of mergers in the industry is greater than five. In Panel B of Table 5, we replace *Threat* with *Merger wave*, and find that the coefficient on the interaction between *Merger wave* and *HTA* is not statistically significant in any specification, except cash holdings (marginally significant but with opposite sign to our baseline results). Thus, it appears that a capital-driven merger wave does not lead to the same effects as those of activism threat.

In Table 6, we provide another piece of evidence that our findings are likely due to activism threat rather than industry shocks. Specifically, we test whether the non-core segments of a diversified firm experience similar policy or performance changes as its core segment (segments are defined as three-digit SIC codes). If such policy changes are driven by shocks to the core segment, we should not observe similar changes in the non-core segments. This test uses business segment data from Compustat and 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. Our analysis includes only non-

[23] Greenwood and Schor (2009) and Boyson, Gantchev, and Shivdasani (2017) show that campaigns that end in a merger yield the highest return for activists.

core segments and the observations are at the segment-year level.

[Insert Table 6]

Focusing on the interaction between *Threat* and *HTA*, we see 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 (Table 3). This test provides evidence that our findings are likely not driven by shocks in the core industry.

4.2 Can differences in director network size or firm characteristics explain our results?

The threat awareness of a firm is naturally positively correlated with the size and quality of its directors' network, and our results may simply reflect such a general network effect. To make sure that this is not the case, in Table IA.4, we replace the cross section of threat awareness with the cross section of network size. *Large director network* is an indicator that equals one if the average *total* connections per director are greater than the industry median and zero otherwise. The results significantly differ from our baseline results, confirming that the variation in threat awareness that drives policy changes comes from connections with past targets, not simply any connections.

We next verify that differences in observable characteristics between peers with high and low threat awareness do not drive our results. We match a firm with *HTA* = 1 to its closest peer with *HTA* = 0 in the same deciles of market capitalization and institutional ownership, two of the most important determinants of activist targeting. This procedure eliminates most of the differences in observable characteristics between the two types of firms, as reported in Table IA.5.[24] The results in Table IA.6 confirm our baseline findings, suggesting that the policy changes we show are not driven by the cross-section of peers with different observable characteristics responding differentially to unobserved industry factors.

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

4.3 Can alternative peer effects mechanisms explain our results?

In this section, we address the second challenge we face – identifying the effects of activism threat from those of alternative peer effects mechanisms. The most plausible such alternative is product market competition whereby peers respond to the improved competitive position of targeted firms rather than to the threat of activism. To test this channel, we follow Fresard (2010) and use reductions of import tariffs as a plausibly exogenous increase in product market competition. Specifically, we define a *Tariff drop* dummy based on whether the average tariff rate in an industry-year falls by more than two standard deviations (calculated within each three-digit SIC code over the period from 1996 to 2015). We estimate the average tariff rate for each industry-year as calculated duties divided by customs value of imports for consumption. Both the duties and customs values are collected by the U.S. International Trade Commission and reported at the ten-digit U.S. Harmonized Code (HC) level. We map multiple ten-digit HCs to each three-digit SIC code using the concordance table provided by Pierce and Schott (2009).

As is common in the literature, we restrict our analysis to manufacturing industries (three-digit SIC codes between 200 and 399) for which the tariff data are available. To make sure that our baseline results are still present in this subsample, in Table IA.7 in the Internet Appendix, we show that manufacturing firms increase book leverage, reduce cash holdings and capital expenditures, and improve return on assets and asset turnover, in line with our full-sample results.

In Table 7, we report the response of manufacturing firms to a tariff drop that increases competition in their industries. The coefficient of the interaction of *Tariff Drop* and *HTA* shows that none of the policies exhibit a significant difference in response to competition shocks across the two threat awareness groups, except return on sales, which has the opposite sign to our baseline findings in Table 3. These results demonstrate that the effects of increased competitive pressure differ from those of activism threat, and cannot explain our baseline findings.

[Insert Table 7]

We also investigate whether firms with high threat awareness compete more closely with activism targets within their network of peers, and hence, might respond more strongly to threat. We use

Hoberg and Philips (2009)'s firm-centric definition of a peer network, which is based on the textual analysis of firm 10K filings. In our full sample, the average similarity with targets is equal to 0.042 for peers with both high and low threat awareness. Restricting the sample to peers in the industries with *Threat* greater than the sample median, we again observe no significant differences in the average similarity with targets across firms with high and low threat awareness. Thus, firms with high threat awareness do not appear to be closer product market competitors to activism targets.

Together, our evidence indicates that the policy improvements we have demonstrated among peers of activist targets are the distinct effects of activism threat, rather than those of time-varying industry conditions or product market competition.

5. Peer firm returns

We continue our investigation of the effects of activism threat by examining changes in peer firms' valuations. Activism threat may impact peer returns through two channels – (i) *anticipatory* whereby market participants update their beliefs about the likelihood of activist targeting based on capital flows to certain hedge funds that drive the variation in our threat variable, and (ii) *policy* whereby returns capture the real policy and performance improvements we have documented earlier. In terms of timing, the anticipatory channel should be detectable earlier (i.e., during the threat year) whereas the policy channel could manifest itself later on (e.g., only after policy changes are implemented).

Table 8 reports the results of this analysis. In column (1), we create a three-digit SIC industry portfolio, rebalanced annually, and investigate whether the value-weighted abnormal returns of firms in the industry vary with our proxy of threat. Here, we calculate the abnormal return by subtracting the return of the CRSP value-weighted index from each firm's stock return. The results show that the long-term valuation effects of threat, as captured by cumulative abnormal returns over three years (*t* to *t*+2), are positive and marginally statistically significant, even though none of the individual year coefficients are.[25] The sum of the three coefficients corresponds to a 5.15% (=0.103 x 0.5) increase in peer valuations for an interquartile increase in *Threat*. Note, however,

[25] Note that *Threat(t-n)* denotes the return *n* years after the threat year, corresponding to event year *t+n*.

that the coefficient for year *t* is effectively zero (0.008), suggesting that the anticipatory channel is likely not the dominant one.

[Insert Table 8]

We repeat this analysis in column (2) but now the observations are industry-HTA group-year, i.e., we form two portfolios for each industry-year corresponding to *HTA* = 1 and *HTA* = 0. We observe very similar coefficients on the main terms – *Threat(t)* to *Threat(t-2)* – and a zero unconditional effect of threat awareness on abnormal returns. Firms in the high and low threat awareness groups have essentially the same average abnormal returns. Although the results in columns (1)-(2) suggest some positive spillover effects of activism, we cannot ascertain that these effects are induced by activism threat. To isolate the threat effects, in column (3), we add the interactions of *Threat* and its two lags with *HTA* and find that the valuation effect of an interquartile increase in *Threat* is only 2.9% (=0.058 x 0.5; over three years) in the low threat awareness group, with an insignificant *F*-statistic of 0.51. In contrast, the sum of the three interaction terms equals 8.3% (*F*-statistic of 2.93), suggesting that the differential valuation effect between the high and low threat awareness groups, or the valuation effect attributable to activism threat, is 4.15% (=0.083 x 0.5). This is consistent with the policy and operational improvements we document in Table 3.

The next two specifications mitigate concerns that the interaction effect is driven by differences in risk exposure, as firms in the two threat awareness groups differ in several respects. Instead of subtracting the market return as a common benchmark, we use instead the value- (column (4)) or equal- (column (5)) weighted Fama-French 25 size and style portfolios. Our results remain robust.

In sum, we find economically and statistically significant effects of activism threat on the market valuations of peer firms. These valuation effects seem to occur 1-2 years after threat, with magnitudes that are significant even when compared to those of actual targets. For example, at *Threat* = 0.75, peers with high threat awareness experience a relative increase in valuation of roughly 6% over three years, in comparison to about 16% for an average target over the same horizon. The timing and magnitude of these valuation effects suggest that they are driven by real policy changes at threatened peer firms rather than the market's anticipation of a higher likelihood of activism.[26]

6. Feedback effect of activism threat

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

In Table 9, we estimate linear probability models of activist targeting where the dependent variable is a dummy equal to one if a hedge fund activist targets a firm during years t to t+2 (matching the horizon for policy changes in Table 3). All the independent 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 t and hedge fund holdings at the end of year t-2, as described in Section 2.

[Insert Table 9]

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 *Threat* at the industry level increases a firm's probability of becoming a target by 1.15% (=0.023 x 0.5), or about 20% of the unconditional probability level over a three-year period.

We estimate the effects of a firm's 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 cross-sectional standard deviation. For performance variables, we use

[26] The latter channel might be hard to detect as even at the 75th percentile of industry-level threat, the probability of activism remains relatively low at roughly 4%, or 2% higher than normal. So, if an average target experiences long-term valuation effects of 16%, as in our sample, then the incremental expected return from the higher likelihood of activism should be just 32 basis points (2% x 16%).

the improvement from years t to t+2. Policy improvements (deteriorations) take positive (negative) values. *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 9 show that policy improvements 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 about two standard deviations of average policy improvements to fully offset the effect of activism threat on the probability of being targeted (i.e., 0.023/(0.024 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 improvement 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. Intuitively, the coefficient on *Abnormal return* is negative (although not statistically significant), suggesting that higher valuation makes it costlier for an activist to initiate a campaign even when the industry is not threatened. More importantly, the coefficient on the interaction between *Threat* and *Abnormal return* is nearly four times as large and significantly negative, indicating that a threatened peer's increased valuation has a large negative effect when the industry is under threat. The interquartile range of *Abnormal return* is 0.40 and the standard deviation is 0.37. Hence, it takes about one and a half standard deviations of annualized abnormal returns to fully offset the effect of activism threat on the probability of being targeted (i.e., 0.023/(0.038 x 0.37)).

The last two columns split the sample of peers into those with low and high threat awareness. The results show that the feedback effect is largely the same for the two groups. Even though firms with high threat awareness are more likely to change, firms with low threat awareness see similar reductions in the probability of being targeted if they improve policies or experience higher valuations. Thus, the changes implemented by peers with high threat awareness do not appear to be driven by firms that are more exposed to threat and/or stand to benefit more from policy improvements. This additionally validates the design of our main tests in Section 3.

Overall, the feedback effect we show supports the idea that activism plays a disciplinary role at non-targeted firms. However, we advocate 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. Without a natural experiment, we are left with somewhat imperfect tests.

7. Conclusion

This paper investigates the role of activism threat in inducing policy changes at non-targeted peers and examines whether such proactive responses are effective in fending off activists. We find that peers respond to activism threat by reducing agency costs and improving operating performance in the same way as the targets. Our empirical design distinguishes the effects of activism threat from those of common industry factors and alternative peer effects mechanisms by using a combination of (i) an exogenous variation in the scale of activism coming from hedge fund capital, and (ii) the cross section of firms whose directors are informed to different degrees about hedge fund activism. We also employ a host of robustness and falsification tests to minimize the scope for alternative mechanisms to explain our results. In addition, we find that the peers' positive policy changes are reflected in stock valuations, and peer firms that improve policies and experience higher valuations appear to face lower ex-post probability of being targeted, indicating that this 'do-it-yourself' activism is indeed effective.

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

References

Aslan, H., Kumar, P., 2016. The product market effects of hedge fund activism. Journal of Financial Economics 119, 226-248.

Bebchuk, L., Cohen, A., Ferrell, A., 2009. What matters in corporate governance? Review of Financial Studies 22, 783-827.

Becht, M., Franks, J., Mayer, C., Rossi, S., 2008. Returns to shareholder activism: evidence from a clinical study of the Hermes UK Focus Fund. Review of Financial Studies 22, 3093-3129.

Bond, P., Edmans, A., Goldstein, I., 2012. The real effects of financial markets. Annual Review of Financial Economics 4, 339-360.

Boyson, N., Gantchev, N., Shivdasani, A., 2017. Activism mergers. Journal of Financial Economics, in press.

Boyson, N., Mooradian, R., 2011. Corporate governance and hedge fund activism. Review of Derivatives Research 14, 169-204.

Bradley, M., Brav, A., Goldstein, I., Jiang, W., 2010. Activist arbitrage: A study of open-ending attempts of closed-end funds. Journal of Financial Economics 95, 1-19.

Brav, A., Jiang, W., Partnoy, F., Thomas, R., 2008. Hedge fund activism, corporate governance, and firm performance. Journal of Finance 63, 1729-1773.

Brav, A., Jiang, W., Kim, H., 2010. Hedge fund activism: A review. Foundations and Trends in Finance 4, 185-246.

Brav, A., Jiang, W., Kim, H., 2015. The real effects of hedge fund activism: Productivity, asset allocation, and labor outcomes. Review of Financial Studies 28, 2723-2769.

Clifford, C., 2008. Value creation or destruction? Hedge funds as shareholder activists. Journal of Corporate Finance 14, 323-336.

Cohen, L., Frazzini, A., Malloy, C., 2008. The small world of investing: Board connections and mutual fund returns. Journal of Political Economy 116, 951-979.

Coval, J., Stafford, E., 2007. Asset fire sales (and purchases) in equity markets. Journal of Financial Economics 86, 479-512.

Cremers, M., Ferrell, A., 2014. Thirty years of shareholder rights and firm valuation. Journal of Finance 69, 1167-1196.

Edmans, A., Goldstein, I., Jiang, W., 2012. The real effects of financial markets: The impact of prices on takeovers. Journal of Finance 67, 933-971.

Engelberg, J., Gao, P., Parsons, C.A., 2012. Friends with money. Journal of Financial Economics 103, 169-188.

Feng, F., Xu, Q., Zhu, H., 2017. Caught in the crossfire: How the threat of hedge fund activism affects creditors. Unpublished working paper. University of Notre Dame.

Fos, V., 2016. The disciplinary effects of proxy contests. Management Science 63, 655-671.

Fos, V., Tsoutsoura, M., 2014. Shareholder democracy in play: Career consequences of proxy contests. Journal of Financial Economics 114, 316-340.

Fracassi, C., Tate, G., 2012. External networking and internal firm governance. Journal of Finance 67, 153-194.

Fresard, L., 2010. Financial strength and product market behavior: The real effects of corporate cash holdings. Journal of Finance 65, 1097-1122.

Gantchev, N., 2013. The costs of shareholder activism: Evidence from a sequential decision model. Journal of Financial Economics 107, 610-631.

Gantchev, N., Jotikasthira, C., 2017. Institutional trading and hedge fund activism. Management Science, in press.

Griffin, J.M., Xu, J., 2009. How smart are the smart guys? A unique view from hedge fund stock holdings. Review of Financial Studies 22, 2531-2570.

Gillan, S., Starks, L., 2007. The evolution of shareholder activism in the United States. Journal of Applied Corporate Finance 19, 55-73.

Gompers, P., Ishii, J., Metrick, A., 2003. Corporate governance and equity prices. The Quarterly Journal of Economics 118, 1007-1155.

Greenwood, R., Schor, M., 2009. Investor activism and takeovers. Journal of Financial Economics 92, 362-375.

Harford, J., 2005. What drives merger waves? Journal of Financial Economics 77, 529-560.

Jensen, M., 1986. Agency costs of free cash flow, corporate finance, and takeovers. American Economic Review 76, 323-329.

Kahan, M., Rock, E., 2007. Hedge funds in corporate governance and corporate control. University of Pennsylvania Law Review 155, 1021-1093.

Karpoff, J., Wittry, M., 2014. Test identification with legal changes: The case of state antitakeover laws. Unpublished working paper. University of Washington.

Karpoff, J., Schonlau, R., Wehrly, E., 2017. Do takeover defense indices measure takeover deterrence? Review of Financial Studies 30, 2359-2412.

Klein, A., Zur, E., 2009. Entrepreneurial shareholder activism: hedge funds and other private investors. Journal of Finance 63, 187-229.

Leary, M., Roberts, M., 2014. Do peer firms affect corporate financial policy? Journal of Finance 69, 139-177.

Manski, C., 1993. Identification of endogenous social effects: The reflection problem. Review of Economic Studies 60, 531-542.

Pierce, J., Schott, P., 2009. Concording U.S. Harmonized System categories over time. NBER Working Paper.

Popadak, J., 2014. Dividend payments as a response to peer influence. Unpublished working paper. Duke University.

Servaes, H., Tamayo, A., 2014. How do industry peers respond to control threats? Management Science 60, 380-399.

Shleifer, A., Vishny, R., 1988. Value maximization and the acquisition process. Journal of Economic Perspectives 2, 7-20.

Shue, K., 2013. Executive networks and firm policies: Evidence from a random assignment of MBA peers. Review of Financial Studies 26, 1401-1442.

Song, M.H., Walkling, R.A., 2000. Abnormal returns to rivals of acquisition targets: A test of the 'acquisition probability hypothesis'. Journal of Financial Economics 55, 143-171.

Zhu, H., 2013. The preventive effect of hedge fund activism. Unpublished working paper. Duke University.

Appendix A: Variable Definitions

Activism threat and its components

Variable	Observation	Definition
Flow	HF-year	*Flow*(h,t) is the sum of dollar flows to hedge fund h in all quarters of year t. Quarterly flow is calculated as the market value of all stock holdings at the end of the current quarter minus the hypothetical market value if end of previous quarter holdings were kept through the current quarter. Source: Thomson Reuters.
Flow-induced fund buys or FIFB	HF-SIC3-year	*FIFB*(h,j,t) is the inflow that hedge fund h may mechanically allocate to prospective industry j in year t. Only the inflow that exceeds 5% of the beginning of year total net assets is considered. Allocations across all prospective industries of hedge fund h are assumed proportional to the market capitalization of all firms in each industry held by fund h at the end of year t-2. $$FIFB(h,j,t) = Flow5(h,t) \times \frac{TNA(h,j,t\text{-}2)}{TNA(h,t\text{-}2)},$$ where $Flow5(h,t) = \left(Flow(h,t) \text{ if } \frac{Flow(h,t)}{TNA(h,t\text{-}1)} > 0.05;\ 0, otherwise\right)$.
Flow-induced buys or FIB	SIC3-year	*FIB*(j,t) is the sum across all funds of flow-induced fund buys in industry j, normalized by the market capitalization of all firms in industry j. $$FIB(j,t) = \frac{\sum_h FIFB(h,j,t)}{MCAP(j,t)}$$
Threat	SIC3-year	*Threat*(j,t) is the percentile rank, across all industry-years in the sample, of flow-induced buys, *FIB*(j,t). Its values range from 0 to 1.

Other variables

Variable	Observation	Definition
Abnormal returns	Firm-year, SIC3-year, SIC3-HTA-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. Industry or Industry-HTA level abnormal returns are value-weighted abnormal returns of all firms in the industry or industry-HTA group. Source: CRSP and Ken French's website.
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 awareness (HTA)	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.

Variable	Observation	Definition
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 compensation)) 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 book values of common equity and debt. Year-end values. Source: CRSP and Compustat.
Market-to-book ratio	Firm-year	Ratio of 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.
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. 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. 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, based on firms with available CRSP/Compustat data.

Appendix B: Manski (1993)'s Peer Effects Model

For clarity, we present the spillover effects of hedge fund activism in the social effects framework of Manski (1993). Following Leary and Roberts (2014), we model a firm's policy, y_{ijt}, as

$$y_{ijt} = \alpha + \beta\overline{y}_{-ijt} + \gamma'\overline{X}_{-ijt} + \lambda'X_{ijt} + U_{jt} + \varepsilon_{ijt}, \tag{B1}$$

where the subscripts i, j, and t correspond to firm, industry, and year, respectively. The covariate $\overline{y}_{-ijt}$ denotes peer-firm average policy (excluding firm i), and the vectors $\overline{X}_{-ijt}$ 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 $\beta\overline{y}_{-ijt}$ as the endogenous effects, $\gamma'\overline{X}_{-ijt}$ 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 $\overline{X}_{-ijt}$ 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 (B1) translates to the following reduced-form regression (ignoring the industry and time fixed effects for convenience):

$$E(y|X,u_j) = \alpha^* + \gamma^{*\prime}E(X|u_j) + \lambda^{*\prime}X + \kappa^{*\prime}u_j, \tag{B2}$$

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 (B2) should be non-zero (i.e., either endogenous or contextual effects or both are present). Therefore, 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 $E(X|u_j)$ 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 $E(X|u_j)$ is linear in $\overline{Z}_j$, then the coefficient of $\overline{Z}_j$ in the reduced-form regression (B2) will be proportional to γ^*. We use as $\overline{Z}_j$ 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 awareness among industry peers. Specifically, we assume that the contextual effects in (B1) 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 awareness (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 awareness is:

$$E(y|X, u_j, D = 1) - E(y|X, u_j, D = 0) = \gamma_1^* E(X|u_j) + \varphi, \quad \text{where} \quad \gamma_1^* = \frac{\gamma_1}{1 - \beta} \tag{B3}$$

If the target frequency, $E(X|u_j)$, is exogenous, then we can estimate γ_1^*, a multiple of the threat effect, by adding D and $D \times E(X|u_j, D)$ to the regression (B2). The coefficient of $D \times E(X|u_j, D)$ would be γ_1^*, the coefficient of D would be φ, and the coefficient of $E(X|u_j, D)$ would be $\frac{\beta \lambda + \gamma_0}{1 - \beta}$. By replacing $E(X|u_j, D)$ with $\overline{Z}_j$ as discussed above, our estimates will be proportional to these reduced-form parameters. We use as D a dummy that equals one if the average target connections per director are higher than the industry-year median, and zero, otherwise.

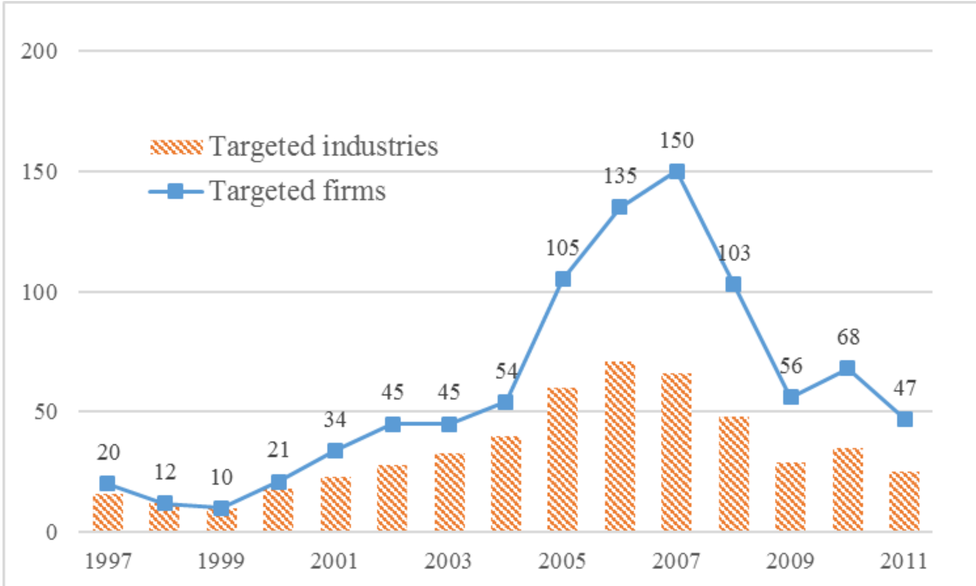

Figure 1: Numbers of Activist-Targeted Firms and Industries over Time. This figure plots frequency counts of firms (blue line with square markers) and three-digit SIC industries (patterned orange bars) targeted by hedge fund activists over the sample period from 1997 to 2011. Included are only targeted firms matched to CRSP, Compustat, Thomson Reuters 13F, and BoardEx data.

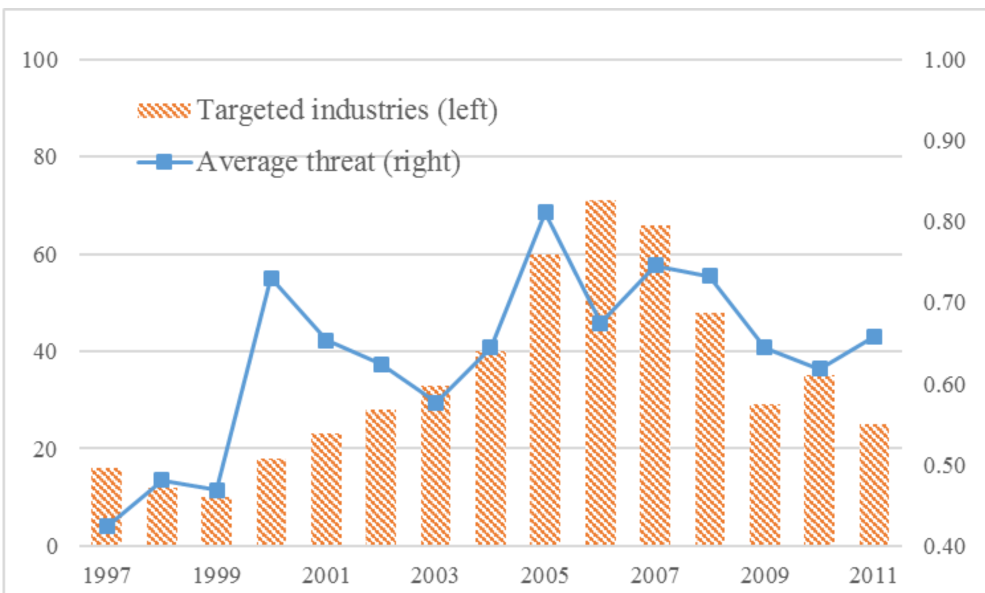

Figure 2: Numbers of Activist-Targeted and Threatened Industries over Time. This figure plots frequency counts of activist-targeted three-digit SIC industries (patterned orange bars, left scale) and average activism threat (blue line with square markers, right scale) over the sample period from 1997 to 2011. Targeted industries are those with at least one firm targeted by an activist hedge fund in a given year. Activism threat is defined in Appendix A. 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 Awareness. This figure plots mean and median differences in financial, investment, and operating policies between peer firms with high and low threat awareness (*High threat awareness* or HTA = 1 and HTA = 0, respectively). The sample period is 1997-2011. The statistics are calculated for event years *t-2* to *t+2*, where year *t* is the year in which the industry threat is in the top quartile of the sample (i.e., greater than 0.75). Threat, HTA, and all policy variables are defined in Appendix A.

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 compensation* 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 compensation ($ 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) *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 flow across industries based on the fund's industry allocation at the end of year *t*-2, considering only the aggregate dollar flow that exceeds 5% of the fund's total net assets at the end of year *t*-1. Finally, to obtain *FIB*, we sum the allocated flow to each industry across all hedge funds, and divide the sum by the industry's total market capitalization at the end of year *t*-1. *FIB* is positive for 2,584 of 2,857 (90%) industry-year observations and zero for the remaining. Of the positive values, the mean and median are 0.0049 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 A. 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 compensation)*, *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	0.808***	0.590**	0.508*			
	(0.193)	(0.282)	(0.281)			
Threat				0.037***	0.032***	0.032***
				(0.005)	(0.004)	(0.006)
Ownership		0.013	0.020		0.011	0.023
		(0.038)	(0.036)		(0.028)	(0.027)
Target frequency(*t*-1)		0.109**	0.070*		0.099*	0.067*
		(0.052)	(0.038)		(0.052)	(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)	0.080	0.091	0.104	0.093	0.102	0.107

Table 3: Policy Changes at Peer Firms Facing Activism Threat

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 awareness (HTA)*, 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. 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.

	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	0.008	-0.006	0.004	0.006	0.032	-0.004	0.014	-0.007
	(0.006)	(0.004)	(0.004)	(0.005)	(0.061)	(0.006)	(0.016)	(0.008)
[HTA] High threat awareness	0.006	0.002	0.003	0.008*	0.034	0.004	-0.005	0.006
	(0.006)	(0.003)	(0.002)	(0.004)	(0.041)	(0.003)	(0.010)	(0.007)
Threat x HTA	0.012**	0.007*	-0.007**	-0.011**	-0.033	0.009*	0.010	0.015*
	(0.006)	(0.004)	(0.003)	(0.005)	(0.062)	(0.005)	(0.016)	(0.008)
Activist target event controls								
Year *t*-1	-0.002	-0.001	-0.008*	-0.002	-0.016	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	0.060	0.010**	0.039*	0.029***
	(0.007)	(0.007)	(0.003)	(0.006)	(0.042)	(0.005)	(0.022)	(0.010)
Year *t*+1	0.014***	0.003	-0.009**	0.005	-0.096***	-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	-0.149***	0.000	0.017	-0.003	0.371	0.018	0.046**	-0.012
	(0.034)	(0.015)	(0.014)	(0.027)	(0.431)	(0.014)	(0.021)	(0.084)
ln(Market cap)	0.011***	0.002***	0.002	-0.006***	0.053***	-0.007***	0.025***	-0.017***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.010)	(0.002)	(0.005)	(0.004)

Cont'd next page

Cont'd from previous page

	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**	0.001**	-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***	0.013	-0.003	-0.315***	-0.135***	-0.320***	-0.205***
	(0.008)	(0.003)	(0.011)	(0.008)	(0.057)	(0.014)	(0.022)	(0.030)
Net PPE/Assets	0.068***	-0.007	-0.031***	-0.035***	0.036	0.014***	0.035**	-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	-0.010	-0.007	0.003	0.027	-0.013	-0.048	0.008
	(0.019)	(0.008)	(0.008)	(0.013)	(0.121)	(0.013)	(0.030)	(0.040)
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	0.041	0.139	0.112	0.156	0.070	0.065	0.094

Table 4: Policy Changes at Threatened Peer Firms Conditional on Policy-Specific Vulnerability

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 awareness* (*HTA*), and their interaction for the subsamples of firms that are vulnerable (Panel A) and not vulnerable (Panel B) to activist targeting, given their current policies. The observations are firm-year, and the sample period is 1997-2011. 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 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. 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.

	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)
Panel A: Vulnerable peers with regard to each policy								
Threat	0.011	-0.001	0.005	0.011	0.036	-0.014	-0.011	-0.012
	(0.009)	(0.004)	(0.009)	(0.007)	(0.083)	(0.008)	(0.018)	(0.014)
[HTA] High threat awareness	-0.009	0.002	0.004	0.008	-0.032	-0.002	-0.007	-0.022
	(0.008)	(0.003)	(0.004)	(0.006)	(0.059)	(0.005)	(0.014)	(0.015)
Threat x HTA	0.015*	0.016**	-0.008**	-0.011	-0.159*	0.015*	0.018	0.030*
	(0.008)	(0.007)	(0.004)	(0.008)	(0.087)	(0.008)	(0.018)	(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	0.116	0.068	0.118	0.039	0.063	0.076
Panel B: Non-vulnerable peers with regard to each policy								
Threat	0.003	-0.001	0.005*	0.007	0.019	0.006	0.021	-0.001
	(0.011)	(0.008)	(0.003)	(0.005)	(0.078)	(0.009)	(0.020)	(0.021)
[HTA] High threat awareness	-0.009	-0.009	0.005*	0.009	0.128**	-0.005	-0.008	0.014
	(0.008)	(0.006)	(0.003)	(0.006)	(0.061)	(0.005)	(0.012)	(0.019)
Threat x HTA	0.007	-0.002	-0.004	-0.012	0.049	0.005	0.010	-0.004
	(0.013)	(0.005)	(0.006)	(0.009)	(0.087)	(0.008)	(0.019)	(0.011)
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	0.076
Controls and FEs as in Table 3 (both panels)	YES	YES	YES	YES	YES	YES	YES	YES

Table 5: 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 awareness* (*HTA*), 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+1for financial and investment policies in columns (1) – (5) or from t to t+2 for operating performance metrics in columns (6) – (8). In the same spirit as Harford (2005), *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)
[HTA] High threat awareness	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 HTA	-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 5, 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)
[HTA] High threat awareness	-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 HTA	-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 6: Policy Changes at Non-Primary Segments of Peer Firms Facing Activism Threat

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 awareness* (*HTA*), 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. All 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	0.004	0.000	0.002	-0.009
	(0.003)	(0.008)	(0.007)	(0.029)
[HTA] High threat awareness	0.007**	0.001	-0.005	-0.004
	(0.003)	(0.007)	(0.007)	(0.027)
Threat x HTA	-0.009*	0.017*	0.021*	0.020
	(0.005)	(0.010)	(0.011)	(0.042)
Activist target event controls				
Year *t*-1	-0.003	0.007	0.002	0.015
	(0.002)	(0.006)	(0.007)	(0.017)
Year *t*	-0.010**	0.015**	0.028**	0.025
	(0.003)	(0.007)	(0.012)	(0.019)
Year *t*+1	-0.002	0.001	-0.004	0.031**
	(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***	-0.253***
	(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	16,521	16,922	17,186	17,139
R-squared (within)	0.055	0.057	0.047	0.044

Table 7: Policy Changes at Peer Firms Facing Increased Product Market Competition (Falsification Test)

This table reports OLS estimates from regressions of changes in policies and performance at peers of activist targets on an industry-level measure of increased product market competition, (firm-level) *High threat awareness* (*HTA*), and their interaction. The observations are firm-year, and the sample period is 1997-2011. The sample includes only firms in manufacturing industries (three-digit SIC from 200 to 399). Following Fresard (2010), we use, as an exogenous increase in competition, the indicator *Tariff drop*, which equals one if the change in tariff rate from years *t*-1 to *t* is negative and greater in magnitude than two times the within-industry standard deviation of yearly tariff rate change. Tariff rate equals calculated duties divided by customs value of U.S. imports for consumption. Both the calculated duties and customs value are from the U.S. International Trade Commission, and aggregated from ten-digit U.S. Harmonized System codes to each three-digit SIC, using the concordance table provided by Pierce and Schott (2009) and assuming that the mappings in 2006 are valid through 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. 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.

	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)
Tariff drop	-0.002	-0.002*	0.006	0.007	0.080	-0.022**	-0.029**	-0.022
	(0.008)	(0.001)	(0.006)	(0.008)	(0.056)	(0.008)	(0.014)	(0.022)
[HTA] High threat awareness	-0.001	0.000	0.001	-0.001	0.017	0.001	0.003	-0.000
	(0.003)	(0.000)	(0.002)	(0.002)	(0.014)	(0.002)	(0.004)	(0.005)
Tariff drop x HTA	0.000	-0.000	-0.001	0.007	0.009	-0.002	-0.011**	-0.012
	(0.010)	(0.001)	(0.002)	(0.013)	(0.053)	(0.008)	(0.005)	(0.013)
Controls and FEs as in Table 3	YES	YES	YES	YES	YES	YES	YES	YES
Observations	17,107	17,107	17,107	17,107	7,782	17,101	17,101	17,101
R-squared (within)	0.110	0.155	0.149	0.122	0.162	0.078	0.072	0.132

Table 8: Abnormal Returns of Peer Firms Facing Activism Threat

This table reports OLS estimates from panel regressions of portfolio abnormal returns on *Threat*, *High threat awareness* (*HTA*), and their interaction. In column (1), the portfolio abnormal return of each industry-year observation is the value-weighted average abnormal return of individual stocks in each three-digit SIC industry, rebalanced each year at the beginning of the year. In columns (2) – (5), the portfolio abnormal return of each industry-HTA-year observation is the value-weighted abnormal return of individual stocks with HTA = 0 or HTA = 1 in each three-digit SIC industry, rebalanced each year at the beginning of the year. Market-adjusted returns are stock returns minus CRSP VW returns. FF25VW (EW)-adjusted returns are stock returns minus value-weighted (equally-weighted) returns of the Fama-French 25 size- and style-matched portfolios (see Appendix A for details). All regressions include industry and calendar year fixed effects. Standard errors, clustered by industry, are in parentheses. F-statistics are reported for the tests of two hypotheses – (i) the sum of the coefficients of *Threat*(*t*), *Threat*(*t*-1), and *Threat*(*t*-2) equals zero, and (ii) the sum of the coefficients of *Threat*(*t*) x *HTA*, *Threat*(*t*-1) x *HTA*, and *Threat*(*t*-2) x *HTA* equals zero. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	Market (1)	Market (2)	Market (3)	FF25VW (4)	FF25EW (5)
Threat(*t*)	0.008	-0.004	-0.002	-0.005	-0.007
	(0.041)	(0.036)	(0.036)	(0.038)	(0.041)
Threat(*t*-1)	0.054	0.053	0.040	0.039	0.039
	(0.035)	(0.035)	(0.034)	(0.034)	(0.037)
Threat(*t*-2)	0.041	0.034	0.020	0.025	0.023
	(0.038)	(0.036)	(0.038)	(0.038)	(0.043)
[HTA] High threat awareness		-0.001	-0.017	-0.009	-0.014
		(0.025)	(0.027)	(0.026)	(0.025)
Threat(*t*) x HTA			-0.004	0.001	0.002
			(0.038)	(0.037)	(0.043)
Threat(*t*-1) x HTA			0.022	0.022	0.020
			(0.039)	(0.037)	(0.039)
Threat(*t*-2) x HTA			0.065**	0.057*	0.061*
			(0.032)	(0.032)	(0.032)
Industry FE	YES	YES	YES	YES	YES
Calendar year FE	YES	YES	YES	YES	YES
F test of H0: Sum of coefficients of Threat(*t*), Threat(*t*-1), and Threat(*t*-2) equals zero.	2.97*	2.87*	0.51	1.18	0.83
F test of H0: Sum of coefficients of the three interaction terms equals zero.			2.93*	2.93*	2.89*
Observations	2,453	4,312	4,312	4,312	4,312
R-squared (within industry)	0.119	0.108	0.109	0.045	0.033

Table 9: Feedback Effects of Policy Changes and Returns at Peer Firms Facing Activism Threat

This table reports OLS estimates from 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. These variables, as well as the control 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 high and low threat awareness, 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			HTA = 0	HTA = 1
	(1)	(2)	(3)	(4)	(5)
Main variables					
Threat	0.023**	0.027***	0.023**	0.026*	0.030**
	(0.009)	(0.010)	(0.011)	(0.014)	(0.014)
Avg. improvement z-score		0.000	0.006	0.001	0.007
		(0.009)	(0.009)	(0.012)	(0.012)
Threat		-0.024**	-0.030**	-0.029*	-0.032*
x Avg. improvement z-score		(0.011)	(0.013)	(0.015)	(0.016)
Abnormal return			-0.010	-0.013	-0.010
			(0.012)	(0.014)	(0.014)
Threat x Abnormal return			-0.038**	-0.036*	-0.042*
			(0.018)	(0.021)	(0.023)
Firm and industry controls					
[HTA] High threat awareness	-0.000	-0.001	-0.000		
	(0.003)	(0.003)	(0.003)		
ln(Market cap)	-0.010***	-0.010***	-0.011***	-0.011***	-0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln(Tobin's Q)	-0.020***	-0.023***	-0.016***	-0.012*	-0.020***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)
Book leverage	0.007	0.009	0.014	0.012	0.016
	(0.008)	(0.009)	(0.009)	(0.012)	(0.012)
Payout/Market cap	-0.019	-0.007	-0.020	-0.021	-0.011
	(0.051)	(0.055)	(0.055)	(0.071)	(0.081)
Sales growth	0.006	0.005	0.002	0.001	0.002
	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)
Return on Assets	-0.011	-0.020	-0.014	-0.008	-0.021
	(0.012)	(0.012)	(0.013)	(0.016)	(0.015)
ln(Stock turnover)	0.183	0.236	0.375	0.512	0.170
	(0.251)	(0.286)	(0.294)	(0.346)	(0.377)

Cont'd next page

Cont'd from previous page

	Full Sample			HTA = 0	HTA = 1
	(1)	(2)	(3)	(4)	(5)
ln(Analysts)	0.000	0.001	-0.000	-0.000	-0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
Inst. ownership	0.072***	0.073***	0.072***	0.076***	0.068***
	(0.008)	(0.009)	(0.009)	(0.012)	(0.012)
Past campaigns	0.498***	0.521***	0.512***	0.593***	0.386***
	(0.069)	(0.073)	(0.076)	(0.099)	(0.126)
Ongoing campaign	0.002	0.009	0.014	-0.017	0.028
	(0.023)	(0.024)	(0.024)	(0.038)	(0.030)
Target frequency during *t*-2 and *t*-1	0.001	0.002	0.003	0.027	-0.025
	(0.022)	(0.024)	(0.025)	(0.032)	(0.035)
Industry FE	YES	YES	YES	YES	YES
Calendar year FE	YES	YES	YES	YES	YES
Observations	34,277	34,277	33,077	18,528	14,549
R-squared (within)	0.031	0.031	0.032	0.035	0.032

Internet Appendix for

Governance under the Gun: Spillover Effects of Hedge Fund Activism

This Internet Appendix provides supplemental analyses to the main tables and figures.

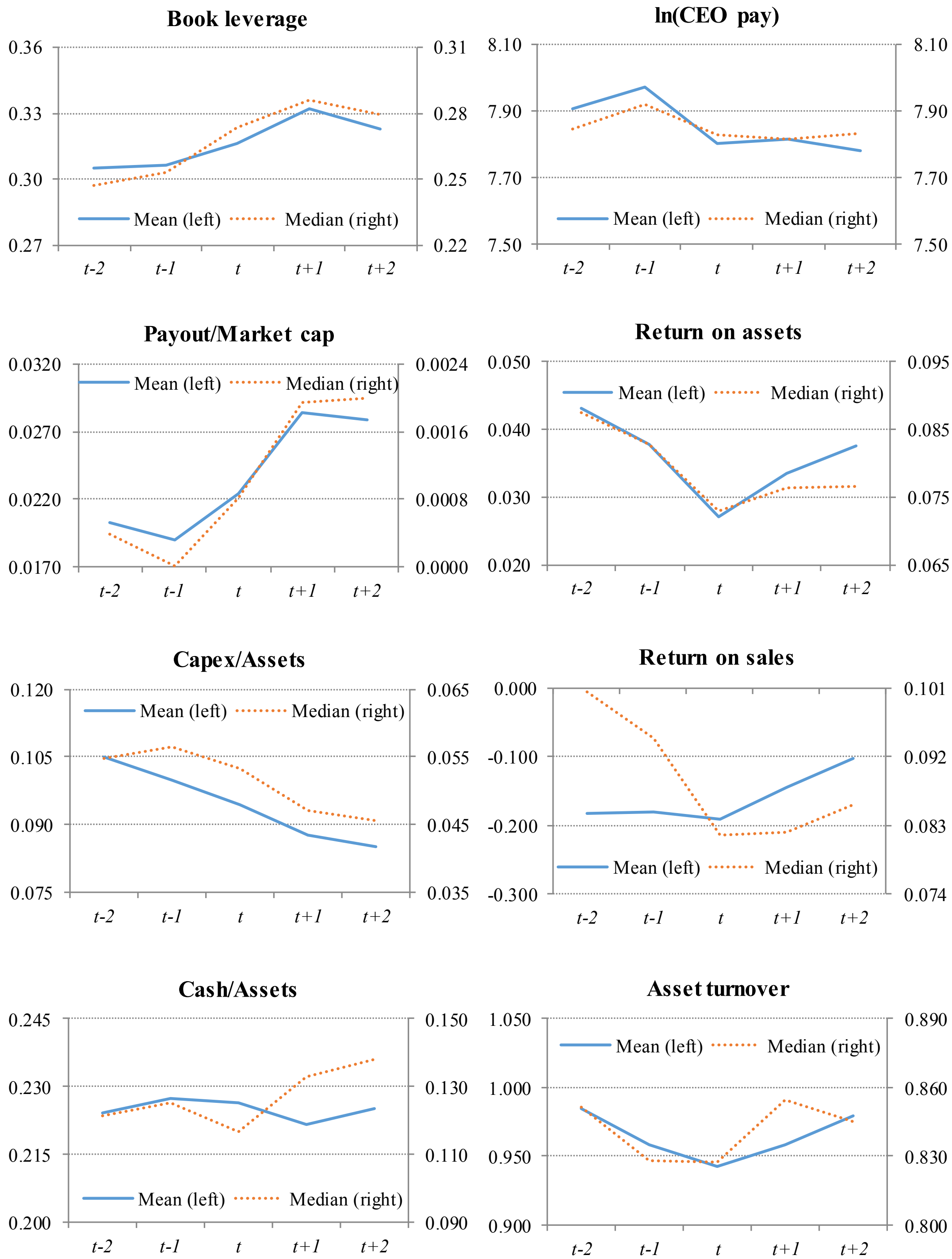

Figure IA.1: Policy Changes at Activist Targets. This figure plots mean and median levels of financial, investment, and operating policies at targets of hedge fund activism. The sample period is 1997-2011. The statistics are calculated for event years *t-2* to *t+2*, where year *t* contains the start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

This table reports summary statistics of select firm-level variables for firms targeted by activist hedge funds (Panel A), firms with high threat awareness (HTA = 1) (Panel B), and firms with low threat awareness (HTA = 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 defined in Appendix A of the paper.

Panel A: Target firms

Number of observations: 905 (total), 349 (with available *CEO compensation*), 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 compensation ($ 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 Awareness

Panel B: Firms with high threat awareness (HTA = 1)
Number of observations: 19,047 (total), 9,571 (with available *CEO compensation*), 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 compensation ($ 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 awareness (HTA = 0)
Number of observations: 26,310 (total), 10,249 (with available *CEO compensation*), 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 compensation ($ 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 Awareness

This table reports counts of activist targets among firms with high and low threat awareness (HTA = 1 and HTA = 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. Both *Threat* and *High threat awareness* are defined in Appendix A of the paper.

	Full Sample		Threat ≤ Median		Threat > Median	
	# Firms	# Targets	# Firms	# Targets	# Firms	# Targets
HTA = 0	26,310	518	14,576	197	11,734	321
HTA = 1	19,047	387	9,386	125	9,661	262
Total	45,357	905	23,962	322	21,395	583

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)

Cont'd next page

Cont'd from previous page

	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 Peer Firms with Large and Small Director Networks

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. All other 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		
	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	0.011	-0.004	0.005	0.006	0.016	-0.003	0.011	-0.003
	(0.010)	(0.005)	(0.005)	(0.005)	(0.057)	(0.007)	(0.019)	(0.016)
[LDN] Large director network	-0.003	0.000	0.003	-0.001	0.043	-0.001	-0.003	0.005
	(0.006)	(0.004)	(0.003)	(0.004)	(0.030)	(0.004)	(0.011)	(0.006)
Threat x LDN	0.003	0.001	-0.004	0.003	0.000	0.005	0.013	-0.005
	(0.009)	(0.007)	(0.003)	(0.006)	(0.047)	(0.005)	(0.015)	(0.008)
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	0.062	0.010**	0.039*	0.030***
	(0.007)	(0.008)	(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	-0.149***	0.000	0.017	-0.004	0.355	0.018	0.045**	-0.011
	(0.034)	(0.014)	(0.014)	(0.028)	(0.436)	(0.014)	(0.020)	(0.084)

Cont'd next page

Cont'd from previous page

	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(Market cap)	0.011***	0.002***	0.002	-0.006***	0.052***	-0.007***	0.025***	-0.017***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.010)	(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	-0.030***	-0.035***	0.036	0.014***	0.035**	-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	-0.009	-0.007	0.002	0.025	-0.012	-0.048	0.009
	(0.019)	(0.008)	(0.008)	(0.013)	(0.121)	(0.013)	(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)	0.093	0.041	0.138	0.112	0.155	0.070	0.063	0.093

Table IA.5: Summary Statistics for Firms with High and Low Threat Awareness Matched by Industry, Size, and Institutional Ownership

This table reports summary statistics of select firm-level variables for firms with high threat awareness (HTA = 1) (Panel A) and firms with low threat awareness (HTA = 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 HTA = 1, matched firm-year observations with HTA = 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. All variables are defined in Appendix A of the paper.

Panel A: Firms with high threat awareness (HTA = 1)
Number of observations: 10,632 (total), 4,901 (with available *CEO compensation*), 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 compensation ($ 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.5, Cont'd: Summary Statistics for Firms with High and Low Threat Awareness Matched by Industry, Size, and Institutional Ownership

Panel B: Firms with low threat awareness (HTA = 0)
Number of observations: 10,632 (total), 4,793 (with available *CEO compensation*), 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 compensation ($ 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.6: Policy Changes at Peer Firms with High and Low Threat Awareness 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 awareness* (*HTA*), and their interaction. The sample includes firms with HTA = 1 and HTA = 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 HTA = 1, matched firm-year observations with HTA = 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. 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		
	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	0.007	-0.001	0.014**	0.009	-0.068	0.001	0.019	0.025
	(0.008)	(0.006)	(0.007)	(0.009)	(0.091)	(0.009)	(0.016)	(0.016)
[HTA] High threat perception	0.009	-0.001	0.007	0.015**	0.134	-0.010	-0.006	-0.001
	(0.009)	(0.004)	(0.006)	(0.007)	(0.098)	(0.009)	(0.017)	(0.012)
Threat x HTA	0.015*	0.008	-0.012*	-0.018**	-0.123	0.017*	0.019	0.028*
	(0.008)	(0.006)	(0.007)	(0.009)	(0.113)	(0.010)	(0.017)	(0.016)
Activist target event controls								
Year *t*-1	-0.012	-0.000	-0.000	-0.012	0.050	0.012	-0.025	-0.002
	(0.010)	(0.006)	(0.002)	(0.008)	(0.107)	(0.013)	(0.020)	(0.022)
Year *t*	0.026**	0.027***	-0.016**	-0.022*	-0.046	0.033**	0.100*	0.072***
	(0.012)	(0.007)	(0.008)	(0.012)	(0.056)	(0.015)	(0.056)	(0.018)
Year *t*+1	0.014	0.005	-0.011	0.002	-0.105**	0.006	-0.001	0.004
	(0.012)	(0.004)	(0.008)	(0.013)	(0.051)	(0.006)	(0.016)	(0.009)
Firm and industry controls								
Bankruptcy	-0.014	0.019***	-0.009	0.015	-0.460	0.030	0.095**	0.041**
	(0.048)	(0.004)	(0.009)	(0.037)	(0.449)	(0.029)	(0.039)	(0.020)

Cont'd next page

Cont'd from previous page

	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**	0.100***	-0.006**	0.040**	-0.014
	(0.004)	(0.001)	(0.002)	(0.003)	(0.024)	(0.002)	(0.016)	(0.009)
ln(Sales)	-0.007	0.002**	-0.005**	0.005**	0.076***	0.012***	-0.035**	0.016*
	(0.004)	(0.001)	(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*	0.007**	0.009	-0.023	-0.383***	-0.140***	-0.289***	-0.160***
	(0.011)	(0.004)	(0.015)	(0.014)	(0.118)	(0.011)	(0.034)	(0.037)
Net PPE/Assets	0.051***	-0.006	-0.040***	-0.048***	-0.027	0.008	0.030	-0.087***
	(0.017)	(0.004)	(0.012)	(0.014)	(0.050)	(0.009)	(0.027)	(0.024)
Target frequency during *t*-2 and *t*-1	0.036	-0.030*	-0.024	0.000	0.150	-0.014	-0.058	-0.045
	(0.039)	(0.016)	(0.018)	(0.020)	(0.267)	(0.028)	(0.120)	(0.076)
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	0.080	0.150	0.134	0.251	0.078	0.074	0.107

Table IA.7: Policy Changes at Peer Firms in Manufacturing Industries

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 awareness (HTA)*, and their interaction for the subsample of firms in manufacturing industries (three-digit SIC from 200 to 399). 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 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		
	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	-0.005	0.006	0.007	0.008	-0.012	0.007	0.010
	(0.010)	(0.003)	(0.004)	(0.005)	(0.058)	(0.009)	(0.015)	(0.011)
[HTA] High threat awareness	-0.012	-0.001	0.005	0.007	0.011	-0.007	-0.007	0.004
	(0.010)	(0.003)	(0.003)	(0.007)	(0.056)	(0.005)	(0.012)	(0.008)
Threat x HTA	0.018*	0.003	-0.012***	-0.018**	-0.025	0.013*	0.014	0.019*
	(0.011)	(0.004)	(0.004)	(0.008)	(0.090)	(0.007)	(0.015)	(0.011)
Activist target event controls								
Year *t*-1	-0.002	0.004	-0.012	-0.008	-0.052	0.017*	0.006	-0.005
	(0.008)	(0.003)	(0.008)	(0.006)	(0.092)	(0.010)	(0.009)	(0.012)
Year *t*	0.007	0.014**	-0.011**	-0.005	0.032	0.017**	0.082*	0.028*
	(0.007)	(0.006)	(0.005)	(0.012)	(0.054)	(0.008)	(0.044)	(0.016)
Year *t*+1	0.011*	0.002	-0.007*	0.004	-0.081	0.008	0.008	0.012
	(0.006)	(0.002)	(0.003)	(0.004)	(0.060)	(0.007)	(0.009)	(0.016)
Firm and industry controls								
Bankruptcy	-0.171***	-0.019	-0.000	0.034	0.649	-0.003	0.067***	-0.044
	(0.055)	(0.029)	(0.012)	(0.036)	(0.638)	(0.014)	(0.021)	(0.158)
ln(Market cap)	0.012**	0.002***	0.003**	-0.005*	0.062***	-0.011***	0.033***	-0.033***
	(0.005)	(0.001)	(0.001)	(0.002)	(0.013)	(0.002)	(0.009)	(0.005)

Cont'd next page

Cont'd from previous page

	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(Sales)	-0.003	0.001**	-0.006***	0.004*	0.071***	0.017***	-0.024***	0.032***
	(0.005)	(0.000)	(0.002)	(0.002)	(0.005)	(0.002)	(0.006)	(0.004)
Market-to-book ratio	-0.004***	-0.001***	-0.002***	0.001***	0.009***	0.000	-0.005***	-0.006***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)	(0.002)	(0.001)
EBITDA/Assets	-0.052***	0.008***	0.020	0.002	-0.395***	-0.135***	-0.342***	-0.194***
	(0.012)	(0.002)	(0.015)	(0.009)	(0.085)	(0.019)	(0.029)	(0.034)
Net PPE/Assets	0.086***	-0.014***	-0.046***	-0.053***	0.042	0.014**	0.045	-0.063***
	(0.011)	(0.002)	(0.006)	(0.011)	(0.081)	(0.006)	(0.030)	(0.015)
Target frequency during *t*-2 and *t*-1	0.041*	-0.015	-0.008	0.002	0.005	-0.023	-0.097	-0.070
	(0.022)	(0.017)	(0.013)	(0.016)	(0.268)	(0.024)	(0.059)	(0.073)
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	17,107	17,107	17,107	17,107	7,782	17,101	17,101	17,101
R-squared (within)	0.110	0.077	0.149	0.122	0.161	0.077	0.072	0.131