Activism Pressure and the Market for Corporate Assets*

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ABSTRACT

We investigate the impact of hedge fund activism on corporate transaction markets. We find that activism targets as well as firms exposed to hedge fund threats receive more merger bids, increase divestitures and make fewer acquisitions, with the acquisition effect concentrated among large firms. We document that the majority of activist campaigns are clustered by industry, and estimate that the simultaneous increase in asset sales and decrease in acquisitions in such activism clusters reduce real asset liquidity for asset sellers by about 35%. The liquidity squeeze produces two effects: transaction prices are reduced, and industry outsiders provide liquidity by purchasing more industry assets. Looking at short-term price pressure and long-run performance, we present evidence that transactions by activist targets are less affected by the reduced asset liquidity than those of other firms.

Key words: activism clusters, real asset liquidity, price pressure, divestitures, mergers, acquisitions, small acquirers, hedge fund activism, activism threat.

JEL classification: G23, G34

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1 Introduction

The rise of shareholder activism in the last two decades has spurred academics to analyze various aspects of effects on activist target firms, such as changes in firm behavior and performance. But to get a full sense of the transformations brought about by activism, it is important to look beyond target firms and understand its impact on stakeholders and markets. Previous evidence on the impact of activism on target firms' M&A behavior shows that activist targets are more likely to be taken over, make fewer acquisitions, and divest more assets. This paper explores whether the uniform direction of this change in behavior has an impact on markets for corporate transactions. We ask whether activism has grown sufficiently in importance to influence the equilibrium in corporate asset markets and to reduce the real asset liquidity in these markets. We investigate in particular whether such effects arise in industries in which activists are clustering, and whether the pressure of activism is sufficiently strong in these industries so that firms not (yet) targeted by activists alter their acquisition behavior in the same direction under the disciplining effect of hedge fund threats.

Our focus on the market externalities of activism is in contrast to most of the literature on shareholder activism that has largely limited its attention to effects on target firms. There is no earlier study on the impact of activism on the acquisition or divestiture behavior of firms only indirectly exposed to activism threats, or on the effect of activism on the equilibrium outcome in asset markets. The literature has not documented before, to our knowledge, the extent to which activist hedge fund campaigns are clustered by industry, or examined its consequences. By doing so, we contribute to the analysis of spillover effects in real asset markets triggered by common shocks to firms' financial conditions.

We document that hedge fund activism is highly concentrated, with a tendency for hedge fund campaigns to cluster in certain industries. 57% of activist campaigns are concentrated in industries (at the 3-digit SIC level) that account for less than 20% of industry-years, according to our main measure of clusters of activism. This clustering means that firms' perception of the risk of being targeted should also be concentrated, and thus leads us to consider firms' exposure to activism threats as a second channel of activism pressure.

For our study of the effect on corporate asset markets, we take into account a wide range of corporate transactions: takeovers and mergers, divestitures, and acquisitions, including acquisitions of private targets. We first confirm that firms directly targeted in activist campaigns are more likely to receive merger bids, make more divestitures, and make fewer acquisitions, with the last effect due to larger firms. Moving to the analysis of disciplinary effects of activism, we first consider the threat impact for firms individually, by estimating their probability of becoming an activism target in the near future. These regressions confirm the industry cluster effect. Building on this insight, our principal measures of the impact of activism threat are aggregated at the industry level. We use the frequency of recent activist campaigns in the industry as our main measure of changes in activism threats, and we use jumps in activist funds' stakes (both active and passive) in the industry as a second measure. Whether we use firm-level or industry-level metrics of HFA threat exposure, we show that firms' behavioral adjustment after threat increases goes in the same direction as the reaction of activism targets: firms sell more assets, are more likely to be acquired, and on average also tend to acquire less. The latter effect, however, is nuanced: only large firms make fewer acquisitions, whereas small firms maintain or increase their acquisitions activity.

Endogeneity is a concern in any study on the impact of activism. Activism targets might be selected because of unobserved characteristics that drive the observed changes in firm behavior, or because activists anticipate value-enhancing developments in those firms rather than being at the origin of those changes. We address these concerns in various ways. First, for target firms (for which such concerns are particularly important since firms exposed to activism threats are not selected firms by activists), we use an approach pioneered by Brav, Jiang, and Kim (2015a) and look at the effect when a hedge fund, for a given hedge fund-activist pair, switches from a sizable passive stake in a given firm (Schedule 13G filing) to an activist stance (Schedule 13D filing). We show that such switches produce a significant change in firms' corporate transactions in the same direction we found earlier, providing a "clean identification of intervention beyond stock picking", in the words of Brav, Jiang, and Kim (2015a).

Second, for firms under activism threat, by using industry-level measures of hedge fund pressure, we eliminate any effect of unobserved firm-level characteristics beyond those common to all firms in the industry. This still leaves the concern that selection effects arise at the level of industries, i.e. hedge funds select entire industries (rather than firms) because of common characteristics associated with the observed change in acquisition markets.

Third, therefore, we address this concern with an instrumental variable that is built on the idiosyncratic fund inflow shock of each activist hedge fund, and we hypothetically reassigns the new fund inflow according to the previous industry holding structure of each hedge fund, similar to the well-known instrument of mutual fund fire sales (Coval and Stafford (2007), Edmans, Goldstein, and Jiang (2012)).[1] Thus, the instrument dissociates the increase in

[1] The same instrument has been used in the previous studies looking at threat effects of hedge fund activism,

activist's targeting from their selection of industries. We find that our findings of the change in corporate asset markets remain in place when we use this instrument. We are also careful to control for any factors that explain the clustering of acquisition activity in industries, or merger waves (Harford (2005)), in order to address potential associations with the target selection of hedge fund activists. We find no clear association between merger waves and hedge fund target selection.[2]

Finally, we address concerns that hedge funds select industries and target firms because of a favorable change in their potential for corporate transactions (reverse causality). We show that neither an increase in the probability of firms being taken over or of making asset disposals, nor a decrease in their propensity to make acquisitions has explanatory power in predicting which firms would be targeted by activists.

Having established that activism pressure affects the behavior of both target firms as well as of firms under activism threat, we try to provide estimates of the importance of the activism threat effect. Activist targets change their behavior dramatically but only a few firms are targeted in a typical industry at any given time, whereas many more firms are exposed to activism threats - our main threat measures assume that *all* firms in the industry are equally exposed - , with moderate impact on their behavior. We find that the overall impact that we attribute to firms under activism threats is nearly the same as that attributed to activist targets, with a larger relative effect on the demand side (acquisitions), and a smaller effect on the supply side (mergers and divestitures).

We estimate that firms in industries in the top quintile of activism pressure sell on average about 23% more assets, and make close to 12% fewer acquisitions, leading to a combined shift in the relation between demand and supply for corporate assets of roughly 35%. We expect this squeeze in real asset liquidity to have an effect both on transaction volume and on transaction prices.

Hence, we consider the impact on liquidity in highly affected industries. When firms in an industry under activism pressure simultaneously aspire to sell more and buy fewer assets, then real asset liquidity dries up, creating a role for outside liquidity providers. Indeed, we find that outside acquirers - private equity funds, private firms, and listed firms in other industries

Gantchev, Gredil, and Jotikasthira (2017), Feng, Xu, and Zhu (2017).

[2]The literature on the relationship between industry takeover activity, industry concentration and industry demand provides the background for such concerns (see Mitchell and Mulherin (1996), Andrade and Stafford (2004), Bernile, Lyandres, and Zhdanov (2012)). No earlier study has looked at determinants of merger waves predicting the selection of activist targets, but Boyson, Gantchev, and Shivdasani (2017) find that merger waves do not lead to more activism mergers.

- provide liquidity and that their acquisition volume increases in affected industries. We show that this difference is due to private equity providing asset liquidity only in industries with high asset redeployability, and that outside asset liquidity provision is stronger in these industries.

We then explore whether the squeeze in real asset liquidity also affects transaction prices. We find evidence consistent with this hypothesis: seller announcement returns are smaller in corporate sales when industries are affected by activist pressure (merger bids and divestiture bids), and buyer announcement returns are (weakly) larger in this case. We do not find evidence for a similar price effect for activist target firms; unlike other firms in industries under heavy activist pressure, activist target firms themselves appear little affected.

Finally, we consider whether the negative externalities of industry clustering affect the long-run performance of corporate transactions undertaken under activism pressure. Looking at accounting measures and Tobin's Q, we isolate the incremental long-run effect of transactions done under activism influence from the documented performance impact of activism campaigns and of corporate transactions. We find positive long-run performance effects when corporate transactions are undertaken by activism targets. We do not find similar effect for transactions undertaken under activism threat. The direct involvement of activists appears to be a necessary ingredient for activism pressure to produce additional efficiency gains in corporate transactions.

Our paper contributes to various strands of the literature. It extends earlier work on activism targets' behavior in corporate transactions (reviewed in the next section) by showing that firms under activism threats adjust their behavior in the same direction. There is a small literature on threat effects of activism (reviewed below) to which our paper adds the insight that such effects can also be detected when looking at corporate transactions. We contribute to this work the analysis of the role of industry clustering of activism and of disciplinary effects in corporate transaction decisions.

The paper is also related to the wider literature on the real effects of hedge fund activism.[3] Academic researchers have analyzed the value gains following activism campaigns (e.g., Brav, Jiang, Partnoy, and Thomas (2008), Greenwood and Schor (2009), Becht, Franks, Grant, and Wagner (2017)) and have shown that activism campaigns improve the operations and profitability of targets (Bebchuk, Brav, and Jiang (2015), Aslan and Kumar (2016), Brav,

[3] See Denes, Karpoff, and McWilliams (2017) and Brav, Jiang, and Kim (2015b) for surveys. The literature has also investigated other topics to which our paper is related, such as the international expansion of activism (see Becht, Franks, Grant, and Wagner (2017)) and the determinants of activism target selection (Brav, Jiang, Partnoy, and Thomas (2008)).

Jiang, and Kim (2015a)),[4] their competitive position in product markets (Aslan and Kumar (2016)), and the quality of their innovation effort (Brav, Jiang, Ma, and Tian (2018)). Our paper contributes several new aspects to this strand of the literature, notably by showing that post-activism corporate transactions improve the economic efficiency of sellers, but less so for firms acting under activism threat, and that only smaller firms generate performance gains from activism acquisitions.

The paper is organized as follows. Section 2 discusses literature and hypotheses. We explain our sample construction and methodology in Section 3. Section 4 analyzes the impact of activism on mergers, divestitures, and acquisitions. In Section 5, we investigate how activism pressure alters the equilibrium in the market for corporate assets and affects real asset liquidity and asset prices. We investigate the impact on the long-run efficiency of corporate transactions in Section 6. Section 7 concludes.

2 Literature and Hypotheses

The view that hedge fund activism affects firm decisions in the market for corporate assets is developed in a number of theoretical and empirical papers. Theoretical models explaining why activism targets frequently become takeover targets include Burkart and Lee (2018) who show that activists reduce ex ante *and* ex post free-riding in takeovers, and Corum and Levit (2017) who demonstrate that activist toeholds act as facilitators of future takeovers. The empirical literature on activism mergers shows that activist targets have a substantially higher probability to receive merger bids (Boyson, Gantchev, and Shivdasani (2017), Becht, Franks, Grant, and Wagner (2017)). Gantchev, Sevilir, and Shivdasani (2018) find that activism campaigns reduce firm's propensity to make acquisitions, increase the frequency of divestiture, and improve the quality of transactions, measured by abnormal long-term buy-and-hold returns.

Concerning activism threats, the idea that firms react to activism pressure even if they are not target firms is related to the literature on the disciplining effect of the market for corporate control (see Grossman and Hart (1980) for a seminal theory contribution and Bertrand and Mullainathan (2003) for evidence). The concept of activism threats has been developed theoretically e.g. in Edmans and Manso (2011) and Fos and Kahn (2016). Thus, when facing heightened activism threat, managers should proactively adjust their behavior in anticipation

[4] There is some controversy concerning the improvement in long-term performance, see deHaan, Larcker, and McClure (2018) for size effects or Grennan (2014) for evidence on short-termism.

of increased activism risk. Gantchev, Gredil, and Jotikasthira (2017), Feng, Xu, and Zhu (2017), and Bourveau and Schoenfeld (2017) present supportive evidence for this view. Besides the disciplining effect of activism threats, there could be other motives that might lead firms under activism threat to adopt behavior similar to that of campaign targets, for examplestrategic interaction effects with activist targets in product or asset markets.[5] Throughout, we remain agnostic about the exact motives that lead to the behavioral change on acquisition markets.

The decrease in real asset liquidity when more assets are sold and fewer are bought is related to the argument by Shleifer and Vishny (1992) that industry peers and hence insiders are the highest-value acquirer of any assets in an industry that is for sale. There is also a substantial theoretical and empirical literature on asset fire sales (see Shleifer and Vishny (2011) for a survey). The concept of real asset liquidity has been explored empirically by Schlingemann, Stulz, and Walkling (2002), Ortiz-Molina and Phillips (2014), and Kim and Kung (2017), among others.

We expect the effect on real asset liquidity to be measurable both along the quantity and the price dimension, following standard economic arguments and the discussion on asset fire sales (see Shleifer and Vishny (2011) for a survey, and e.g. Pulvino (1998) for a seminal paper). Listed firms in an industry affected by a high level of hedge fund activism will feel under pressure to sell assets and curtail acquisitions. They are unlikely to be providers of asset liquidity. This creates a role in the provision of liquidity for outsiders: private equity, private firms, and firms that operate predominantly in other industries.

When studying the effect of activism on the efficiency of corporate transactions, two literatures are relevant. On one hand, the neoclassical view holds that corporate acquisitions serve the purpose of reallocating assets to more efficient uses. While long dominating economics (Jovanovic and Rousseau (2002)), the evidence is mixed: Maksimovic and Phillips (2001) find that plant-level efficiency improves following a merger, but studies based on Tobin's Q do not yield a clear consensus. On the other hand, the literature on the relationship between corporate governance and acquisition markets has considered empire building and value-destroying acquisitions as a prominent dimension of managerial agency costs (Jensen (1986), Morck, Shleifer, and Vishny (1990)), and has emphasized the disciplining role of the market for cor-

[5]Strategic interaction effects between activism targets and rival firms, however, do not yield a unique prediction. From a theory point of view, the sign of the predicted rival reactions in response to the changed behavior of campaign targets depends on whether firms compete in strategic substitutes or strategic complements. Aslan and Kumar (2016) find that activism targets increase their market share and profitability whereas product market rivals suffer reductions in market share and mark-ups, consistent with rivals' reactions being strategic substitutes.

porate control on acquisition behavior (Mitchell and Lehn (1990)). Indeed, acquirer returns in acquisitions of public targets are low, though the ex post performance of mergers and acquisitions has generally been shown to be positive (Andrade, Mitchell, and Stafford (2001)). There is evidence that acquirers with better corporate governance have higher acquisition returns (Masulis, Wang, and Xie (2007)). There is also work showing that acquirer returns and long-term post-acquisition performance are significantly higher for smaller acquirers (Moeller, Schlingemann, and Stulz (2004), and Gorton, Kahl, and Rosen (2009). In view of this evidence, it seems plausible that activism targets achieve higher efficiency of transactions since the presence of activists is a positive governance shock, that the effect increases in the intensity of the activism-led governance shock, and decreases in firm size.

To summarize the hypotheses that guide our analysis, we expect activism targets as well as firms under activism threat to be more likely to make divestitures or to be sold, and to make fewer acquisitions compared with other firms. Small firms are possibly under less pressure to adjust their acquisition behavior to the extent that their acquirer returns are positive.

We expect these common trends to affect the equilibrium in corporate asset markets: in industries with heightened activism pressure, the supply of real assets should increase and the demand for real assets decrease. The ensuing reduction in the liquidity of corporate asset markets should lead to a squeeze in transaction prices, and create a role for asset liquidity provision by outside market participants. Hedge fund activists should react to such market externalities. If they are capable of producing efficiency gains and earning satisfactory returns from corporate transactions in spite of activism pressure, then we can explain why activists may choose to ignore negative spillovers from activism industry clusters. If this is not the case, one would expect hedge funds to run campaigns that use crowded corporate transaction markets more parsimoniously.

3 Sample Construction and Methodology

A Samples of activism events and corporate transactions

We construct a comprehensive sample of hedge fund activism (henceforth: HFA) by combining two data sources: the sample originally studied in Brav, Jiang, Partnoy, and Thomas (2008) that has been updated by Alon Brav, Wei Jiang and Song Ma to include the more recent time period[6] and the FactSet SharkWatch database. The two databases are only partially

[6] We are grateful to Alon Brav, Wei Jiang and Song Ma for generously sharing their proprietary data with us.

overlapping as they use complementary sampling strategies: Brav and Jiang identify hedge fund activism campaigns mainly through the initial (the first relevant) Schedule 13D filling submitted to the Securities and Exchange Commission (SEC)[7] whereas FactSet SharkWatch focuses on public campaigns and identifies them from various sources, such as press releases, financial news, Schedule 13D fillings and proxy statements, and thus is able to track public campaigns also when activists have ownership below 5%. When combining the two samples, we carefully screen the data and remove any duplicates. We find that 1,728 of 3,537 campaigns in Brav, Jiang and Ma's extended sample are also recorded in FactSet SharkWatch.[8] We follow Boyson, Gantchev, and Shivdasani (2017) and merge multiple hedge fund activism campaigns targeting a single firm in any calendar year as a single activism observation, starting at the first recorded announcement date. We obtain a total sample of 4,380 HFA events. We further limit the sample to HFA events that target firms incorporated in the U.S. and included in the CRSP-Compustat Merged Database. This process yields a sample of 3,551 unique HFA campaigns in the U.S. (see Table 1, Panel A), and of 862 hedge funds that operate as activist hedge funds at least once in our sample and that we use to distinguish between activist hedge funds and other institutional investors. The activism sample covers the period from 1994 - 2016. We fix 1994 as the start date, the earliest year with significant activity by hedge fund activists, consistent with earlier literature.

We use SDC Platinum to extract and construct three separate samples of corporate transactions during the 1994-2016 period, covering respectively (1) mergers (U.S. listed firms being acquired), (2) divestitures (sellers are U.S. listed firms), and (3) acquisitions (acquirers are U.S. listed firms).[9] For all three types of transactions, we use identical filters and only retain transactions with a control change (the acquirer owns less than 50% of shares before the bid and the percentage of shares sought is larger than 50%) and with a (non-missing) transaction value of at least \$10 million. For the merger sample, we exclude divestitures, spinoffs, recapitalizations, self-tender offers, repurchases, partial equity stakes, acquisitions of remaining interest, privatizations, as well as deals in which the target or the acquirer is a government agency. For the divestiture sample, we only retain transactions that are marked in SDC Platinum as either "divestiture" or "division" and are completed, for which no other

[7]A 13D filing with SEC within 10 days is mandatory when an investor (or a group of investors) owns more than 5% of any class of public shares of the company and intends to influence the management, corporate policy and control.

[8]We only retain HFA events from SharkWatch if at least one of the activists is a hedge fund and if the campaign target is not a fund (such as a closed end or real estate fund). We also drop 292 activist campaigns involving risk arbitrage as in Boyson, Gantchev, and Shivdasani (2017).

[9]Mergers and divestitures constitute disjoint samples. By contrast, the acquisitions sample contains the buy side of many, but not all, of the transactions for which the sell side is in the merger or divestiture sample.

information leads us to conclude that it is not a sale of a corporate unit or subsidiary, and we exclude spinoffs and splitoffs. For the acquisition sample, we include all SDC M&A transactions where targets are U.S. based listed firms, private firms, or subsidiaries, and the acquirer a listed firm in the CRSP-Compustat Merged Database. We exclude transactions involving spinoffs, splitoffs, self-tenders and share repurchases.

Finally, patents data are accessed from the sample of Kogan et. al. (2017). We keep all patents applied by US incorporated public firms from 1994 to 2009 and match them to Compustat and SDC M&A database.

B Firms and industries

The universe of U.S. firms in the CRSP-Compustat Merged Database serves as our baseline sample, comprising firms that operate under the impact of activism (the treated sample) and firms that we consider as unaffected by activism influence (the control sample). We exclude all firms that are not incorporated and headquartered in the U.S., and exclude firm-years with missing historical SIC codes and with missing or negative total sales, yielding a baseline sample of 116,448 firm-year observations from 1994 to 2016. From CRSP-Compustat, we get information. We complement the financial and stock price data with data on institutional ownership from ThomsonReuters' (now Refinitiv's) 13F database. We match our list of 862 activist hedge funds with the ownership 13F database and obtain passive ownership information of those hedge funds (the majority of investments by activist hedge funds are passive investments) and for other institutional investors. Alon Brav and Song Ma graciously provided us with data on 13G filings.

We study markets for corporate assets at the industry level, using 3-digit SIC industries as the baseline to identify corporate asset markets, with a total of 277 industries in our sample. Real assets, in particular intangible assets, are often industry-specific, and industry peers are the most frequent buyers and highest-value bidders for corporate assets (see Shleifer and Vishny (1992)).

C Measures of activism impact

We consider two channels of activism impact, HFA campaigns on one hand and the threat impact of activism on the other hand, and hence define two separate groups of firms affected by activism, firms that are HFA targets and firms under HFA threat. We define the control group as the group of all other firms. At any given point in time, the two groups of firms exposed to activism (the treated firms) are disjoint groups; however, firms frequently change their group assignment over the course of our panel study.[10]

For the first group, HFA targets, we use our sample of 3,551 HFA events to define a dummy variable, D[Activist], that is equal to one when an activism event is recorded and for a two-year period afterwards. The two-year horizon is taken from Boyson, Gantchev, and Shivdasani (2017).[11]

For the second group, firms under activism threat, we begin with firm-level threat measures. Our variable of choice is the predicted probability of a firm to become a hedge fund activism target in the following year, similar to estimations used in Brav, Jiang, Partnoy, and Thomas (2008), Klein and Zur (2009), Feng, Xu, and Zhu (2017), and Gantchev, Gredil, and Jotikasthira (2017). We use (large) passive stakes of activist hedge funds as a second firm-level threat measure since activists often use passive stakes as launch pad for activism campaigns.

We construct two industry-level metrics that are identical for all firms in an industry as our main measures of the intensity of activism threats. We focus on industry-level measures because real asset markets are best aggregated at the industry level, and because they help to address concerns about selection bias.[12] Our main variable is the fraction of recent HFA targets in the industry (at the 3 digit SIC level), i.e. firms that have been targeted by activist hedge funds in last three years. The resulting variable, Industry HFA Frequency, exhibits a strong component of year-to-year fluctuations that should capture changes in the industry-wide threat perception.

The second variable, Industry HFStake Frequency, measures the fraction of firms with strong increases in passive and active share holdings by activist hedge funds in the industry level. We compile information from 13F filings (using Thomson Reuters 13F database) that record all activist hedge funds holdings, and aggregate the quarterly total ownership by activist hedge funds in firm level. We only include 13F filings of hedge funds on our list of 832 activist funds, thus excluding all other hedge funds and institutional investors. For each firm we define an HF stake jump dummy, D[HFStake], that is equal to one in year t if the total ownership of

[10]Such transitions in group assignments are expected considering that activism threats are not permanent and that firms under HFA threat are more likely to be targeted than firms in the control group.

[11]An extended horizon of activism impact follows earlier work showing long-run effects of HFA targeting (see Brav, Jiang, Partnoy, and Thomas (2008), Bebchuk, Brav, and Jiang (2015)) and applies it to activism targets' behavior in asset markets (see also Gantchev, Sevilir, and Shivdasani (2018)).

[12]More precisely, they address endogeneity concerns about selection effects the firm level, but still leave open the possibility that hedge funds select firms as targets based on unobserved common industry characteristics and that we address with our instrumental variable approach. Since within a given industry, threat levels vary, our focus on industry-level threat measures should be conservative and weaken our estimated reactions when compared with threat measures that incorporate firm-level heterogeneity.

hedge funds increases during year t by more than 5%. We then aggregate this information at the industry level. The resulting variable, Industry HFStake Frequency, records the fraction of firms (in the industry) that had at least one HF stake jump within last 3 years.

In order to address endogeneity concerns, we construct an additional plausibly exogenous measure of changes in activism threats. Inspired by Edmans, Goldstein, and Jiang (2012) and following Gantchev, Gredil, and Jotikasthira (2017) and Feng, Xu, and Zhu (2017), we construct the variable Flow Induced Fund Buy (FIFB) that removes the hedge funds' possibly endogenous choice of industries in which they increase their holdings whenever they experience a discontinuous rise in inflows. We first construct a fund inflow shock dummy for each activist hedge fund that is equal to one when the hedge fund's new inflow is larger than 5% of its total net assets measured at the end of the previous year. If this variable is equal to one, we allocate the new fund inflow hypothetically to each industry exactly in the proportions that replicate the fund's industry portfolio structure in the previous year, following exactly the definition of FIFB introduced by Gantchev, Gredil, and Jotikasthira (2017). Finally, we sum up the new fund inflows at the industry-year level and obtain the variable FIFB that removes the endogenous firm- and industry-level allocation decision. Whereas Industry HFStake Frequency is based on hedge funds' actual industry allocations, FIFB assigns hypothetical industry weights based on the past industry structure, thus removing industry-level endogeneity.[13]

D Summary statistics

Our sample of HFA events is fairly well distributed over the sample period (Panel A of Table 1),with a peak in 2006-2008, two slowdowns during stock market downturns (1999-2001 and 2009-2010), and a strong rebound after 2011. The number of firms in the baseline peaks at 6,850 in 1996 and then steadily declines to 3,990 firms in 2016, largely reflecting the intense M&A activity among listed U.S. firms. (see Doidge, Kahle, Karolyi, and Stulz (2018)).

Panel B of Table 1 presents summary statistics of our threat exposure variables. On average, 6.0% of firms in an industry are recent or current activism targets, and 10.1% of firms experience a recent or current increase in hedge funds ownership of more than 5%.

Panel C reports commonly used firm characteristics, splitting our sample in HFA target

[13]This argument is supported by at least two observations: (*i*) idiosyncratic fund inflow shocks are very likely to be orthogonal to any unobservable industry characteristics since most of activist hedge funds are general investors, i.e. they diversify investments across industries; and (*ii*) we focus only on large inflows (5%) and allocate them according to the fund's past portfolio following the argument that hedge funds tend to invest quickly and in a mechanical manner when they experience large inflow (Coval and Stafford 2007).

firms (N = 3,551) and the remaining firm-year observations in the baseline sample (N = 112,897). In line with earlier papers (starting with Brav, Jiang, Partnoy, and Thomas (2008)), we find that the differences in institutional ownership, Tobin's Q, market capitalization (in logs), as well as those in dividend yield, cash flow, ROA, sales growth, asset growth, recent stock performance (one-year CAR) and industry concentration are all significant. We control for these and other firm-level characteristics in our regressions, and discuss (Section E) how they help to explain the selection of hedge fund targets.

In Panel D, we split firm observations by activism threats, sorting them into terciles according to our leading industry-level activism threat variable, Industry HFA Frequency (industries may be assigned to different terciles in different years). The panel shows substantial variation across tercile averages and medians, but the percentage differences are small, with the exception of dividends and cash holdings, and there is hardly any monotonic trend in the variables: differences between the bottom tercile and the middle tercile revert back when we move to the top tercile of industry HFA threats, with few exceptions.[14]

[Insert Table 1 Here]

E Do our measures of activism threats measure heightened target probabilities?

An important question is how well our variables on industry-level activism threat perform in predicting changes in the probability of individual firms to become activism targets. We use a logit model to predict the probability of becoming an HFA target, similar to the models used in Brav, Jiang, Partnoy, and Thomas (2008), Klein and Zur (2009), Gantchev, Gredil, and Jotikasthira (2017), and include all variables that have been shown to affect target probability.

The results are presented in Table 2. Column (1) reports the benchmark and confirms all the known strong predictors, in particular small size, low Tobin's Q, extensive institutional ownership, low dividends and cash flows or ROA, large cash holdings, and underperforming recent stock returns, and their combined power to predict future hedge fund targeting (pseudo-R^2 = 0.086). We then add our industry-level variables of activism threat in columns (2) to (4). We find that each of our three industry measures strongly predicts that firms will become hedge fund targets in the near future, at a 1% level of significance. The contribution to the predictive power is particularly impressive for Industry HFA Frequency, our main

[14] There are four exceptions, consistent with Panel A and the determinants of hedge fund targeting (see Table 2): hedge funds are more likely to exert pressure in industries with smaller firms, more institutional ownership, lower dividends and larger cash reserves.

variable: our capacity to predict that individual firms will be targeted in the near future increases by 52% ($R^2 = 0.129$). The increase in the predictive power is substantially smaller for other two variables, Industry HFStake Frequency (column (3)) and FIFB (column (4)). FIFB, our synthetic variable neutralizing hedge funds' actual choices of industries, is also strongly predicting future activism frequency in the industry ((columns (8) and (9)). These regressions confirm that our industry-level activism measures significantly determine future target probabilities and, hence, express threat levels for firm managers. They show that a substantial fraction of hedge fund threats is driven by a common industry component, and that it is rational for firms to change their behavior in reaction to variations in industry threat levels. The probability of being targeted also increases substantially when the firms had a recent build-up in activist investors passive ownership, as we show in the Table 5, Panel B.

[Insert Table 2 Here]

4 Deal Activity and Activism

A Deal frequencies

We begin with the univariate evidence for the three types of transactions.[15] Following Boyson, Gantchev, and Shivdasani (2017), we define an *activism merger* as a merger bid that falls within a two-year window after the public announcement of an activist campaign (13D filing or announcement date). Panel A of Table 3 shows year-by-year transaction frequencies. On average, 5.17% of firms in the CRSP-Compustat sample are targets of a merger bid (including unsuccessful bids).[16] For HFA target firms, the average frequency is 10.19%, almost twice as large. The bid frequency is substantially higher in every single year.

Panel A also tabulates the merger frequencies for firms that are under High HFA Threat, defined as industries in the top tercile of our Industry HFA Frequency variable (and excluding firms not targeted by activists in the current or the two previous years, in order to disentangle the threat effect from the HFA target effect). The average annual merger bid rate increases to 5.38 %, which is 24% higher than the 4.34% for the firms under Low HFA Threat.

[Insert Table 3 Here]

[15] Greenwood and Schor (2009) show that the bulk of shareholder returns in the wake of activist campaigns can be attributed to activism mergers; Boyson, Gantchev, and Shivdasani (2017) and Becht, Franks, Grant, and Wagner (2017) find that the probability of firms being acquisition targets increases very strongly after activism campaigns are launched.

[16] The ratios of bids per firm (not reported) are higher since some firms receive multiple bids in a given year.

Panel B, the same breakdown for divestitures, shows that each year on average 5.19 % of listed firms divest business units. This frequency rises by more than 50% to 7.81 % for *activism divestitures* (divestitures occurring in a two-year window after the start of an activist campaign).[17] For divestitures under High HFA Threat (top tercile of Industry HFA Frequency), the divestiture frequency seems to be decreasing slightly when compared with the full sample, but it is 13 % higher than the frequency of low threat firms.

In Panel C, we look at acquisitions, including acquisitions of private firms and business units. On average, the annual rate of making acquisitions is 15.06%, a percentage that decreases to 11.82% for *activism acquisitions* (acquisitions in a two-year window after an activist campaign). For acquisitions under High HFA Threat (top tercile), the acquisition frequency decreases slightly to 14.51%, 7.7% lower than for firms in the low HFA threat tercile (15.72%).

Panel D looks only at acquisitions of private targets (private acquisitions henceforth). They account for 45.8% of acquisitions, have no overlap with the previous panels,[18] and they represent a deal flow of sellers immune to hedge fund pressure (as they are private), allowing us to better isolate fluctuations stemming from the demand side. The annual rate of private acquisitions is 7.68%, which decreases by 28.5% to 5.49% for activism acquisitions of private targets, a higher relative decrease than for all acquisitions (Panel C.) The annual frequency of private acquisitions in the high HFA threat tercile also decreases, to 7.50%.

B Corporate transactions of activism targets

Turning to multivariate regressions for campaign targets, Table 4 shows logit regressions for our firm-year panel where the variable of interest is D[Activist], a dummy variable tracking whether the firm is an HFA campaign target in the 2 years prior to a transaction (a transaction is a merger bid in Panel A, a divestiture in Panel B, etc.).[19] We include an extensive list of variables known to contribute to the frequency of corporate transactions or the probability of facing an activism campaign, such as Tobin's Q, size, leverage, institutional ownership, cash, dividends, cash flow, asset and sales growth, recent stock market return, industry concentra-

[17] Gantchev, Sevilir, and Shivdasani (2018) also document an increase in activism divestitures.

[18] Since firms under activism impact sell more assets and are more likely to be acquired, there will be a corresponding increase in the acquisition numbers in Panel C that reflects this supply-driven surge. Panel A (mergers) and Panel B (divestitures) look at the sell-side of transactions; Panel C reports the entire buy-side of the corporate asset market, and hence also includes a major part of the buy-side for the transactions for which the sell-side is reported in Panels A and B (the completed transactions sold to listed firms dominate our sample).

[19] More precisely, D[Activist] is equal to one in year t if activists launch a campaign against the firm during the 730 calendar days prior to the transaction event, or, if there is no transaction event for the firm in year t, during the 2 calendar years prior to the median date of all transaction events of other firms in year t.

tion (HHI), real asset liquidity (specified as in Ortiz-Molina and Phillips (2014)), and industry and year fixed effects. In Panel A, we analyze the probability of receiving a merger bid in column (1), and find a very strong effect D[Activist] (t-value 12.9), implying an estimated increase in the probability of receiving a merger bid of 92 % (10.49 % vs. 5.45 %). The results are similar when we consider merger bids from strategic competitors, from financial buyer groups, or unsolicited bids separately (columns (2) to (4)), so the type of buyer does not seem to matter.

[Insert Table 4 Here]

In Panel B, we consider divestitures, using the same set of control variables. The results are again strong, with D[Activist] being highly significant ($t = 5.22$ in regression (1)) and HFA campaign targets having a 41 % higher annual frequency of undertaking a divestiture (6.44% vs. 4.57%) compared with all firms. An even higher frequency of divestitures occurs among activist target firms when the activists mention divestitures as an explicit campaign goal (11.63%, column (2)). Regressions (3) and (4) split the sample by type of buyer (strategic buyer or private equity), regressions (5) and (6) by related vs. unrelated assets[20], without finding any important difference in either case.

In Panel C, we turn to acquisitions. We find a highly significant decrease in acquisitions in our benchmark specification in regression (1) ($t = 3.56$), but the effect is driven by acquisitions of private targets, as is clear when comparing private acquisitions (regression (3), $t = 3.57$) and acquisitions of public targets that show no significant coefficient (regression (5)). In regressions (2) and (4), we split the variable of interest D[Activist] by firm size, inspired by the literature on firm size and acquirer performance (Moeller, Schlingemann, and Stulz (2004)); we find that only firms with above-median size (market capitalization) significantly cut back on acquisitions, whereas the variable is insignificant for firms of below-median size. This result is robust when we use a more granular sample split by firm size (Table IA.3, Panel A, in the Online Appendix). We do not find similar size effects for mergers and divestitures (not reported in tables), and find no difference between acquisitions of related and unrelated assets (columns (6) and (7)).

We are concerned about endogeneity affecting the regression set-up of Panels A to C in Table 4. A major concern is that activists' selection of target firms and their change of behavior in the market for corporate assets might be driven by selection bias in the data, such as omitted variable bias. To address these concerns, we deploy in Panel D methodology first

[20]Related assets are assets that share the same 3-digit SIC code as the seller firm's core activity.

proposed by Brav, Jiang, and Kim (2015a) and distinguish between passive (13G filing) and active stakes (13D filing switched from 13G) by the same activist hedge funds in our sample.[21] The results in Panel D show that mergers become significantly more likely and acquisitions less likely when hedge funds acquire stakes of 5% or more and declare having no activism intentions (13G filings are mandatory in this case), consistent with our hypothesis that activism threats matter and affect behavior. We find no effect on divestitures and private acquisitions. When the same activist hedge funds later on switch from passive stake to declaring activist intentions (the interaction term D[Post] × D[13G to 13D Switcher] captures these events), divestitures and merger become significantly more likely, and private acquisitions significantly less likely. These findings show that it is not just possible selection biases of firms by hedge funds that explains the association between hedge fund exposure and acquisition behavior.

C Firm-level activism threats

Turning to the multivariate analysis of activism threats, we first investigate the disciplinary effect of activism threats using firm-specific threat measures. Since we focus on threat perceptions, we exclude activism events.[22] We use two different measures of such threat levels for each firm that are idiosyncratic and may vary widely across industries. First, we use the predicted probability of becoming an activism target according to regression (1) in Table 2. Panel A of Table 5 shows the results for all three types of corporate transactions. We also aggregate mergers and divestitures to a single variable "corporate sales" in column (3), and separate between acquisitions of private targets and others in column (5). Second, we use a dummy equal to one if the combined passive ownership by activist hedge funds is at least 5% for the firm in year t as the firm specific threat measure. We find highly significant results showing an increase in merger bids and divestitures, and a decrease in acquisition frequencies for large firms but not for small ones (See Panel B of Table 5).[23]

[Insert Table 5 Here]

[21] 13G fillings are similar to 13D fillings except that the filer acquiring the stake in the company is only a passive investor and does not intend to exert control. If these criteria are not met and the size of the stake exceeds 20 percent, form 13D must be filed.

[22] Specifically, we exclude the HFA event-year and the three following years from our panel.

[23] Both firm-level threat measures are potentially affected by endogeneity concerns that we address in the next two subsections.

D Corporate transactions under industry-wide activism threats

We now consider our industry-level measures of activism threats that by construction take the same value for all firms in a given industry-year. We again exclude activism events. In order to control for industry shocks driving both the activism threat and changes in asset markets, we add the industry-level controls proposed by Harford (2005), such as industry-year median absolute change of ROA, Sales Growth, Employee Growth, and Turnover (sales scaled by lagged book assets), as well as the full set of firm-level controls used in Tables 4 and 5.

Table 6 presents the results. In Panel A, we show that Industry HFA Frequency, our main threat variable, leads to a significant increase in divestitures and in sales (mergers and divestitures combined) ($p < 0.05$), but not in mergers.[24] When we look at acquisitions, we again split the sample according to size (median split). We find that activism threat leads to a significant decrease in acquisitions and private acquisitions only for large firms ($p < 0.01$) as predicted, whereas for below-median firms in terms of firm value, there is a highly significant *positive* effect ($p < 0.01$) on acquisitions and private acquisitions. We return to this puzzling funding in Section 6.B.

[Insert Table 6 Here]

Panel B looks at our alternate measure of industry activism threats, Industry HFStake Frequency, indicating the proportion of firms experiencing a more than 5% increase in exposure (active and passive) to activist hedge funds. We find even stronger results, with divestitures and mergers increasing significantly ($p < 0.05$), and a stronger reaction when we combine them to sales of assets ($p < 0.01$). Again only for large firms do we find a negative reaction of acquisitions following heightened hedge fund threats, whereas the sign is positive and significant for small firms.

Despite our extensive effort to control for all possible industry shocks and characteristics, unobserved industry characteristics may still bias our analysis. To address this concern, we use the instrument FIFB introduced in Section 3. FIFB is based on large idiosyncratic fund inflow shocks ($> 5\%$), and most activist hedge funds are general investors in their passive investments. They tend to invest quickly and in a mechanical manner in a diversified cross-section of industries when experiencing large inflows (Coval and Stafford 2007). Therefore, it is reasonable to assume they will not allocate these inflows to industries according to unobserved industry trends that could be associated with corporate transactions activity. In

[24] It is perhaps not surprising that the disciplinary effect induces "partial" transaction-based reactions (asset sales, acquisitions) but is not strong enough on average for firms to actively pursue giving up their independence.

Table 2, columns (6) to (7) show that the variable FIFB satisfies the relevance criterion, as it is strongly associated with Industry HFA Frequency. We then apply the reduced form 2SLS approach, using FIFB as instrument for Industry HFA Frequency, our main variable of interest.[25] The results, presented in Panel C of Table 6, show that mergers, divestitures and sales become significantly more likely and acquisitions by large firms less likely when using the FIFB instrument.

In conclusion, we find that, on average,firms under heightened activism threat divest more and are more frequently acquired, and make fewer acquisitions. These results extend findings by Gantchev, Sevilir, and Shivdasani (2018) and Boyson, Gantchev, and Shivdasani (2017) by showing that firms under activism threat make similar changes in their behavior compared with target firms. There are, however, two important differences: first, the effect on merger bids is strong for target firms, and, probably unsurprisingly, weak for firms under threats. Concerning acquisitions, we find that the size difference observable for target firms (where only larger firms make fewer acquisitions), is exacerbated for firms under activism threat: large firms make fewer acquisitions, whereas smaller firms make *more* acquisitions, but they do not necessarily pursue an (inorganic) growth strategy because at the same time they divest more.

E Do activist campaigns cluster by industry?

Much of our analysis focuses on industry-years in which activism campaigns are concentrated and, therefore, market externalities in asset markets are most likely prevalent. Panel A of Table 7 shows descriptive evidence on the importance of activism clustering by industry. Our preferred measure in the subsequent sections is the top quintile of industry-years by Industry HFA Frequency, listed in column (2). In column (3), we require in addition that at least two campaigns occur in the industry (in years t-2, t-1, or t), and we call industry-years that satisfy this double criterion *industry HFA clusters*. As columns (2) and (3) show, the vast majority of activist campaigns occurs in clusters: 57% are located in the top-quintile by Industry HFA Frequency (column (2)) and 52% in industry HFA clusters (column (3)). By contrast, the number of industry-years that exhibit hedge fund clustering is rather small in either case: 19% are in the top quintile of industry-years by Industry HFA Frequency (column (2)), and less than 15% of industry-years are industry HFA clusters (column (3). In other words, the

[25] We follow Gantchev, Gredil, and Jotikasthira (2017) when deploying this approach for the analysis of FIFB. To check robustness, we also use a standard 2SLS estimator and find qualitatively similar, but less robust results, explaining the preference for the reduced-form approach.

distribution of campaigns over industry-years is very uneven.[26] Table 1 shows in Panel A (columns (4) and (5)) the year-by-year frequencies of activist campaigns and industries that we classify as industry HFA clusters, and their persistence and importance: in every year after 2004 (with 2010 the only exception) more than 50% of campaigns occur in industry HFA clusters.

Table IA.1 in the Online Appendix lists the industries in which activism clusters occur most frequently during the 20-year period 1997-2016. The top industries (retail-department stores, hotels & motels) are industry HFA clusters in more than 40% of years. Industry HFA clusters seem to concentrate in service sectors and basic industry such as food, mining and plastic materials. Our descriptive evidence suggests that activism campaigns are not randomly distributed across industries, but to a large extent concentrated in industry clusters.

[Insert Table 7 Here]

F Do activists select firms and industries for their restructuring propensity or asset market liquidity?

An important endogeneity concern is that the observed patterns in corporate transactions are not the consequence of activism pressure, but rather the effect of activists picking industries that are conducive to the transactions they prefer (and in the process creating activism clusters). This concern is essentially about reverse causality, but on the scale of selecting industries rather than individual firms.

We address this concern by investigating possible associations between trends in industries' acquisition markets and clustering of hedge fund activists. We use two standard measures of transaction activity and corporate asset market liquidity, Harford's (1999) measure of merger waves and Schlingemann, Stulz, and Walkling (2002)'s measure of asset liquidity, the volume of corporate transactions in an industry (normalized by market capitalization).[27] For the asset liquidity measure, we also define a similar variable based purely on Private Equity transactions. Columns (5) to (7) and column (9) in Table 2 show that neither of these variables is significant in explaining which firms or industries are likely to be targeted (the results are unchanged if we add variables sequentially). Thus, industry-level measures of transaction frequency and asset liquidity do not seem to explain which industries HFAs prefer and where activism clusters

[26] In column (4), we tabulate the top-decile of industry-years by Industry HFA Frequency and impose that there are at least two campaigns: more than 20% of campaigns occur in these strong clusters, and almost half of activist funds participate in them at least once.

[27] We deploy the version of Ortiz-Molina and Phillips (2014) and cumulate transactions over three years.

emerge.

We also explore the question whether hedge funds select target firms and industries because their propensity to engage in corporate restructuring has changed. We develop firm-level measures of a firm's probability to undertake corporate transactions, and then explore whether innovations in these propensities explain whether a firm will be targeted by hedge fund activists. We follow recent takeover prediction models (Cremers, Nair, and John (2009), Karpoff, Schonlau, and Wehrly (2017)) for the estimation of the probability of a company to become a merger target, and use the same comprehensive set of explanatory variables and controls in models predicting the other transaction types, divestitures and acquisitions. Our main variable of interest is the change from year $t-1$ to t in the estimated probability to engage in any of the three transaction types. In Table 7, Panel B, we successively include these estimated innovations in transaction probabilities in our model predicting the likelihood of a firm to become a HFA campaign target (see Table 2). We find that the variables of interest, the innovations in transaction probabilities, are not significant (only the change in merger bids is weakly significant at the 10% level, but exhibits the wrong sign).

To conclude, we do not find evidence that the selection of hedge fund targets is driven by considerations of transaction activity or asset liquidity, or by changes in firms' proclivity to initiate restructuring transactions.

5 Activism and the Market for Corporate Assets

A The combined impact of activism on real asset markets

Our next step is to gain some perspective on the joint impact and the relative importance of the two channels of activism pressure, the direct target impact and threat impact. We use logit regressions to jointly analyze the asset market impact of the two groups of treated firms (the main difference to our previous analyses is that they are analyzed separately in Tables 4 and 6). D[Activist] and D[High HFA Threat], the variables of interest for the two groups of treated firms, are mutually exclusive.[28]

Results are presented in Table 8. In Panel A, we find that both the dummy for activism targets and the dummy for high HFA threat lead to more divestitures and more corporate sales (a variable that combines mergers and divestitures); when looking at merger bids we find a

[28] D[Activist] is defined as in Table 4 and D[High HFA Threat] is a dummy variable that is equal to one for firms in the top quintile of Industry HFA Frequency (activist targets are again excluded); we use a dummy variable instead of the continuous variable to facilitate comparisons.

significant effect of D[Activist], but no significant effect for D[High HFA Threat]. Concerning acquisitions in Panel B, the regression confirms our earlier findings that only large firms under High HFA Threat acquire less, with a strong and significant effect ($p < 0.01$). Small firms under High HFA Threat make actually more acquisitions.

[Insert Table 8 Here]

The most interesting insights of Table 8 can be gleaned from the model's estimate of conditional probabilities of corporate transactions and marginal effects. After estimating the logit model, we calculate conditional probabilities of transactions by fixing all other controls at the mean values of the treated group. We define the marginal effect as the estimated increase in the probability of a transaction when the HFA exposure dummy (either D[Activist] or D[High HFA Threat]) is switched from 0 to 1.[29] As reported in Panel A of Table 8, the probability of receiving merger bids for activism targets increases by 5.31%, and for firms under High HFA Threat it increases by 0.28%. Concerning corporate sales, activism targets are 7.44% more likely to sell corporate assets according to the marginal effect of activists, and firms under High HFA Threat are 0.81% more likely to sell assets. Concerning acquisitions in Panel B, large activism targets are 4.55% less likely to undertake acquisitions, and large firms under High HFA Threat undertake 2.16% less acquisitions.

Activism targets exhibit a much stronger reaction, but are less frequent compared with firms under HFA threat that show a weaker reaction but are more numerous. This comparison hints at the possible interest of appraising the relative importance of the two channels of activism pressure. We suggest a rather simple method for such an appraisal, and do so by focusing on industries with high activism pressure, that is industry-years in the top quintile of Industry HFA Frequency over the entire sample. The mean value of Industry HFA Frequency in these industry-years is around 0.25, i.e. 25% of firms in these industries are currently or in the past two years activism targets; the remaining 75% of firms are firms entering our estimates of the effect of High HFA Threat. As a result, the overall impact is that a firm in an industry under high activism pressure will increase its annual frequency of selling an asset by $0.25 \times 7.44\% + 0.75 \times 0.81\% = 2.47\%$. Since the average annual frequency of corporate sales is 10.36%,[30], this means that corporate sales in industries under high activism

[29] Since we have two different treated groups, HFA targets and firms with High HFA Threat, we estimate the probability of transactions conditional on HFA Targets by fixing D[Activist] = 1, D[High HFA Threat] = 0, D[Mid HFA Threat] = 0, and by fixing other controls at the mean of the target firm sample; we calculate the probability conditional on High HFA Threat by fixing D[Activist] = 0, D[High HFA Threat] = 1, D[Mid HFA Threat] = 0, and by fixing other controls at the mean value of the High HFA Threat sample.

[30] See Table 3: we add the average frequency for mergers of 5.17% (Panel A) and for divestitures of 5.19% (Panel B).

pressure increase by 23.84%(= 2.47/10.36). On the acquisition side, we need to distinguish between small and large firms since activism pressure affects them in opposite directions. For large firms (above median in size), the overall impact of high HFA pressure is equal to $(0.25 \times -4.55\% + 0.75 \times -2.16\%) = -2.76\%$ less acquisitions; for small firms, the overall increase in acquisitions is $(0.25 \times -0.40\% + 0.75 \times +1.50\%) = 1.03\%$. Thus, the overall activism pressure effect on acquisitions in top quintile industries will be a decrease by $-2.76\% + 1.03\% = -1.73\%$. In relation to an annual frequency of acquisitions of 15.06% for the entire sample (See Table 3, Panel C), this means that firms in high activism pressure industries decrease their frequency of acquisitions by $-1.76/15.06 = -11.69\%$ on average.

We can also estimate the combined impact on the equilibrium in corporate asset markets under activism pressure: in these industries, firms on average undertake 23.84% more corporate sales and 11.69% less acquisitions, meaning that in the top quintile of affected industry-years, activism pressure creates an imbalance of more than 35% between the supply and the demand for corporate assets.

B Activism and real asset liquidity

We next assess the impact of activism on the asset market equilibrium in affected industries. We begin by investigating the impact on the industry equilibrium in terms of transaction activity. Firms in an industry with heightened hedge fund pressure tend to sell more assets and simultaneously are less willing to buy assets, as estimated in the last subsection, hence they are less likely to appear as liquidity providers in corporate asset markets in industries affected by activism pressure. Our hypothesis suggests, therefore, that industry outsiders (buyers that are not affected by the industry-specific activism pressure) should be a possible source of asset liquidity. These buyers are firms outside the affected industry and financial buyers (private buyers), but also private buyers located in the industry itself.

Our measure of real asset liquidity (RAL) records the total number of transactions of industry assets in a given industry-year, that is the sum of *completed* merger bids, divestitures, and acquisitions, but counts each transaction only once, following Ortiz-Molina and Phillips (2014) and Schlingemann, Stulz, and Walkling (2002). We look both at Frequency (number of deals scaled by number of firms in the industry) as well as at Transaction Value (sum of transaction value scaled by sum of market value of public firms).

How much of the imbalance in corporate asset markets created by hedge fund activism is absorbed by insiders, and how much by outsiders? Table 9 presents the results of industry-year regressions to answer this question. The main explanatory variable is D[Industry HFA Freq P80], a dummy that is equal to one if Industry HFA Frequency is in the top quintile of the entire industry-year sample. We require that industry-years must have at least 3 public firms to be included in our regression analysis. We first investigate the overall impact on real asset liquidity: Does the frequency of industry assets transactions rise or decline in industries under heightened HFA pressure? The answer is not obvious since activism leads to a simultaneous shift in supply and demand (an increase in supply and less demand) for corporate assets, and we only observe transactions in which buyers and sellers can be matched. Panel A of Table 9 provides the answer. We find an increase in transaction activity (measured in transaction value) in the top quintile of Industry HFA Frequency, and no effect on transaction frequency, hinting there must be some elasticity in asset demand to absorb the increased supply.

[Insert Table 9 Here]

We try to disentangle the source of asset liquidity provision. We sort sellers and buyers of assets in insiders and outsiders according to their relationship to the industry in which the transaction takes place (i.e., industry of the corporate asset in each transaction): buyers and/or sellers are "insiders" if they are publicly listed firms with a primary SIC 3-digit code identical to that of the transaction;[31] only publicly listed firms can be insiders since only listed firms can be affected by HFA pressure. All other sellers and acquirers are "outsiders", consisting of three main categories: (*i*) listed firms in other industries or countries; (*ii*) private firms; (*iii*) financial buyers, in particular private equity firms. The distinction tries to isolate as "insiders" firms affected by hedge fund activism and activist threats in the corresponding industry.

In Panel B of Table 9, we distinguish only by status of asset buyers, that is between insider buyers and outsider buyers, but do not yet sort transactions by seller category. We calculate the RAL absorbed by inside buyers and outsider buyers respectively. Buyers are "insiders" in 8,279 out of a total of 23,704 transactions. Consistent with our hypothesis, the results reveal that real asset liquidity provided by industry outsiders increases in top-quintile industries by activism pressure (2.52% increase measured in frequency and 1.62% increase measured in transaction value). By contrast, the real asset liquidity provided by industry insiders decreases, albeit not significantly so, as indicated by the negative coefficients in all regressions.

[31] There are discrepancies between Compustat's and SDC's SIC classifications at the 3-digit level, see Kahle and Walkling (1996) for a discussion. We give priority to Compustat classifications, but try to also include the information content in SDC classifications. We discuss our methodology of assigning industries in the case of discrepancies that affect our insider/outsider classification in Appendix B.

In Panel C of Table 9, we sort also by seller category. We run separate regressions for each possible pairing of seller and buyer according to their status as insiders and outsiders, that is, for the four possible buyer-seller pairings as, respectively, outsider-outsider, outsider-insider, insider-outsider, and insider-insider, we calculate the sub-sample RAL. Panel C shows that assets sold by insiders are significantly more frequently acquired by outsiders when the industry is subject to severe activism pressure (columns (1) and (2)). By contrast, we find no such increase when we look at the liquidity provided by insiders, consistent with the idea that insiders are reluctant to buy when subject to heightened HFA pressure (columns (3) and (4)). We also find a similar positive reaction when regressing the outsider buyer's ratio in the industry as shown in Panel D.

By contrast, when the seller is also an outsider, then there is no significant impact of the industry HFA exposure on the frequency of assets transaction by outsiders (columns (5) and (6)), by insiders (columns (7) and (8)).

To conclude, Table 9 provides evidence for a shift from insider buyers to outsider buyers when there is an increase in activism pressure, and confirms our hypothesis: as hedge fund pressure increases in an industry, inside real asset liquidity is drying up. As a consequence, acquirers from other industries will step in and provide some real asset liquidity.

C Asset redeployability and private equity

In Table 10, we report the transaction-level regressions studying industry activism pressure, asset redeployability and type of outside buyers. Panel A of Table 10 shows that scarce asset liquidity in industries with heightened activism pressure is mainly filled by one type of industry outsiders, private equity.[32] In Panel B, we present results interacting with Kim and Kung (2017)'s asset redeployability score that measures how many industries real assets of an industry are sold in secondary markets, using a median split. Regression (1) of Panel B shows that outside provision of liquidity is stronger in industries under HFA pressure and with high asset redeployability. In regression (2), we probe further and find that this effect can be entirely attributed to private equity buyers: they will only provide real asset liquidity in industries with high asset redeployability. As a result, the squeeze in real asset liquidity should be particularly severe in industries with low asset redeployability.[33] We find similarly significant results (not

[32]A possible alternative explanation is that activist hedge funds might select target industries with more potential private equity buyers. However, this kind of explanation is rejected by our results in Table 2, where we show PE transaction waves are irrelevant or even negatively correlated with Industry HFA Freq.

[33]Indeed, we find that the transaction price reacts and decreases more when industry with low asset redeployability score is under activism pressure. See the next subsection (Table 11, Panel B).

reported in tables) for alternative measures of liquidity or redeployability of industry assets, such as Gopalan, Kadan, and Pevzner (2012)'s weighted asset liquidity measure (WAL), asset tangibility, or the absence of knowledge or specific assets (proxied by R&D expenditure).

[Insert Table 10 Here]

D Price pressure

We expect the squeeze in real asset liquidity to also have an impact on deal pricing. We use the two measures for transactions price effects most frequently used in the literature, deal premiums and cumulative abnormal returns (CAR) around the deal announcement. We do not observe deal premiums in divestitures, and hence can only analyze cumulative abnormal returns in this case.

We use regressions to look at the seller CARs for the two of our three transaction samples, mergers and divestitures, that allow to observe seller price reactions. Our acquisition sample adds acquisitions of private targets, but the sellers of private acquisitions are not publicly listed, so we cannot observe seller CARs in this case. The variables of interest are again our two measures of industry level activism pressure, Industry HFA Frequency and Industry HFStake Frequency, both measured in the industry of the transaction (corporate asset). We include relevant transaction level controls that are known to affect seller announcement returns.[34] We look at the divestitures and mergers sample separately, using standard event windows: for divestitures, we look at a short and a longer symmetric event window around the deal announcement (CAR[-2, +2] and CAR[-5, +5]); for mergers, we use a long pre-announcement window of three months to account for pre-deal price run-ups, and we also look at the price premium (offer price relative to stock price one month before).

Panel A of Table 11 reports our findings for sellers. We look at HFA targets and firms under HFA threats separately, which explain our use of the interaction of the variable of interest with the dummy D[Activism on Seller] and its complement, D[No Activism].[35] We find a significant and robust negative effect for transactions under high industry activism pressure but the seller recently is not under the HFA campaign (Industry HFA Freq × D[No

[34] The transaction level controls are dummies for payment by stock, Ortiz-Molina and Philips'(2014) TotM&A_3yr (measured in the transaction industry), Institutional Ownership, Tobin's Q, ln(MV), Book Leverage, Dividend Yield, Cash Flow, Sales Growth, Asset Growth, R&D, and Excess Cash (accounting measures are seller's in Panel A and buyer's in Panel B). In regressions of the merger sample, we also include controls (dummies) for competing bids, successful bids, and unsolicited bids.

[35] D[Activism on Seller] is a dummy equal to one if activists launch a campaign against the seller in the two calendar years prior to the merger or divestiture. D[No Activism] is its complement.

Activism] = 1) in all regressions with a level of significance of at least 5%. For divestitures, we find effects that are slightly stronger for the longer window. For mergers, we find consistently negative results (significance increase to 1% in the case of deal premiums). The effects are somewhat weaker for Industry HFStake Frequency. We find similar results for shorter run-up periods or symmetric CAR windows (not reported in Table 11).

By contrast, for the sample of activism targets (D[Activism on Seller] = 1), we find no significant effect of the industry activism pressure, in any of our eight regressions. This means that activists appear to succeed in isolating target firms from the adverse price pressure effect that afflict firms in industry with high exposure to activism.

Panel B shows that the negative price pressure effect is clearly much more pronounced in industries with low asset redeployability. This finding complements our result in the previous section that outsider buyers, and in particular private equity, provide real asset liquidity only in industries with highly redeployable or liquid assets (Table 11). Consequently, the price pressure effect is essentially driven by low asset liquidity industries in which private equity does not act as liquidity provider.

[Insert Table 11 Here]

In Panel C, we look at the price pressure effect on buyers, using the same samples of divestitures and mergers and regressions. The sample size shrinks because only about half of the assets are bought by listed acquirers. We find the expected positive effect for top-quintile industries in terms of activism pressure, but the effect is rather weak since it is only statistically significant in three out of eight regressions. For the sample of HFA target firms, we find similar weak effects, significant in two cases. For buyer returns, we find similar results when the sellers is an activist target or acting under activism threat.

Overall, our analysis of deal pricing yields a picture that is consistent with our hypotheses: as supply of corporate assets in affected industries increases and demand decreases, asset liquidity is affected. This leads to lower seller returns and also (weakly) higher buyer returns. Weak price reactions are to be expected since, as Table 9 shows, outsiders step up and provide real asset liquidity, mitigating the squeeze in asset prices.

E Are acquisitions by smaller firms different?

Table 4, Panel C, shows that smaller activism targets do not reduce acquisitions as much as larger firms do, and this effect is even more pronounced for smaller firms under activism threat (Table 5 for firm-level and Table 6 for industry-level evidence). This size difference in the response deserves further examination. We explore three possible explanations: first, small acquirers may feel less pressure to abstain from acquisitions if activists show a less hostile reaction to their acquisitions than to acquisitions by large firms. Second, small firms might trigger a less hostile response by activists to the extent that they acquire higher-value targets. Finally, they might continue to undertake or even intensify performance-enhancing acquisitions in the hope that hedge funds could view such acquisitions more positively.

Relevant for the first possible explanation, Gantchev, Sevilir, and Shivdasani (2018) show that activists are more likely to target firms that have historically been busy acquirers, particularly firms with poor past acquisition performance. We define a new variable, NumAcq, that counts the number of acquisitions undertaken in the past three years, and include NumAcq in our regressions predicting whether firms become activist targets (introduced in Table 2). We want to explore whether the activism threat increases in the frequency of recent acquisitions in industries under activism pressure, and whether the effect differs by firm size. Hence we focus on the interaction of NumAcq with our proxies for activism pressure, Industry HFA Frequency and Industry HFStake Frequency. As reported in Panel A and B of Table 12, we find that the probability of becoming an activist target increases in the number of recent acquisitions and in the industry activism pressure for large firms, but not for small firms (median split by market capitalization). That is, large firms increase their activism threat level when undertaking acquisitions while their industry is under activism pressure, suggesting that they act rationally when reducing acquisitive behavior under strong activism pressure, but there is no corresponding disciplinary effect for small firms. We find no difference between large and small firms when we do not differentiate by industry activism pressure. When we partition firms by size quantiles of finer granularity, we find that the effect is robust and monotonic (Table IA.4 in the Online Appendix).

[Insert Table 12 Here]

We then turn to the second possible explanation, suggesting that smaller firms may target higher-quality targets. Panels C and D of Table 12 examine the quality difference between target firm and acquirer firm along a number of widely used performance metrics. We match our sample with metrics on patent productivity (the number of patents, number of patent citations, and the patent value are estimated according to Kogan, Papanikolaou, Seru, and Stoffman (2017)). The unit of observations are acquisitions where both acquirer and target firm are publicly listed and in the Compustat baseline sample. Panel C shows that small firms indeed choose acquisition targets that add significantly to the quality of the combined firm: for Tobin's Q, for ROA and for our three measures of patent productivity, the mean (median) difference between target and acquirer is significantly larger for acquisitions by small firms. Also, the difference between target and acquirer is positive and significant, whereas it is insignificant for large firms. This difference offers a rationale for activists to react differently to acquisitions by small firms. In Panel D, we look at the impact on acquisition quality when industries are under activism pressure. Interacting the dummies for small and large firms with our Industry HFA Frequency variable, we find that both small firms and large firms further increase the quality difference between target and acquirer firm (the effect is highly significant only for the three patent measures). For smaller acquirers, this threat-induced quality increase is in addition to the significantly higher quality difference absent any activism threats. In summary of the results reported in Table 12, when exposed to activism pressure, large acquirers reduce the number and increase the quality of acquisitions as their acquisitions are viewed negatively by hedge fund activists, whereas small acquirers further increase their already higher acquisition quality but do not reduce their acquisition frequency, in line with the finding that activists do not exert the same disciplinary pressure on them.

The third possible explanation, that small firms might be less pressed to reduce acquisitions because their acquisitions tend to create better long-run value for shareholders, is discussed in the next section (Part B) that collects all findings on post-transaction performance.

6 Do Activism-Induced Transactions Suffer from Industry Clustering?

A natural follow-on question, given that activism tends to cluster by industry and to create negative externalities on corporate asset markets, is whether the ensuing equilibrium dislocation negatively affects the long-run performance of corporate transactions in affected industries, a question that seems relevant in view of the importance of corporate transactions as a performance driver for activists (see Section 2).

A Evidence on post-transaction performance: asset sellers

We first consider the possible effect on asset sellers. We limit this analysis to divestitures as we cannot analyze mergers or private acquisitions for lack of a satisfactory counterfactual for the question how the seller would have performed as an independent firm after the transaction.

It is well-known that activism campaigns lead to long-run positive effects in market and accounting performance for target firms (see Bebchuk, Brav, and Jiang (2015)). Thus, it is important to disentangle the long-run performance enhancing effect of activism campaigns from the additional effect of activism divestitures. Gantchev, Sevilir, and Shivdasani (2018) document the positive long-run stock market performance of seller firms in corporate activism divestitures, but do not address the likely overlap with the long-run performance-enhancing effect of the post-activism period.

We consider three different long-run performance measures providing a cross-section of accounting-based and stock market based performance metrics: Tobin's Q; ROA; and the Sales/Assets (Turnover) ratio that is correlated with economic efficiency. In each case, we look at a period of two years after the divestiture event.[36] We report our findings in Table 13, looking in Panel A at activism divestitures. The key variable of interest is the interaction term D[Post Divestiture] × D[Activism Divestiture]. We find a positive and significant response to this interaction variable, for both Tobin's Q and for ROA. Only Sales/Assets does not show a significant long-run performance effect. Thus, we are able to uncover a positive value effect over two years, in addition to the positive effects (in regression (1)) of having undertaken divestitures and having gone through an activism campaign that are accounted for by D[Post Divestiture] and D[Activism Divestiture], respectively.

[Insert Table 13 Here]

Panel B repeats the analysis for firms under high HFA threat, using our standard cluster measure of firms in the top quintile of industry-years by of Industry HFA Frequency. We do not find an analogous performance-enhancing effect for activism divestitures when done under HFA threat: the interaction term D[Post Divestiture] × D[High HFA Threat] does not show any sign of a significant difference for any of our three performance variables. Thus, it appears that divestitures undertaken under the disciplinary effect of HFA threats do not show evidence in favor of long-run efficiency gains for sellers, in contrast to columns (1) and (2) in Panel A that show significant differences for activism divestitures. Taken together, the two panels show a clear difference between activism divestitures and divestitures done under elevated HFA threat: efficiency gains are limited to corporate sales of activism targets.

These findings suggest a possible rationale for hedge fund activists not to be too concerned about negative market externalities of industry clustering of activism: on average, activist targets seem to be able to isolate their transaction strategies from negative spillovers of crowded asset markets, as measured by long-run performance, whereas other firms operating in the same environment seem to be more exposed to market externalities.

[36] The two-year window is a demanding test considering that several studies show that the efficiency gains of activism targets tend to accumulate over longer windows (see Bebchuk, Brav, and Jiang (2015).

In addition, we find activist targets less often announce campaign goals related to corporate sales, and reduce transactions in industries that might be adversely affected by a an activism-induced reduction in real asset liquidity (see Panel C and D of Table IA.6 in the Online Appendix). Taking together these results suggest that the benefits of contrarian hedge fund strategies seeking to avoid activism clusters might be limited.

B Post-transaction performance of asset buyers and the role of small firms

We conclude by analyzing the long-run performance effect on the buyer side for acquisitions. Specifically, we are interested to find out whether we find evidence for a possible third explanation for the observation that small firms acting under heightened HFA threats do not reduce the frequency of acquisitions in the same way as large firms and activism targets do. Therefore, we differentiate by buyer size.[37]

Table 14 presents the findings, looking in Panel A at activism acquisitions. We find a strong performance-enhancing effect ($p < 0.05$) for two out of three measures of long-run performance, ROA and Sales/Assets for activism acquisitions of small firms, captured by the triple interaction term D[Post Acquisition] $\times$ D[Activism Acquisition] $\times$ D[Small], but not for the third variable, Tobin's Q. We do not find any comparable significant effect for large firms (not reported in tables).

Panel B repeats the same test for firms in industries in the top quintile in terms of activism threat. We split the sample again at the median by size. The triple interaction term [Post Acquisition] $\times$ D[Activism Acquisition] $\times$ D[Small] is positive, albeit not significant. We find a significant reaction for ROA and Sales/Assets when expanding the subsample to the top tercile of firms under activism threat (Table IA.5 in the Online Appendix.).

Measured by long-run efficiency, small firms seem to do well when undertaking acquisitions under HFA pressure. Similar to divestitures, the gains are stronger for target firms than for firms acting under HFA threats. These gains are in addition to the strong positive long-run gain that can be attributed to their smaller size. Overall, these findings are consistent with the observation (Table 6) that only large firms react to an increase in HFA threats with a reduction in their acquisition activity.

[Insert Table 14 Here]

[37]See Section 5.E. The literature has noted before that acquisitions by small acquirers differ substantially as far as short- and long-run performance are concerned (Moeller, Schlingemann, and Stulz (2004) and Gorton, Kahl, and Rosen (2009)) but satisfactory explanations are largely missing.

7 Conclusions

This paper explores the impact of hedge fund activism on corporate asset markets. Besides activist target firms, we consider a second channel of activism pressure, the disciplining effect on firms exposed to activism threats. We propose measures of activism threats at the firm level and at the industry level. We find that firms exposed to either channel of activism pressure are more likely to receive merger bids, and to make more divestitures and fewer acquisitions. There are subtle differences: firms acting under threat divest more, but are only marginally more likely to be sold entirely. Only large firms under threat reduce their acquisition activity, whereas small firms expand it.

Comparing these two parallel channels of hedge fund pressure, we find that they contribute about equally to the change in deal activity in highly affected industries exposed, with activism threats being more important for acquisitions, and directly being targeted in an activist campaign more important for corporate sales. We consider the impact on real asset liquidity: when firms in affected industries push in the same direction of simultaneously selling more and buying less assets, then real asset liquidity is reduced by more than a third, creating a role for outside liquidity providers. We find that acquirers from outside the affected industry - private equity funds and listed firms in other industries - provide real asset liquidity, and more so in industries with high asset redeployability.

We find evidence that the squeeze on real asset liquidity also affects transaction prices. The effects are stronger in industries with low redeployability. We find that transactions done by activist targets resist the price pressure remarkably well. Finally, we consider whether the negative market externalities of activism pressure affects the efficiency of activism-led transactions. We find positive long-run performance effects for corporate transactions undertaken by activism targets, but not for transactions undertaken under activism threat. In industries with strong activism clustering, hedge fund targets reduce somewhat transactions that could be adversely affected. Thus, hedge fund activists seem to be able to partially shield firms from the negative market externalities of industry activism clusters.

Overall, our paper shows that activism creates important market externalities, by changing the environment and behavior in acquisition markets even for firms that are not targeted in activism campaigns.

Appendix A: Definition of the Variables

Variables name	Definition and construction of variables	Data source
Activism and threat variables		
D[Activist]	Indicator variable tracking whether the firm is an HFA campaign target in the 2 years prior to each type of transaction.D[Activist] is equal to 1 in year t if activists launch a campaign against the firm during the 2 calendar years (730 calendar days) prior to the transaction event, or, if there is no transaction event for the firm in year t, during the 2 calendar years prior to the median date of all transaction events of other firms in year t	SharkWatch & Brav and coauthors
D[Activist's Goal on Restructure]	Indicator variable equal to 1 if D[Activist] is equal to 1 and activists' goal in the campaign is to restructure the targeted company	SharkWatch & Brav and coauthors
D[13G to 13D Switcher]	Indicator variable equal to 1 if activists switch from the 13G filling to 13D against the targeted firm	Brav and coauthors
Industry HFA Freq	Fraction of firms in industry j and year t that have been targeted by activist hedge funds in last three years	
Industry HFStake Freq	Fraction of firms in industry j and year t that have experienced at least one activist hedge fund's stake jump within last 3 years	Thomson Reuters 13f & SharkWatch
FIFB	Flow induced fund buy (FIFB) measure introduced by Gantchev, Gredil and Jotikatshira (2017), defined as follows, $$FIFB_{j,t} = \frac{\sum_h \left[Inflow5_{h,t} \times \frac{TNA_{h,j,t-1}}{TNA_{h,t-1}} \right]}{Market\ Cap_{j,t}}$$ where $Inflow5$ is the fund specific inflow shock measured in million dollars (shock is defined as the increase of hedge fund's inflow which is larger than 5% of its total net assets in the start of year t), $\frac{TNA_{h,j,t-1}}{TNA_{h,t-1}}$ is the distribution of assets the hedge fund h invested in year t-1 across industries, and $Market\ Cap$ is the sum of market capitalization of firms in the industry. We assign the idiosyncratic fund-level shock according to the past (year *t-1*) distribution of its total net assets in the stock market and sum up the measure at the industry-year level. See the details in Gantchev, Gredil and Jotikatshira (2017)	Thomson Reuters 13f, SharkWatch, and CRSP
D[Industry HFA Freq P80]	Dummy equal to 1 if Industry HFA Freq is in the top quintile of baseline industry-year sample.	
D[High HFA Threat]	Dummy equal to 1 if Industry HFA Freq is in the top quintile of baseline industry-year sample and D[Activist] = 0.	
D[Medium HFA Threat]	Dummy equal to 1 if Industry HFA Freq is in the second or third highest quintiles of baseline industry-year sample and D[Activist] = 0	
Variables for transactions of corporate assets		
Merger	Dummy equal to 1 if the firm receives a merger bid (or bids) in year t. We construct similar dummies for different types of merger bids (bids from strategic buyers, from financial buyers, and unsolicited bids)	Thomson Reuters SDC M&A
Divestiture	Dummy equal to 1 if the firm divests assets in year t. We construct similar dummies for different types of divestitures (sold to strategic buyer, sold to financial buyer, core assets, unrelated assets)	Thomson Reuters SDC M&A

Continued on next page

Appendix A continued from previous page

Variable name	Definition and construction of variable	Data source
Sale	Dummy equal to 1 if either the firm divests assets or receives merger bids in year t	Thomson Reuters SDC M&A
Acquisition	Dummy equal to 1 if the firm makes at least one acquisition in year t. We construct similar dummies for different types of acquisitions (public firms, private firms, related assets, unrelated assets)	Thomson Reuters SDC M&A
<u>*Other control variables*</u>		
TotM&A_3yr	Ortiz-Molina and Philips' (2014) measure of real asset liquidity. It is defined as the value of asset transaction activity involving public targets (sellers) in the industry scaled by industry book assets. We average the ratio over the past 3 years (including year t)	Thomson Reuters SDC M&A
TotPE_3yr	Measure of PE transaction waves, defined similar as TotM&A_3yr, but only includes transactions where the buyer is a private equity fund	Thomson Reuters SDC M&A
D[Merger Wave]	Dummy equal to 1 if industry j in year t is in the industry merger wave interval as defined in Harford (2005)	Thomson Reuters SDC M&A
Institution Ownership	Total ownership (as % of shares outstanding) of institutional investors that file 13F reports	Thomson Reuters 13f
Tobin's Q	Market-to-book ratio in assets. Market value of assets equals book value of assets (item AT_t) + market value of common equity at fiscal year-end (item $CSHO_t$ × item $PRCC\_F_t$) − book value of common equity (item CEQ_t) − balance sheet deferred taxes (item $TXDB_t$)	Compustat
Ln(age)	Natural logarithm of years since the firm first appears in CRSP	CRSP
Ln(MV)	Natural logarithm of the firm's market capitalization (item $CSHO_t$ × item $PRCC\_F_t$)	Compustat
Book Leverage	Defined as debt including long-term debt (item $DLTT_t$) plus debt in current liabilities (item DLC_t) divided by the sum of debt and book value of common equity (item CEQ_t)	Compustat
Dividend Yield	Defined as [common dividend (item DVC_t) + preferred dividends (item DVP_t)]/[market value of common stocks + book value of preferred (item $PSTK_t$)]	Compustat
Cash Flow	Defined as [net income (item NI_t) + depreciation and amortization (item DP_t)] scaled by lagged book assets	Compustat
ROA	Return on assets defined as EBITDA scaled by lagged book assets	Compustat
Sales Growth	Growth rate of total sales over the previous year (total sales: item $SALE_t$)	Compustat
Sales/Assets(lag)	Total sales scaled by lagged book assets	Compustat
Assets Growth	Growth rate of book assets over the previous year	Compustat
R&D	R&D (item XRD_t) scaled by lagged book assets (we replace missing with 0 for item XRD_t)	Compustat
Excess Cash	Industry median adjusted cash and cash equivalents (item CHE_t) scaled by lagged book assets	Compustat
HHI	Hirschman-Herfindahl index of sales in the industry	Compustat
CAR[Year t-1]	Cumulative abnormal return in year $t-1$ (applying monthly data and market model)	CRSP

Appendix B: Details about Industry and Insiders/Outsiders Classification

This appendix provides a detailed description of the method used in our industry classification. First, we use the CRSP-Compustat historical SIC 3-digit codes (Compustat item $SICH_t$), identifying the primary industry in which the firm operates, to define industries and classify listed firms into industries. As a result, our three industry HFA threat measures are constructed overwhelmingly based on Compustat SIC-3 classifications.

For the industry classification of the target or asset being sold (which is the industry in which the transaction takes place), we proceed as follows.

1. For mergers of public targets, the target's primary industry SIC-3 defines the industry in which the transaction takes place. We use the Compustat SIC-3 of the target firm to define this industry if there is a conflict between the Compustat SIC-3 and the SDC SIC-3 classification of the target firm. We do so to be consistent with industry HFA threat measures.
2. For divestitures and acquisitions of private firms, only SDC's primary SIC-3 for the target (or asset) is available, and we use the SDC SIC-3 classification to define the industry in which the transaction takes place.

In Section 5.B, for the industry classification of other firms needed to categorize seller and buyer of each asset as insiders and outsiders according to their relationship with the industry in which the transaction takes place (in which the firm or asset being sold is located), we proceed as follows. We define a buyer (seller) as an insider if the buyer (seller) is a public firm with its primary SIC-3 code equal to the asset's SIC-3 code, defined as above. If we have two observations on the buyer's (seller's) SIC-3 code, one from Compustat and one from SDC, which only happens when the buyer (seller) is a public firm, we define the buyer (seller) as an insider if either Compustat's SIC-3 or SDC's SIC-3 of the buyer (seller) is equal to the asset's SIC-3 code, and define it as an outsider in all other cases. Our reasoning is that when Compustat's and SDC's SIC-3 classifications differ, it is plausible that both contain relevant information on the firm's (buyer or seller) actual industry and product portfolio, and hence are indicative of the buyer (seller) being exposed to the industry in which the transaction takes place.

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Table 1: Hedge fund activism and characteristics of firms under HFA impact

This table reports annual frequencies of HFA events (Panel A), summary statistics of industry HFA threat variables (Panel B), and characteristics of firms under HFA impact (Panels C and D). Panel A reports the annual number of firms and of HFA campaigns in the CRSP-Compustat universe and of campaigns in industry HFA clusters. An Ind. HFA cluster is defined as an industry-year where the fraction of firms targeted in years t-2, t-1, or t is in the top quintile of the industry-year sample and at least 2 activist campaigns take place. Panel B presents the summary statistics of three industry HFA threat variables. Industry HFA Freq is defined as the fraction of firms in industry j and year t that have been targeted by activist hedge funds in the previous three years. Industry HFStake Freq is defined as the fraction of firms in industry j and year t that have experienced at least one activist hedge funds' stake jump in years t-2, t-1, or t. The third measure FIFB, constructed following Gantchev, Gredil, and Jotikasthira (2017), hypothetically assigns the fund inflow shock of activist hedge fund k to industry j and in year t according to industry weight of j in k's portfolio in year t-1. Panel C reports characteristics of firms in the year in which they are targeted by activist hedge funds (HFA Target Firms). Variables are measured in the year prior to the HFA event. The Remaining Sample is the CRSP-Compustat universe excluding the HFA Target Firms sample. We report the differences in mean and median values between the target and non-target sample of firm-years, and conduct t tests for differences in means and Wilcoxon tests for differences in medians (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). Panel D reports firm characteristics sorted by terciles of Industry HFA Freq. Panels B and D exclude firm-year observations of firms that are HFA targets in year t for observations of years $[t, t + 3]$.

Panel A: Frequency of HFA campaigns and industry HFA clustering

Calendar year	(1) Number of firms (all)	(2) Number of HFA campaigns	(3) Proportion of firms targeted by HFA	(4) Number of HFA campaigns in Ind. HFA clusters	(5) Fraction of industries with Ind. HFA clusters
1994	6,176	12	0.19%	1	0.00%
1995	6,372	33	0.52%	2	0.00%
1996	6,850	90	1.31%	19	1.11%
1997	6,847	170	2.48%	32	3.31%
1998	6,408	131	2.04%	26	4.04%
1999	6,226	90	1.45%	27	3.68%
2000	5,986	86	1.44%	20	3.72%
2001	5,296	79	1.49%	16	4.89%
2002	4,911	121	2.46%	27	6.04%
2003	4,635	118	2.55%	39	4.96%
2004	5,066	128	2.53%	63	6.51%
2005	4,977	211	4.24%	129	12.17%
2006	4,888	273	5.59%	186	18.11%
2007	4,758	319	6.70%	216	24.24%
2008	4,487	256	5.71%	170	25.48%
2009	4,252	134	3.15%	77	21.84%
2010	4,125	149	3.61%	67	13.90%
2011	4,002	172	4.30%	107	11.24%
2012	3,940	174	4.42%	105	14.01%
2013	4,001	197	4.92%	132	16.53%
2014	4,152	236	5.68%	163	19.11%
2015	4,103	203	4.95%	120	22.67%
2016	3,990	169	4.24%	85	19.84%
Total	116,448	3,551	3.05%	1,829	11.02%

Panel B: Summary statistics of industry HFA threat variables (Firm-year sample)

Industrial HFA Threat Variable	Mean	Min	P25	Median	P75	Max	S.D.
Industry HFA Freq	0.060	0.000	0.000	0.037	0.087	0.857	0.070
Industry HFStake Freq	0.102	0.000	0.012	0.077	0.157	1.000	0.107
FIFB (Fund Inflow / Ind Market Cap)†	0.005	0.000	0.001	0.002	0.005	13.549	0.064

†: Since FIFB is highly skewed, we use the percentile rank of FIFB throughout the whole paper.

Panel C: Characteristics of activism target firms

	HFA Target Firms (N = 3,551)			The Remaining Sample (N = 112,897)			Difference Targets - Non-targets	
	Mean	Median	S.D.	Mean	Median	S.D.	Mean	Median
Institutional Ownership	0.512	0.527	0.288	0.427	0.403	0.296	0.086***	0.124***
Tobin's Q	1.655	1.286	1.153	1.988	1.401	1.706	-0.333***	-0.115***
ln(MV)	5.499	5.314	1.821	5.626	5.599	2.026	-0.127***	-0.285***
Book Leverage	0.333	0.282	0.318	0.329	0.293	0.296	0.003	-0.011
Excess Cash	0.037	0.000	0.178	0.035	0.000	0.174	0.002	0.000
Dividend Yield	0.010	0.000	0.024	0.014	0.000	0.026	-0.004***	0.000***
Cash Flow	0.010	0.049	0.191	0.026	0.066	0.206	-0.016***	-0.017***
ROA	0.053	0.081	0.186	0.073	0.100	0.203	-0.019***	-0.019***
Sales Growth	0.106	0.044	0.389	0.160	0.081	0.441	-0.055***	-0.037***
Sales/Assets(lag)	0.984	0.831	0.781	1.016	0.844	0.872	-0.032**	-0.013
Assets Growth	0.082	0.022	0.359	0.139	0.060	0.386	-0.056***	-0.038***
R&D	0.045	0.000	0.089	0.045	0.000	0.099	0.000	0.000
HHI	0.193	0.137	0.166	0.182	0.127	0.164	0.011***	0.010***
CAR [12 months]	-0.056	-0.073	0.542	0.049	0.011	0.597	-0.105***	-0.084***
TotM&A_3yr	0.075	0.043	0.097	0.078	0.043	0.096	-0.003*	0.000

Panel D: Characteristics of firms under high, medium and low threat (Industry HFA Freq)

Tercile of Industry HFA Freq	Bottom Tercile (N = 42,908)			Medium Tercile (N = 31,552)			Top Tercile (N = 32,729)		
	Mean	Median	S.D.	Mean	Median	S.D.	Mean	Median	S.D.
Institution Ownership	0.416	0.394	0.288	0.419	0.387	0.296	0.430	0.407	0.303
Tobin's Q	1.757	1.266	1.448	2.278	1.544	2.091	2.028	1.490	1.574
ln(MV)	5.716	5.732	2.043	5.609	5.568	2.004	5.564	5.522	2.056
Book Leverage	0.379	0.377	0.285	0.279	0.203	0.291	0.316	0.268	0.300
Excess Cash	0.034	0.000	0.145	0.033	0.000	0.199	0.038	0.000	0.180
Dividend Yield	0.018	0.006	0.028	0.012	0.000	0.026	0.010	0.000	0.021
Cash Flow	0.048	0.065	0.167	0.000	0.061	0.245	0.033	0.075	0.202
ROA	0.093	0.100	0.166	0.044	0.092	0.241	0.083	0.112	0.199
Sales Growth	0.151	0.078	0.402	0.185	0.092	0.499	0.163	0.087	0.430
Sales/Assets(lag)	0.995	0.793	0.930	0.944	0.778	0.811	1.121	0.955	0.869
Assets Growth	0.140	0.064	0.359	0.155	0.065	0.421	0.136	0.061	0.380
R&D	0.023	0.000	0.072	0.073	0.008	0.122	0.044	0.000	0.092
HHI	0.225	0.154	0.208	0.129	0.100	0.091	0.181	0.133	0.141
CAR [12 months]	0.027	0.005	0.529	0.088	0.031	0.661	0.038	0.000	0.591
TotM&A_3yr	0.064	0.028	0.094	0.086	0.062	0.086	0.084	0.048	0.104

Table 2: Industry activism threat and HFA target probability

This table reports the relationship between industry measures of activism threat and the HFA target probability. Columns (1) – (7) report logit regressions for our firm-year sample. The left-hand side variable D[HFA] is a dummy that is equal to one if activists initiate a new campaign against the firm in year t. We use 3 variables to measure industry HFA threat. Industry HFA Freq is defined as fraction of firms in industry j and year t that have been targeted by activist hedge funds within last three years. Industry HFStake Freq is defined as the fraction of firms in industry j and year t that had experienced at least one activist hedge funds' stake jump within last 3 years. The last one, FIFB, hypothetically assigns the fund inflow shock of activist hedge fund k to industry j and in year t according to industry weight of j in k's portfolio in year t-1. Columns (8) – (9) report OLS regressions for the industry-year sample; in this case all controls are industry-year medians. In above regressions, all firm-level control variables are one year lagged except for industry threat measures, TotM&A_3yr, TotPE_3yr, and D[Merger Wave]. All regressions include year and industry fixed effects. Standard errors are clustered at the firm level in columns (1) - (7) and at the industry level in columns (8) – (9) (standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Firm-year regression							Industry-year regression	
	Logit D[HFA]	Logit D[HFA]	Logit D[HFA]	Logit D[HFA]	Logit D[HFA]	Logit D[HFA]	Logit D[HFA]	OLS Industry HFA Freq (year t)	OLS Industry HFA Freq (year t)
Industry HFA Freq		7.752***			7.753***				
		(0.304)			(0.305)				
Industry HFStake Freq			1.825***			1.825***			
			(0.220)			(0.220)			
FIFB (Percentile Rank)				0.366***			0.366***	0.0149***	0.0151***
				(0.140)			(0.140)	(0.00570)	(0.00570)
D(Merger Wave)					0.0173	-0.0166	-0.0417		-0.00485
					(0.0839)	(0.0860)	(0.0896)		(0.00486)
TotM&A_3yr	0.472	0.164	0.436	0.458	0.157	0.442	0.473	0.0199	0.0207
	(0.381)	(0.401)	(0.381)	(0.389)	(0.400)	(0.380)	(0.389)	(0.0179)	(0.0179)
TotPE_3yr	0.0721	-0.00634	-0.155	0.0841	0.00598	-0.163	0.0598	-0.0629**	-0.0639**
	(0.660)	(0.764)	(0.663)	(0.696)	(0.763)	(0.662)	(0.696)	(0.0306)	(0.0306)
Institutional Ownership	1.459***	1.415***	1.419***	1.466***	1.416***	1.419***	1.465***	0.0178	0.0171
	(0.116)	(0.118)	(0.116)	(0.117)	(0.118)	(0.116)	(0.118)	(0.0124)	(0.0125)
Tobin's Q	-0.320***	-0.312***	-0.320***	-0.321***	-0.311***	-0.321***	-0.321***	-0.00676*	-0.00690**
	(0.0353)	(0.0355)	(0.0354)	(0.0358)	(0.0356)	(0.0355)	(0.0359)	(0.00346)	(0.00347)
ln(MV)	-0.200***	-0.194***	-0.196***	-0.200***	-0.194***	-0.196***	-0.199***	-0.00329	-0.00320
	(0.0208)	(0.0210)	(0.0208)	(0.0211)	(0.0210)	(0.0208)	(0.0211)	(0.00216)	(0.00216)
Book Leverage	0.325***	0.342***	0.330***	0.316***	0.342***	0.330***	0.316***	0.00796	0.00821
	(0.0920)	(0.0942)	(0.0919)	(0.0935)	(0.0942)	(0.0919)	(0.0935)	(0.0115)	(0.0115)
Dividend Yield	-4.046***	-4.093***	-4.014***	-3.753**	-4.091***	-4.015***	-3.757**	-0.383***	-0.379***

	(1.479)	(1.508)	(1.476)	(1.484)	(1.508)	(1.475)	(1.483)	(0.143)	(0.143)
Cash Flow	-0.285	-0.318*	-0.261	-0.303*	-0.317*	-0.262	-0.305*	-0.0226	-0.0225
	(0.177)	(0.181)	(0.177)	(0.179)	(0.181)	(0.177)	(0.179)	(0.0291)	(0.0291)
Sales Growth	-0.0642	-0.0548	-0.0537	-0.0700	-0.0552	-0.0533	-0.0690	-0.0108	-0.0105
	(0.0689)	(0.0677)	(0.0684)	(0.0698)	(0.0677)	(0.0683)	(0.0697)	(0.0121)	(0.0121)
Asset Growth	-0.176*	-0.135	-0.167*	-0.190**	-0.135	-0.167*	-0.191**	-0.0359**	-0.0361**
	(0.0907)	(0.0904)	(0.0904)	(0.0926)	(0.0904)	(0.0904)	(0.0926)	(0.0146)	(0.0146)
R&D	0.516	0.453	0.520	0.519	0.451	0.522	0.525	-0.308*	-0.301*
	(0.380)	(0.381)	(0.379)	(0.382)	(0.382)	(0.380)	(0.382)	(0.171)	(0.171)
HHI	-0.388	-0.842***	-0.313	-0.476	-0.843***	-0.311	-0.470	0.0550**	0.0547**
	(0.278)	(0.316)	(0.280)	(0.291)	(0.316)	(0.280)	(0.291)	(0.0261)	(0.0261)
Excess Cash	0.620***	0.649***	0.613***	0.631***	0.648***	0.614***	0.633***	0.0580**	0.0586**
	(0.156)	(0.157)	(0.156)	(0.157)	(0.158)	(0.156)	(0.157)	(0.0283)	(0.0283)
CAR [12 months]	-0.125***	-0.116**	-0.124***	-0.113**	-0.116**	-0.124***	-0.113**	-0.00280	-0.00281
	(0.0479)	(0.0489)	(0.0478)	(0.0485)	(0.0489)	(0.0479)	(0.0485)	(0.00552)	(0.00552)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	68228	68228	68228	65934	68228	68228	65934	4517	4517
pseudo R^2 / adj. R^2	0.086	0.129	0.089	0.087	0.129	0.089	0.087	0.071	0.071

Table 3: Descriptive statistics of corporate transactions by period

This table reports descriptive statistics of corporate transaction activities by period. We report the number and annual frequencies of each type of transaction. In Panel A, we report merger bids received by CRSP-Compustat firms. In Panel B, we report divestitures in which CRSP-Compustat firms are sellers of the divested assets. Panel C reports acquisitions of public, private and subsidiary firms by CRSP-Compustat firms. Panel D reports acquisitions of private target firms only by CRSP-Compustat firms. An activism transaction (activism merger in Panel A, activism divestiture in Panel B, activism acquisition in Panels C and D) is defined as a transaction by a company targeted by activist hedge funds in the 2 years (730 days) prior to the transaction (column (3) of each panel). Column (4) of each panel is defined as the number of firms with activism transactions divided by the total number of firms that have been targeted by activists in the past 2 years. In columns (5)–(7) of each panel, we report the number of transactions sorted by industry HFA threat. Firms with high (low) HFA threat are defined as firms not targeted by activist hedge funds but with an Industry HFA Frequency measure in the top (bottom) tercile of that year.

Panel A: HFA campaigns and merger bids

Calendar year	(1) Number of merger bids	(2) % of firms with merger bids	(3) Number of activism mergers	(4) % of firms with activism mergers	(5) Number of merger bids under high HFA threat	(6) % of firms with mergers under high HFA threat	(7) % of firms with mergers under low HFA threat
1994 – 1995	378	2.92%	0	0.00%	107	2.82%	2.78%
1996 – 2000	2,209	6.58%	91	10.17%	641	6.21%	6.65%
2001 – 2005	1,192	4.62%	98	10.89%	417	5.34%	3.45%
2006 – 2010	1,317	5.58%	227	11.70%	405	5.68%	4.04%
2011 – 2016	1,137	4.57%	216	11.78%	372	4.79%	3.65%
Total	6,233	5.17%	632	10.19%	1,942	5.38%	4.34%

Panel B: HFA campaigns and divestitures

Calendar year	(1) Number of divestiture	(2) % of firms with divestiture	(3) Number of activism divestiture	(4) % of firms with activism divestiture	(5) Number of divestiture under high HFA threat	(6) % of firms with divestiture under high HFA threat	(7) % of firms with divestiture under low HFA threat
1994 – 1995	612	3.89%	3	5.26%	93	2.94%	3.96%
1996 – 2000	2,200	5.23%	63	6.25%	493	6.00%	5.42%
2001 – 2005	1,764	5.29%	98	7.84%	445	6.81%	5.26%
2006 – 2010	1,535	5.39%	185	7.51%	337	4.79%	5.33%
2011 – 2016	1,741	5.52%	225	8.60%	361	5.19%	5.62%
Total	7,852	5.19%	574	7.81%	1,729	5.16%	4.58%

Panel C: HFA campaigns and acquisitions of public, private, and subsidiary firms

Calendar year	(1) Number of acquisitions	(2) % of firms with acquisitions	(3) Number of activism acquisitions	(4) % of firms with activism acquisitions	(5) Number of acquisitions under high HFA threat	(6) % of firms with acquisitions under high HFA threat	(7) % of firms with acquisitions under low HFA threat
1994 – 1995	2,036	11.53%	4	5.26%	319	10.17%	12.09%
1996 – 2000	8,464	16.86%	238	16.54%	1,418	14.87%	17.21%
2001 – 2005	4,969	14.66%	117	10.01%	1,080	14.67%	15.51%
2006 – 2010	4,280	14.16%	214	9.49%	950	14.58%	15.60%
2011 – 2016	5,133	15.65%	265	12.00%	1,102	15.23%	17.91%
Total	24,882	15.06%	838	11.82%	4,869	14.51%	15.72%

Panel D: HFA campaigns and acquisitions of private firms

Calendar year	(1) Number of private acquisitions	(2) % of firms with private acquisitions	(3) Number of activism private acquisitions	(4) % of firms with activism private acquisitions	(5) Number of private acquisitions under high HFA threat	(6) % of firms with private acquisitions under high HFA threat	(7) % of firms with private acquisitions under low HFA threat
1994 – 1995	794	5.10%	3	2.63%	131	4.12%	5.26%
1996 – 2000	3,989	9.00%	152	6.38%	733	7.64%	8.71%
2001 – 2005	2,154	7.16%	73	4.01%	529	7.25%	7.29%
2006 – 2010	2,043	7.42%	113	4.82%	530	8.09%	7.89%
2011 – 2016	2,417	7.97%	140	5.82%	588	8.08%	9.06%
Total	11,397	7.68%	481	5.49%	2,511	7.50%	7.71%

Table 4: Hedge fund activism and corporate transactions

This table presents regressions investigating corporate transaction activities of activism target firms. Panel A studies the probability of receiving a merger bid following an HFA event, Panel B studies the probability of divestiture, and Panel C investigates the probability of acquisitions of public and private firms. Panel D documents the probability of mergers, divestitures, sales and acquisitions following filing switches from 13G-to-13D filings. Panel A to Panel C present logit regressions, and Panel D OLS regressions. In each panel, the left-hand side variable is a dummy that takes the value one if the firm undertakes a transaction receives in year t (a merger bid in Panel A, divestiture in Panel B, etc.) The main explanatory variable D[Activist] is an indicator variable tracking whether the firm is an HFA campaign target in the 2 years prior to each type of transaction (a transaction event is a merger bid in Panel A, a divestiture in Panel B, etc.); D[Activist] is equal to one in year t if activists launch a campaign against the firm during the 730 calendar days prior to the transaction event, or, if there is no transaction event for the firm in year t, during the 730 calendar days prior to the median date of all transaction events of other firms in year t. All panels include the following firm-level control variables: TotM&A_3yr, Institutional Ownership, Tobin's Q, ln(MV), Book Leverage, Dividend Yield, Cash Flow, Sales Growth, Asset Growth, R&D, Excess Cash, HHI, CAR[Year t-1], and D[Divestiture][t-1] (D[Divestiture][t-1] only in Panel B). All firm-level controls are one-year lagged. In Panel C, D[Large] (D[Small]) is a dummy equal to 1 if the firm's size is larger (smaller) than the industry-year median size of firms in year t-1.

In Panel D, we merge the data of 13G fillings and 13G-to-13D switchers with the CRSP-Compustat universe. The dataset includes 4,488 13G filings and 227 13G-to-13D switchers. The regression sample includes firm-year observations from 5 years prior to and 5 years post the 13G filling or 13D switcher filling. Following Brav, Jiang, Ma, and Tian (2016)'s setting, we apply the following difference in difference specification:

$$y_{i,t} = \alpha_t + \delta_j + \beta_1 D[Post] + \beta_2 D[Post] \times D[13G\ to\ 13D\ Switcher] + \beta_3 D[13G\ to\ 13D\ Switcher] + \gamma Control_{i,t} + \varepsilon_{i,t}$$

where $D[Post]$ is a dummy variable equal to 1 if the firm-year observation is within $[t+1, t+5]$ years post the event year. The event year is the year of the filing of Schedule 13G for non-switchers or the year of the switch for the switcher sub-sample. $D[13G\ to\ 13D\ Switcher]$ is a dummy variable equal to one if there is a 13-G to-13D switch for a firm during the event year (as opposed to remaining with Schedule 13G status). Sale is a dummy that is equal to one of there is a merger bid or a divestiture. Definitions of all other variables can be found in Appendix A. Industry fixed effects and year fixed effects are always included in each panel. Standard errors are clustered at the firm level (standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Activism targets and mergers

	(1)	(2)	(3)	(4)
	Logit	Logit	Logit	Logit
	Merger bids	Merger bids	Merger bids	Merger bids
		Strategic buyer	Financial buyer	Unsolicited bids
D[Activist]	0.710***	0.611***	0.858***	1.206***
	(0.0550)	(0.0620)	(0.103)	(0.160)
Firm-level control variables	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes
N	71879	71534	66332	51167
pseudo R^2	0.051	0.049	0.107	0.088
Unconditional prob.	5.45%	4.43%	0.79%	0.33%
Prob. conditional on HFA targets	10.49%	7.86%	1.86%	1.10%

Panel B: Activism targets and divestitures

	(1) LOGIT Divestiture	(2) LOGIT Divestiture	(3) LOGIT Divestiture Strategic buyer	(4) LOGIT Divestiture Financial buyer	(5) LOGIT Divestiture Core assets	(6) LOGIT Divestiture Unrelated assets
D[Activist]	0.362***	0.259***	0.332***	0.461***	0.294***	0.414***
	(0.0694)	(0.0746)	(0.0762)	(0.139)	(0.0967)	(0.0921)
D[Activist's Goal is Restructure]		0.748***				
		(0.191)				
Firm-level control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	68772	68772	68471	61622	64434	67666
pseudo R^2	0.182	0.183	0.176	0.192	0.169	0.194
Unconditional prob.	4.57%	–	4.34%	0.36%	1.44%	2.99%
Prob. conditional on HFA targets	6.44%	11.63%†	5.95%	0.58%	1.93%	4.46%

†: The probability is conditional on activist's goal to restructure the target firm.

Panel C: Activism targets and acquisitions of public and private firms

	(1) LOGIT Acquisition	(2) LOGIT Acquisition	(3) LOGIT Acquire Private firms	(4) LOGIT Acquire Private firms	(5) LOGIT Acquire Public firms	(6) LOGIT Acquisition Related	(7) LOGIT Acquisition Unrelated
D[Activist]	-0.210***		-0.335***		-0.156	-0.187**	-0.152**
	(0.0584)		(0.0839)		(0.122)	(0.0808)	(0.0756)
D[Activist] × D[Large]		-0.252***		-0.387***			
		(0.0793)		(0.119)			
D[Activist] × D[Small]		-0.0642		-0.208*			
		(0.0865)		(0.126)			
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	69541	66346	69118	66069	67308	68664	69148
pseudo R^2	0.124	0.125	0.102	0.104	0.134	0.129	0.126
Unconditional prob.	14.42%	–	6.40%	–	3.65%	6.46%	7.33%
Prob. conditional on HFA targets	12.02%	–	4.66%	–	2.51%	5.41%	6.36%

Panel D: Activists' switch in filing status from 13G to 13D

	(1) OLS Merger	(2) OLS Divestiture	(3) OLS Sale	(4) OLS Acquisition Public	(5) OLS Acquisition Private
D[Post]	0.0579***	-0.00379	0.0504***	-0.0197**	-0.00799
	(0.00403)	(0.00525)	(0.00630)	(0.00773)	(0.00583)
D[Post] × D[13G to 13D Switcher]	0.0383**	0.0294**	0.0614***	-0.0179	-0.0207**
	(0.0167)	(0.0128)	(0.0191)	(0.0145)	(0.0100)
Firm-level control variables	Yes	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes	Yes
N	15933	15144	15933	15144	15144
adj. R^2	0.035	0.065	0.052	0.075	0.040

Table 5: Firm-level HFA threat and corporate transaction

This table provides evidence on the relationship between firm-level threats of hedge fund activism and asset transaction activities of firms not (yet) targeted by activists. The dependent variable is a dummy that is equal to one if a transaction of the designated type occurs in year t. Sale is equal to one if a merger or a divestiture occurs in year t. If a firm is targeted by an activist hedge fund in year t, we exclude for that firm years $[t, t+3]$ from the sample to eliminate the direct activism target impact. In Panel A, we use $Pr(Target)$ to measure the firm-level activism threat, where $Pr(Target)$ is the estimated probability of being targeted by an activist hedge fund. To obtain this measure, we first run a logit regression as in column 1 of Table 2. We use the post estimation probability as $Pr(Target)$. In Panel B and C, we use D[Passive Stake] to measure the activism threat, where D[Passive Stake] is a dummy equal to 1 if the combined ownership by activist hedge funds is at least 5% in year t. All panels include the following firm-level control variables: Institutional Ownership, Tobin's Q, ln(MV), Book Leverage, Dividend Yield, Cash Flow, Sales Growth, Asset Growth, R&D, Excess Cash, HHI, CAR[Year t-1], and D[Divestiture][t-1] (D[Divestiture][t-1] only used in regression of divestiture). All firm controls are one year lagged. D[Large] (D[Small]) is a dummy equal to 1 if the firm's size is larger (smaller) than the industry-year median size of firms (all measured in year $t-1$). Industry fixed effects and year fixed effects are included in all regressions. Standard errors are clustered at the firm level (standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Corporate transactions and firm-level HFA threat: Pr(Target)

	(1) Merger	(2) Divestiture	(3) Sale	(4) Acquisition	(5) Acquire Private
$Pr(\widehat{Target})$	0.622***	0.536***	1.149***		
	(0.164)	(0.140)	(0.215)		
$Pr(\widehat{Target})$ × D[Small]				-1.108***	-0.294***
				(0.129)	(0.0955)
$Pr(\widehat{Target})$ × D[Large]				-2.011***	-0.527***
				(0.183)	(0.141)
Firm-level control variables	Yes	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes	Yes
N	65429	62934	65429	60601	60601
adj. R^2	0.018	0.073	0.045	0.079	0.042

Panel B: Passive stake and HFA target probability

	(1) D[HFA]	(2) D[HFA]	(3) D[HFA]	(4) D[HFA]
D[Passive Stake]	1.545***		1.516***	1.520***
	(0.0519)		(0.0527)	(0.0524)
D[Passive Stake](lag)		0.722***		
		(0.0521)		
Industry HFA Freq			7.674***	
			(0.314)	
Industry HFStake Freq				0.810***
				(0.224)
Firm-level controls included	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes
N	68228	68228	68228	68228
pseudo R^2	0.135	0.096	0.175	0.136

Panel C: Corporate transactions and firm-level HFA threat: D[Passive Stake]

	(1) Merger	(2) Divestiture	(3) Sale	(4) Acquisition	(5) Acquire Private
D[Passive Stake]	0.0414***	0.0131***	0.0513***		
	(0.00347)	(0.00330)	(0.00445)		
D[Passive Stake] × D[Small]				-0.00469	-0.00545
				(0.00553)	(0.00420)
D[Passive Stake] × D[Large]				-0.0151*	-0.0167***
				(0.00795)	(0.00561)
Firm-level control variables	Yes	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes	Yes
N	65430	62935	65430	60602	60602
adj. R^2	0.021	0.069	0.047	0.086	0.044

Table 6: Industry HFA threat and corporate transactions

This table presents evidence on the relationship between industry activism threat and corporate transaction activities. The dependent variable is a dummy that is equal to one if a transaction of the designated type occurs in year t; Sale is equal to one if a merger or a divestiture occurs in year t. We report OLS regressions in all panels. If a firm is targeted by an activist hedge fund in year t, we exclude years $[t, t+3]$ for that firm to eliminate the direct activism target impact. Panel A and Panel B measure the industry threat with Industry HFA Freq and Industry HFStake Freq, respectively, and Panel C reports estimates from a reduced form 2SLS regression, where we use FIFB as an instrument for Industry HFA Freq and Industry HFStake Freq. All panels include firm-level controls and industry-level controls. Firm-level control variables include Institutional Ownership, Tobin's Q, ln(MV), Book Leverage, Dividend Yield, Cash Flow, Sales Growth, Asset Growth, R&D, Excess Cash, HHI, CAR[Year t-1], and D[Divestiture][t-1] (D[Divestiture][t-1] only used in regression of divestiture). All firm controls are 1 year lagged. Industry-level control variables include TotM&A_3yr, HHI, Industry-year median Tobin's Q, Industry-year S.D. of Tobin's Q, and Industry-year median absolute change of ROA, Sales Growth, Employee Growth, and Turnover (as proposed in Harford (2005); all measured in year t-1). D[Large] (D[Small]) is a dummy equal to 1 if the firm's size is larger (smaller) than the industry-year median size of firms (all measured in year $t-1$). Industry fixed effects and year fixed effects are included in all regressions. Standard errors are clustered at the firm level (standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Measuring industry HFA threat by Industry HFA Freq

	(1) Merger	(2) Divestiture	(3) Sale	(4) Acquisition	(5) Acquire Private
Industry HFA Freq	0.00168	0.0425***	0.0480**		
	(0.0140)	(0.0160)	(0.0213)		
Industry HFA Freq × D[Small]				0.0634**	0.0558**
				(0.0300)	(0.0227)
Industry HFA Freq × D[Large]				-0.0910**	-0.0435*
				(0.0366)	(0.0255)
Firm-level control variables	Yes	Yes	Yes	Yes	Yes
Industry-level control variables	Yes	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes	Yes
N	60618	58307	60618	56512	56512
adj. R^2	0.018	0.074	0.045	0.075	0.041

Panel B: Measuring industry HFA threat by Industry HFStake Freq

	(1) Merger	(2) Divestiture	(3) Sale	(4) Acquisition	(5) Acquire Private
Industry HFStake Freq	0.0281**	0.0280**	0.0538***		
	(0.0111)	(0.0125)	(0.0160)		
Industry HFStake Freq× D[Small]				0.0677***	0.0266*
				(0.0224)	(0.0161)
Industry HFStake Freq× D[Large]				-0.0477**	-0.0394***
				(0.0223)	(0.0151)
Firm-level control variables	Yes	Yes	Yes	Yes	Yes
Industry-level control variables	Yes	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes	Yes
N	60618	58307	60618	56512	56512
adj. R^2	0.018	0.074	0.046	0.076	0.041

Panel C: Measuring industry HFA threat by FIFB (Reduced-form 2SLS regression)

	(1) Merger	(2) Divestiture	(3) Sale	(4) Acquisition	(5) Acquire Private
FIFB (Percentile Rank)	0.0114**	0.0131**	0.0233***		
	(0.00556)	(0.00580)	(0.00769)		
FIFB (PR) × D[Small]				0.0107	0.000152
				(0.00933)	(0.00688)
FIFB (PR) × D[Large]				-0.0438***	-0.0153*
				(0.0115)	(0.00850)
Firm-level control variables	Yes	Yes	Yes	Yes	Yes
Industry-level control variables	Yes	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes	Yes
N	58898	56659	58898	54988	54988
adj. R^2	0.018	0.074	0.046	0.076	0.041

Table 7: Industry HFA clusters and predicted probability of corporate transactions

This table reports summary statistics on industry HFA clusters and regressions predicting the probability of corporate transactions. In Panel A, we report summary statistics about Industry HFA clusters. An Industry HFA cluster is defined as an industry-year where the fraction of firms targeted in years t-2, t-1, or t is in the top quintile of the industry-year sample (i.e., D(Industry HFA Freq P80) = 1) and at least 2 activist campaigns take place. An alternative threshold for Industry HFA Freq, the top decile, is also reported. Panel B reports logit regressions of HFA targeting probability including predicted probability of corporate transactions. The regression setup follows that of Table 2. We estimate the probability of the three transaction types (receiving a merger bid, divesting assets, and acquisitions) in (unreported) first stage logit regressions where all controls are as in Table 2, Column (1). Δ Pr(Transaction type) is defined as the estimated probability in this first-stage regression minus the estimated probability in year t -1. We then include Δ Pr(Transaction type) as independent variable in a regression that follows Table 2, Column (1).

Panel A: Summary statistics of Industry HFA Clusters

	(1) Total Sample	(2) Top Quintile	(3) Top Quintile	(4) Top Decile
		Industry HFA Freq		
Min. Num. HFA campaigns in cluster		≥ 1	≥ 2	≥ 2
Num. of HFA campaigns	3,551	2,035	1,829	715
Num. of industry-years (present in activism clusters)	6,028	1,162	664	269
Num. of hedge funds participating in clusters:				
- at least once	862	559	527	420

Panel B: Predicted probability of corporate transactions and HFA targeting

	(1) Logit D[HFA]	(2) Logit D[HFA]	(3) Logit D[HFA]
ΔPr(Merger bid)	-2.893*		
	(1.597)		
ΔPr(Divestiture)		1.287	
		(0.997)	
ΔPr(Acquisition)			-0.120
			(0.600)
Firm-level controls included	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes
N	55451	55357	55702
pseudo R^2	0.087	0.086	0.087

Table 8: Overall impact of HFA pressure on corporate transaction activity

This table reports logit regressions investigating the overall impact of HFA on corporate transactions. We estimate the HFA target effect (separately analyzed in Table 4) and the industry HFA threat effect (separately analyzed in table 6) in one combined framework. D[Activist] is defined as in Table 4. D[High HFA Threat] is a dummy for high industry HFA threat, which equals 1 if the firm is in the top quintile of Industry HFA Freq and D[Activist] = 0. D[Medium HFA Threat] is a dummy for mid industry HFA threat, which equals 1 if the firm is in the second and third highest quintile of Industry HFA Freq and D[Activist] = 0. Prob. conditional on HFA targets is the estimated probability fixed the D[Activist] = 1, D[High HFA Threat] = 0, D[Mid HFA Threat] = 0, and other controls are fixed at the mean values of the HFA targets sample. Prob. conditional on High HFA Threat is calculated in the same way but fixing other controls at the mean values of the sample of High HFA Threat firms. Marginal effect is defined as the prob. conditional on HFA exposure minus the conditional probability if the exposed firms were not exposed. Firm-level control variables are the same as in Table 4. Industry fixed effects and year fixed effects are always included. Standard errors are clustered at the firm level (standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Logistic regressions and marginal effects (mergers and divestitures)

	(1) Logit Merger	(2) Logit Divestiture	(3) Logit Sale
D[Activist]	0.756***	0.474***	0.676***
	(0.0656)	(0.0818)	(0.0536)
D[High HFA Threat]	0.0609	0.145**	0.106**
	(0.0592)	(0.0642)	(0.0447)
D[Medium HFA Threat]	0.0547	0.0515	0.0546
	(0.0468)	(0.0519)	(0.0352)
Firm-level control variables	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes
N	71879	68772	72357
pseudo R^2	0.051	0.173	0.071
Marginal effect of Activist	+5.31%	+2.60%	+7.44%
Prob. conditional on HFA targets	*10.56%*	*7.22%*	*16.68%*
Marginal effect of High HFA Threat	+0.28%	+0.52%	+0.81%
Prob. conditional on High HFA Threat	*4.92%*	*3.97%*	*8.64%*

Panel B: Logistic regressions and marginal effects (acquisitions)

	(1) Logit Acquisition
D[Activist] × D[Small]	-0.0610
	(0.0956)
D[High HFA Threat] × D[Small]	0.219***
	(0.0646)
D[Medium HFA Threat] × D[Small]	0.0169
	(0.0554)
D[Activist] × D[Large]	-0.317***
	(0.0901)
D[High HFA Threat] × D[Large]	-0.128***
	(0.0480)
D[Medium HFA Threat] × D[Large]	0.00613
	(0.0389)
Firm-level control variables	Yes
Industry and Year fixed effect	Yes
N	66896
pseudo R^2	0.111
For Small Firms:	
Marginal effect of Activist	-0.40%
Prob. conditional on HFA targets	*6.26%*
Marginal effect of High HFA Threat	+1.50%
Prob. conditional on High HFA Threat	*8.22%*
For Large Firms:	
Marginal effect of Activist	-4.55%
Prob. conditional on HFA targets	*15.18%*
Marginal effect of High HFA Threat	-2.16%
Prob. conditional on High HFA Threat	*20.29%*

Table 9: Activism pressure and industry asset liquidity

This table reports industry-year regressions linking activism pressure and industry real asset liquidity. We assign each corporate transaction to the industry in which the transaction takes place (in which the firm or asset sold is located). We require at least 3 public firms in each industry-year to be included in our regression sample. We determine the real asset liquidity (RAL) using two dimensions of deal activity, Frequency (number of transactions) and Transaction Value (sum of all transaction values). For Frequency, we define real asset liquidity as the number of transactions divided by the number of public firms in industry j and in year t (transaction frequency). For Transaction Value, we define real asset liquidity as the total value of transactions divided by the total market value of public firms in industry j and in year t, similar to Ortiz-Molina and Phillips (2014)'s measure. We only consider completed transactions, and each transaction is counted only once. Panel A reports the baseline regression of real asset liquidity, without distinction by buyer/seller relation. In Panel B, we distinguish the transactions by status of buyer (insider v. outsider), and in Panel C, we distinguish the transactions by status of buyer and status of seller (insider v. outsider). Insiders are public firms (buyers or sellers) with primary 3-digit SIC code in the same industry in which the transaction takes place; outsiders are all other buyers or sellers. Outsiders include in particular public firms in other industries, private firms, and private equity sponsors. Panel D reports regressions of ratio of transactions with outside buyers, where the dependent variable is the percentage of transactions acquired by outside buyers in industry j and in year t; regressions in Panel D only use the sample of transactions with inside sellers. The main explanatory variable, D[Industry HFA Freq P80], equals 1 if Industry HFA Freq of the industry-year is in the top quintile of the whole industry-year sample. The industry-year control variables, including HHI, Industry-year median of Tobin's Q, Leverage, Cash Flow, Sales Growth, Cash, R&D, and Assets Growth, and the Industry-year S.D. of Tobin's Q, are controlled in all panels. Industry fixed effects and year fixed effects are always included. All coefficients are multiplied by 100 for readability. Standard errors are clustered at the industry level (standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Total real asset liquidity

	Dependent Variable: Real Asset Liquidity (RAL)	
	(1)	(2)
Measure of RAL:	Frequency	Transaction Value
D[Industry HFA Freq P80]	2.501	1.528**
	(1.623)	(0.725)
Industry-level control variables	Yes	Yes
Industry and Year fixed effect	Yes	Yes
Number of Industry-Year obs.	4783	4783
adj. R^2	0.574	0.233
Number of transactions	23,704	23,704

Panel B: Real asset liquidity sorted by outsider/insider buyer

	Dependent Variable: Real Asset Liquidity (RAL)			
	(1)	(2)	(3)	(4)
Buyer status:	Buyer = Outsider		Buyer = Insider	
Measure of RAL:	Freq	Value	Freq	Value
D[Industry HFA Freq P80]	2.519*	1.616**	-0.0159	-0.0868
	(1.464)	(0.720)	(0.467)	(0.130)
Industry-level control variables	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes
Number of Industry-Year obs.	4783	4783	4783	4783
adj. R^2	0.584	0.230	0.158	0.149
Number of transactions	15,425	15,425	8,279	8,279

Panel C: Real asset liquidity sorted by outsider/insider buyer and seller

Dependent Variable: Real Asset Liquidity (ral)				
	(1)	(2)	(3)	(4)
Seller/buyer status:	Seller = Insider Buyer = Outsider		Seller = Insider Buyer = Insider	
Measure of RAL:	Freq	Value	Freq	Value
D[Industry HFA Freq P80]	1.706***	1.439**	0.0553	0.0416
	(0.607)	(0.653)	(0.136)	(0.105)
Number of Industry-Year obs.	4783	4783	4783	4783
Number of transactions	5,776	5,776	2,579	2,579
	(5)	(6)	(7)	(8)
Seller/buyer status:	Seller = Outsider Buyer = Outsider		Seller = Outsider Buyer = Insider	
Measure of RAL:	Freq	Value	Freq	Value
D[Industry HFA Freq P80]	0.802	0.175	-0.0619	-0.128*
	(1.229)	(0.420)	(0.445)	(0.0749)
Number of Industry-Year obs.	4783	4783	4783	4783
Number of transactions	9,649	9,649	5,700	5,700

Panel D: Regression of outsider buyer's ratio

Dependent Variable: Outsider Buyer's Ratio		
	(1)	(2)
Measure of ratio:	Ratio of Frequency	Ratio of Transaction Value
D[Industry HFA Freq P80]	4.337*	4.274*
	(2.241)	(2.450)
Industry-level control variables	Yes	Yes
Industry and Year fixed effect	Yes	Yes
Number of Industry-Year obs.	2267	2267
adj. R^2	0.145	0.144

Table 10: Activism pressure, asset redeployability and outsider buyers

This table reports transaction-level regressions on the relationship between industry activism pressure, asset redeployability and type of buyer. The regression sample includes 8,355 transactions of industry assets with insiders as sellers, as defined in Table 8. We only include transactions that occur in industry-years with at least 3 public firms in the baseline sample. In Panel A, the left-hand side variable is a dummy variable equal to one if the buyer in the transaction is from outside the industry, the private equity fund outside the industry, and the strategic buyer outside the industry respectively. The main explanatory variable, D[Industry HFA Freq P80], equals one if Industry HFA Freq is in the top quintile of the sample. D[Activism on Seller] is a dummy equal to one if there is an activism campaign (or several campaigns) launched against the seller in the 2 years prior to the transaction announcement. In Panel B, we interact the Redeploy Score with D[Industry HFA Freq P80]. We obtain industry-level Redeploy Score from online appendix of Kim and Kung (2017). High (Low) Redeploy Score is a dummy equal to one if the industry-level Redeploy Score is above (below) the median of the whole sample. Firm-level controls are the same as in Table 4. Standard errors are clustered at the industry level (standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Regression of probability of buyer type

	(1) D[Outsider]	(2) D[Outsider:PE]	(3) D[Outsider:SB]
D[Industry HFA Freq P80]	0.0309**	0.0290*	0.00137
	(0.0134)	(0.0167)	(0.0184)
D[Activism on Seller]	0.0173	0.0151	-0.000125
	(0.0247)	(0.0192)	(0.0276)
Firm-level control variables	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes
N	5824	5824	5824
adj. R^2	0.089	0.094	0.053

Panel B: Regression of probability of buyer type (Interaction with Redeploy Score)

	(1) D[Outsider]	(2) D[Outsider:PE]	(3) D[Outsider:SB]
D[Industry HFA Freq P80] × High Redeploy Score	0.148***	0.0889***	0.0553
	(0.0486)	(0.0309)	(0.0423)
D[Industry HFA Freq P80] × Low Redeploy Score	0.102**	0.0198	0.0806*
	(0.0395)	(0.0262)	(0.0454)
High Redeploy Score	0.0119	0.0295*	-0.0167
	(0.0420)	(0.0173)	(0.0374)
Firm-level control variables	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
N	5452	5452	5452
adj. R^2	0.031	0.043	0.013

Table 11: Price pressure under HFA impact

This table reports transaction-level regressions investigating the price pressure hypothesis. We only include transactions that occur in industry-years with at least 3 public firms in the baseline sample. Panel A reports the regressions of Seller CARs and premiums, Panel B provides the estimate of interaction with Redeploy Score, and Panel C reports regressions of Buyer CARs. Industry HFA Freq and Industry HFStake Freq are both measured for the industry in which the transaction takes place (in which the firm or firm asset is located). D[Activism on Seller] is a dummy equal to one if activists launch a campaign against the seller in the 2 calendar years prior to the transaction (either a merger or a divestiture); D[No Activism] is equal to $1 -$ D[Activism on Seller]. The transaction level controls are a dummy for payment by stock, TotM&A_3yr (measured in asset industry), Institutional Ownership, Tobin's Q, ln(MV), Book Leverage, Dividend Yield, Cash Flow, Sales Growth, Asset Growth, R&D, and Excess Cash (accounting measures are those of the seller in Panel A and B and those of the buyer in Panel C). In regressions of the merger sample, we also include control dummies for competing bids, successful bids, and unsolicited bids. All left-hand side variables are winsorized at the 1% and 99% level. All CARs are estimated with a market model using daily stock prices data in CRSP. Asset industry fixed effects and year fixed effects are always included. Standard errors are clustered at the firm level (standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Price pressure for sellers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sample of Divestitures				Sample of Mergers			
	Seller's CAR [-2d, +2d]		Seller's CAR [-5d, +5d]		Premium [1 month]		Target's CAR [-43d, +1d]	
Industry HFA Freq × D[No Activism]	-0.0283**		-0.0428**		-0.272***		-0.226**	
	(0.0139)		(0.0180)		(0.102)		(0.0878)	
Industry HFA Freq × D[Activism on Seller]	0.00975		0.0317		-0.0805		-0.125	
	(0.0418)		(0.0520)		(0.170)		(0.127)	
Industry HFStake Freq × D[No Activism]		-0.0224*		-0.0277		-0.187**		-0.111
		(0.0127)		(0.0169)		(0.0837)		(0.0700)
Industry HFStake Freq × D[Activism on Seller]		0.00423		0.0362		-0.100		-0.104
		(0.0388)		(0.0422)		(0.154)		(0.105)
Transaction-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5420	5420	5422	5422	4100	4100	4024	4024
adj. R^2	0.034	0.034	0.024	0.023	0.118	0.117	0.162	0.161

Panel B: Price pressure for sellers (interaction with Redeploy Score)

	(1)	(2)	(3)	(4)
	Sample of Divestitures		Sample of Mergers	
	Seller's CAR [-2d, +2d]	Seller's CAR [-5d, +5d]	Premium [1 month]	Target's CAR [-43d, +1d]
Industry HFA Freq × D[Activism on Seller]	0.00418	0.0325	-0.151	-0.159
	(0.0448)	(0.0552)	(0.179)	(0.135)
Industry HFA Freq × D[No Activism] × High Redeploy Score	-0.0257	-0.0434	-0.288*	-0.262*
	(0.0214)	(0.0268)	(0.168)	(0.156)
Industry HFA Freq × D[No Activism] × Low Redeploy Score	-0.0361**	-0.0491**	-0.350***	-0.276***
	(0.0171)	(0.0233)	(0.123)	(0.0933)
Transaction-level controls	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes
N	5173	5176	3911	3853
adj. R^2	0.035	0.025	0.120	0.164

Panel C: Price pressure for buyers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sample of Divestitures				Sample of Mergers			
	Buyer's CAR [-2d, +2d]		Buyer's CAR [-5d, +5d]		Acquirer's CAR [-2d, +2d]		Acquirer's CAR [-5d, +5d]	
Industry HFA Freq × D[No Activism]	-0.0240		-0.0137		0.0299		0.0659*	
	(0.0254)		(0.0329)		(0.0290)		(0.0396)	
Industry HFA Freq × D[Activism on Seller]	0.116*		0.142*		-0.0540		0.00288	
	(0.0652)		(0.0762)		(0.0505)		(0.0583)	
Industry HFStake Freq × D[No Activism]		0.0370		0.0758**		0.0352		0.0644**
		(0.0286)		(0.0354)		(0.0218)		(0.0263)
Industry HFStake Freq × D[Activism on Seller]		0.0573		0.0455		-0.0426		0.0371
		(0.0570)		(0.0648)		(0.0488)		(0.0580)
Transaction-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2845	2845	2845	2845	2168	2168	2173	2173
adj. R^2	0.000	0.000	0.019	0.020	0.076	0.077	0.048	0.048

Table 12: Past acquisition behavior, HFA target probability, and target characteristics

Panel A and B of this table show the relation among activism threat, past acquisition behaviors and HFA target probability. We run OLS regressions with the triple interaction (Industry HFA threat measure × NumAcq × firm size dummy) for our firm-year sample. All double interactions are included but, for simplicity, only the interaction NumAcq × firm size reported. NumAcq is defined as the number of acquisitions completed by firm i in the past three years. Panel A measures Industry HFA threat with Industry HFA Freq; and Panel B uses Industry HFStake instead. Panel C and D investigate acquirer and target characteristics in acquisitions by small acquirers. Regressions are at the transaction level; for these regressions, we require both acquirer and target to be publicly listed firms with non-missing information on Tobin's Q and ROA. All characteristics are measured one year before the bidding year. NumPats, NumCites, and PatValue denote, respectively, the number of patents, number of citations, and Kogan, et. al. (2017)'s estimated patent value (in nominal dollars). Patent data are from Kogan, et. al. (2017). Standard errors are clustered at the firm level.

Panel A: Measuring industry HFA threat by Industry HFA Freq

Explanatory Var. NumAcq (past 3 years) includes	(1) OLS D(HFA) All acquisitions	(2) OLS D(HFA) Private acquisitions
Industry HFA Freq × NumAcq × D(Large)	0.0753***	0.128***
	(0.0275)	(0.0369)
Industry HFA Freq × NumAcq × D(Small)	0.0225	0.0910
	(0.0544)	(0.0713)
NumAcq × D(Large)	-0.00421*	-0.00287
	(0.00238)	(0.00327)
NumAcq × D(Small)	-0.000172	-0.00419
	(0.00439)	(0.00568)
Year F.E.	Yes	Yes
Industry F.E.	Yes	Yes
Num. Obs.	61187	61187
Adj. R^2	0.023	0.023

Panel B: Measuring industry HFA threat by Industry HFStake Freq

Explanatory Var. NumAcq (past 3 years) includes	(1) OLS D(HFA) All acquisitions	(2) OLS D(HFA) Private acquisitions
Industry HFStake Freq × NumAcq × D(Large)	0.0420***	0.0589***
	(0.0161)	(0.0223)
Industry HFStake Freq × NumAcq × D(Small)	0.00219	0.0199
	(0.0324)	(0.0417)
NumAcq × D(Large)	-0.00575**	-0.00425
	(0.00286)	(0.00407)
NumAcq × D(Small)	0.000183	-0.00268
	(0.00535)	(0.00698)
Year F.E.	Yes	Yes
Industry F.E.	Yes	Yes
Num. Obs.	61187	61187
Adj. R^2	0.027	0.027

Panel C: Quality difference between target and acquirer, by acquirer size (large or small)

Target's − Acquirer's:	(1) Tobin's Q	(2) ROA	(3) NumPats	(4) NumCites	(5) PatValue
D(Small)	0.292***	0.0289**	0.414***	1.344***	1.753***
	(0.104)	(0.0137)	(0.0372)	(0.103)	(0.108)
Year F.E.	Yes	Yes	Yes	Yes	Yes
Acquirer Industry F.E.	Yes	Yes	Yes	Yes	Yes
Target Industry F.E.	Yes	Yes	Yes	Yes	Yes
Num. Obs.	1644	1601	1782	1782	1782
Adj. R^2	0.096	0.137	0.407	0.450	0.518

Panel D: Quality difference between target and acquirer under high HFA threat, by acquirer size (large or small)

Target's − Acquirer's:	(1) Tobin's Q	(2) ROA	(3) NumPats	(4) NumCites	(5) PatValue
Industry HFA Freq × D(Large)	1.304	0.243	3.549***	7.211***	9.715***
	(1.200)	(0.154)	(0.424)	(1.199)	(1.236)
Industry HFA Freq × D(Small)	-0.437	0.0772	1.475***	3.031**	4.105***
	(1.462)	(0.187)	(0.515)	(1.454)	(1.499)
D(Small)	0.378***	0.0363**	0.522***	1.591***	1.992***
	(0.134)	(0.0177)	(0.0499)	(0.141)	(0.145)
Year F.E.	Yes	Yes	Yes	Yes	Yes
Acquirer Industry F.E.	Yes	Yes	Yes	Yes	Yes
Target Industry F.E.	Yes	Yes	Yes	Yes	Yes
Num. Obs.	1644	1601	1782	1782	1782
Adj. R^2	0.096	0.137	0.407	0.450	0.518

Table 13: HFA impact on the efficiency of divestitures

This table studies the ex-post operating performance of sellers in divestitures. We include observations from 5 years prior to 5 years after each divestiture. Panel A studies the performance of sellers in activism divestitures. D[Activism Divestiture] is a dummy variable equal to one if the divestiture is an activism divestiture, defined as a divestiture in which the seller was targeted by activist hedge funds in the 2 years (730 days) prior to the divestiture announcement. D[Post Divestiture] is a dummy variable equal to one if the firm is within $[t+1, t+5]$ years after the divestiture announcement. D[Post HFA] is a dummy variable equal to one in the post $[t+1, t+5]$ HFA event period. Panel B investigates the ex-post operating performance of sellers under high industry HFA threat. In Panel B, we drop all activism divestitures from the sample. We use Industry HFA Freq as our measure of industry HFA threat. D[High HFA Threat] is a dummy equal to one if the firm is in the top quintile of Industry HFA Freq in the year when the divestiture is announced and is not a current activism target. Following Bebchuk, Brav, and Jiang (2015), we include ln(MV) and ln(Age) as controls in each regression. Year fixed effects and firm fixed effects are always included. Standard errors are clustered at the firm level (standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Efficiency of divestitures by HFA target firms

	(1) Tobin's Q	(2) ROA	(3) Sales/Assets(lag)
D[Post Divestiture]	0.0629***	-0.00271	-0.00664
	(0.0186)	(0.00237)	(0.00915)
D[Post Divestiture] × D[Activism Divestiture]	0.147***	0.0131**	0.0430
	(0.0561)	(0.00631)	(0.0292)
D[Post HFA]	0.0933***	-0.00517	-0.00953
	(0.0344)	(0.00446)	(0.0163)
Firm-level controls	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
N	24121	22816	24589
adj. R^2	0.562	0.632	0.813

Panel B: Efficiency of divestiture by firms under high HFA threat

	(1) Tobin's Q	(2) ROA	(3) Sales/Assets(lag)
D[Post Divestiture]	0.0621***	-0.00162	-0.00149
	(0.0202)	(0.00257)	(0.0102)
D[Post Divestiture] × D[High HFA Threat]	0.0242	-0.00350	-0.0152
	(0.0295)	(0.00368)	(0.0161)
D[Post HFA]	0.151***	-0.00102	0.0121
	(0.0360)	(0.00457)	(0.0173)
Firm-level controls	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
N	22839	21537	23261
adj. R^2	0.562	0.636	0.817

Table 14: HFA impact on the efficiency of acquisitions

This table studies the ex-post operating performance of acquirers in acquisitions of public and private firms and subsidiaries of public firms. We require all acquisitions to be completed. We include observations from 5 years prior to and 5 years post each completed acquisition. Panel A studies the performance of acquirers in activism acquisitions. D[Activism Acq] is a dummy variable equal to one if it is an activism acquisition, defined as an acquisition in which the acquirer was targeted by activists in the 2 years (730 days) prior to the acquisition announcement. D[Post Acquisition] is a dummy variable equal to one if the firm is within $[t+1, t+5]$ years after the acquisition announcement. D[Post HFA] is a dummy variable equal to one in the post $[t+1, t+5]$ HFA event period. Panel B investigates the ex-post operating performance of acquirers under high industry HFA threat. In Panel B, we drop all activism acquisitions from the sample. We use Industry HFA Freq as our measure of the industry HFA threat. D[High HFA Threat] is a dummy equal to one if the firm is in the top quintile of Industry HFA Freq in the year when the acquisition is announced and is not a current activism target. D[Small] is a dummy equal to one if the firm's size is smaller than the industry-year median size of firms in the year before the announcement of acquisition. Following Bebchuk, Brav, and Jiang (2015), we include ln(MV) and ln(Age) as controls in each regression. Year fixed effects and firm fixed effects are always included. Standard errors are clustered at the firm level (standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Efficiency of acquisitions by HFA target firms

	(1) Tobin's Q	(2) ROA	(3) Sales/Assets(lag)
D[Post Acquisition]	-0.330***	-0.0138***	-0.109***
	(0.0213)	(0.00205)	(0.00834)
D[Post Acquisition] × D[Small]	0.238***	0.0162***	0.0583***
	(0.0271)	(0.00308)	(0.0124)
D[Post Acquisition] × D[Activism Acq]	-0.0671	-0.00576	-0.0159
	(0.0620)	(0.00615)	(0.0222)
D[Post Acquisition] × D[Activism Acq] × D[Small]	0.0257	0.0252**	0.0935**
	(0.118)	(0.0126)	(0.0380)
D[Post HFA]	0.136***	0.000345	0.0187
	(0.0283)	(0.00337)	(0.0136)
Firm-level controls	Yes	Yes	Yes
Year and Firm fixed effect	Yes	Yes	Yes
N	50335	47484	50087
adj. R^2	0.553	0.621	0.800

Panel B: Efficiency of acquisitions by firms under high HFA threat

	(1) Tobin's Q	(2) ROA	(3) Sales/Assets(lag)
D[Post Acquisition]	-0.185***	-0.0170***	-0.0931***
	(0.0331)	(0.00326)	(0.0125)
D[Post Acquisition] × D[Small]	0.195***	0.0125**	0.0401*
	(0.0597)	(0.00635)	(0.0235)
D[Post Acquisition] × D[High HFA Threat]	0.000568	-0.000647	-0.0115
	(0.0518)	(0.00494)	(0.0214)
D[Post Acquisition] × D[High HFA Threat] × D[Small]	-0.0133	0.0133	0.0962
	(0.114)	(0.0142)	(0.0600)
D[Post HFA]	0.0566	-0.00698	-0.0345*
	(0.0507)	(0.00590)	(0.0190)
Firm-level controls	Yes	Yes	Yes
Year and Firm fixed effect	Yes	Yes	Yes
N	49293	46525	49110
adj. R^2	0.556	0.620	0.800

Online Appendix for
Activism Pressure and Market for Corporate Assets

Ulrich Hege and Yifei Zhang

Content

Table IA.1: Industries with most frequent industry HFA clusters

This table lists all industries (3-digit SIC code) with industry HFA clusters occurring in 25% of all years or more. An industry HFA cluster is defined as an industry-year where the fraction of firms targeted within years (t-2, t-1, or t is in the top quintile of the industry-year sample (i.e., D(Industry HFA Freq P80) = 1) and with at least 2 activist campaigns. Frequency in % is calculated as the fraction of years in the whole sample of Compustat.

Industry (SIC-3)	Industry description	Frequency in % years
531	Retail-department stores	40%
701	Hotels & motels	40%
200	Food and kindred products	35%
271	Newspapers: publishing or publishing & printing	35%
731	Services-advertising	35%
784	Services-video tape rental	35%
100	Metal mining	30%
750	Services-automotive repair, services & parking	40%
122	Bituminous coal & lignite mining	25%
282	Plastic material, synth resin/rubber, cellulos (no glass)	25%
386	Photographic equipment & supplies	25%
596	Retail-nonstore retailers	25%
655	Land subdividers & developers (no cemeteries)	25%
720	Services-personal services	25%
808	Services-home health care services	25%

Table IA.2: Summary statistics of corporate transactions by year

This table reports descriptive statistics of corporate transaction activities by calendar year. Definitions of all variables and the structure follow that of Table 3. Table 3 reports cumulative values for five-year periods and this table reports annual data by calendar year.

Panel A: Activism campaigns and merger bids

Calendar year	(1) Number of merger bids	(2) % of firms with merger bids	(3) Number of activism merger	(4) % of firms with merger bids among HFA targets	(5) Number of merger bids under high HFA threat	(6) % of firms with mergers under high HFA threat	(7) % of firms with mergers under low HFA threat
1994	91	1.47%	0	0.00%	11	1.11%	1.55%
1995	287	4.37%	0	0.00%	96	4.53%	4.02%
1996	307	4.36%	8	10.13%	96	4.41%	4.65%
1997	426	5.97%	18	9.68%	130	5.57%	5.59%
1998	502	7.44%	27	10.98%	119	6.23%	7.63%
1999	536	8.16%	22	10.05%	164	8.00%	8.15%
2000	438	6.96%	16	10.00%	132	6.84%	7.23%
2001	306	5.54%	21	14.89%	80	4.90%	4.07%
2002	199	3.95%	17	11.26%	86	5.46%	2.68%
2003	219	4.59%	18	9.63%	84	5.56%	3.52%
2004	195	3.75%	13	6.74%	61	4.32%	2.70%
2005	273	5.29%	29	11.93%	106	6.48%	4.26%
2006	336	6.58%	49	13.07%	105	6.42%	6.15%
2007	337	6.75%	65	15.55%	93	5.98%	5.51%
2008	227	4.91%	59	12.63%	70	4.23%	2.53%
2009	191	4.37%	32	8.44%	66	5.41%	2.18%
2010	226	5.28%	22	8.80%	71	6.39%	3.85%
2011	185	4.49%	33	14.80%	52	4.19%	4.07%
2012	195	4.80%	37	12.63%	71	5.68%	3.15%
2013	170	4.14%	30	9.68%	54	4.18%	3.10%
2014	167	3.93%	37	11.28%	47	3.40%	2.82%
2015	216	5.11%	44	12.19%	76	5.54%	4.10%
2016	204	4.97%	35	10.09%	72	5.78%	4.69%
Total	6,233	5.17%	632	10.19%	1,942	5.38%	4.34%

Panel B: Activism campaigns and divestitures

Calendar year	(1) Number of divestiture	(2) % of firms with divestiture	(3) Number of activism divestiture	(4) % of firms with divesti- -ture among HFA targets	(5) Number of divestiture under high HFA threat	(6) % of firms with divestiture under high HFA threat	(7) % of firms with divestiture under low HFA threat
1994	287	3.63%	0	0.00%	24	0.00%	3.68%
1995	325	4.16%	3	10.53%	69	5.88%	4.25%
1996	406	4.54%	7	7.04%	116	7.17%	4.03%
1997	444	4.91%	13	5.81%	96	5.14%	5.13%
1998	477	5.48%	16	7.05%	97	5.58%	5.94%
1999	455	5.62%	17	7.31%	77	5.07%	6.47%
2000	418	5.60%	10	4.03%	107	7.04%	5.52%
2001	312	4.78%	11	8.53%	94	6.81%	4.14%
2002	322	4.89%	9	4.79%	100	9.21%	4.17%
2003	352	5.31%	21	7.78%	70	5.21%	6.13%
2004	365	5.27%	22	7.57%	88	7.36%	5.14%
2005	413	6.21%	35	10.53%	93	5.48%	6.74%
2006	391	6.12%	50	9.22%	95	5.41%	3.84%
2007	382	6.20%	44	8.38%	82	5.28%	6.78%
2008	261	5.08%	44	7.57%	53	4.46%	5.80%
2009	250	4.70%	26	5.66%	49	4.18%	4.31%
2010	251	4.85%	21	6.75%	58	4.62%	5.95%
2011	252	4.95%	21	8.13%	44	3.64%	5.23%
2012	286	5.66%	25	7.30%	57	5.39%	5.50%
2013	315	6.17%	36	8.42%	70	5.27%	6.89%
2014	321	5.92%	60	12.58%	62	4.90%	6.25%
2015	282	4.97%	33	6.82%	68	5.19%	5.43%
2016	285	5.46%	50	8.33%	60	6.75%	4.43%
Total	7,852	5.19%	574	7.81%	1,729	5.32%	4.77%

Panel C: Activism campaigns and all acquisitions

Calendar year	(1) Number of acquisitions	(2) % of firms with acquisitions	(3) Number of activism acquisitions	(4) % of firms with acquisi- -tions among HFA targets	(5) Number of acquisitions under high HFA threat	(6) % of firms with acquisitions under high HFA threat	(7) % of firms with acquisitions under low HFA threat
1994	933	10.64%	0	0.00%	93	9.36%	10.89%
1995	1,103	12.43%	4	10.53%	226	10.99%	13.29%
1996	1,483	14.16%	29	14.49%	324	15.31%	15.60%
1997	1,910	16.66%	64	17.83%	311	14.40%	17.50%
1998	2,009	19.28%	78	21.33%	293	16.18%	19.24%
1999	1,631	17.68%	45	17.21%	261	15.15%	17.76%
2000	1,431	16.54%	22	11.84%	229	13.34%	15.95%
2001	937	13.29%	8	5.60%	183	11.67%	13.97%
2002	857	13.15%	15	8.22%	243	15.40%	12.55%
2003	892	14.50%	22	10.17%	213	14.85%	15.29%
2004	1,046	15.34%	25	10.50%	171	13.91%	17.27%
2005	1,237	17.04%	47	15.58%	270	17.52%	18.45%
2006	1,175	17.31%	52	11.61%	274	18.38%	20.06%
2007	1,089	16.62%	61	12.37%	245	18.15%	19.53%
2008	739	13.24%	40	8.43%	143	12.73%	14.03%
2009	494	9.81%	35	8.20%	117	9.06%	9.12%
2010	783	13.82%	26	6.87%	171	14.60%	15.26%
2011	840	15.87%	37	13.94%	218	17.08%	17.03%
2012	890	16.17%	30	8.12%	176	15.52%	19.13%
2013	846	14.77%	31	8.75%	169	14.32%	18.70%
2014	962	17.34%	50	13.46%	214	17.14%	22.29%
2015	864	15.94%	70	16.36%	187	15.25%	14.46%
2016	731	13.81%	47	11.35%	138	12.09%	15.84%
Total	24,882	15.06%	838	11.82%	4,869	14.51%	15.72%

Panel D: Activism campaigns and acquisitions of private targets

Calendar year	(1) Number of private acquisitions	(2) % of firms with private acquisitions	(3) Number of activism private acquisitions	(4) % of firms with private acquisitions among HFA targets	(5) Number of private acquisitions under high HFA threat	(6) % of firms with private acquisitions under high HFA threat	(7) % of firms with private acquisitions under low HFA threat
1994	369	4.70%	0	0.00%	36	3.62%	4.91%
1995	425	5.51%	3	5.26%	95	4.62%	5.62%
1996	668	7.47%	20	5.80%	184	8.70%	7.16%
1997	913	9.20%	40	8.28%	169	7.82%	9.78%
1998	981	10.10%	50	8.00%	141	7.79%	9.91%
1999	746	9.33%	27	6.51%	127	7.37%	9.29%
2000	681	8.87%	15	3.29%	112	6.52%	7.40%
2001	359	5.99%	7	0.80%	87	5.55%	5.47%
2002	339	5.82%	10	2.74%	110	7.00%	5.52%
2003	354	6.69%	17	2.26%	107	7.60%	6.09%
2004	490	7.99%	17	3.87%	86	7.00%	8.61%
2005	612	9.32%	22	10.39%	139	9.10%	10.77%
2006	593	9.66%	31	5.65%	163	10.86%	11.06%
2007	540	9.23%	31	6.58%	146	10.81%	10.18%
2008	349	6.82%	14	5.62%	74	6.59%	6.76%
2009	197	4.26%	19	4.10%	51	3.97%	3.49%
2010	364	7.15%	18	2.15%	96	8.20%	7.98%
2011	394	8.27%	20	6.25%	130	9.75%	8.85%
2012	426	8.38%	12	4.80%	104	9.17%	9.64%
2013	389	7.60%	18	4.04%	78	5.86%	10.26%
2014	499	9.37%	23	7.05%	116	9.63%	12.32%
2015	400	7.82%	40	6.97%	93	7.85%	7.23%
2016	309	6.37%	27	5.83%	67	6.19%	6.04%
Total	11,397	7.68%	481	5.49%	2,511	7.50%	7.71%

Table IA.3: Robustness checks for Table 4 and Table 6

This table reports robustness checks for our finding that firms' acquisition behavior under HFA pressure differs according to firm size (Table 4 for HFA target and Table 6 for firms under HFA threats). Instead of a median split as in Table 4 and Table 6, we sort firms into firm size terciles in this table. Definitions of all variables follow the corresponding tables (Table 4 and Table 6) in the paper.

Panel A: Replicate Table 4 – Panel C

Explained Var.	(1) LOGIT Acquisition	(2) LOGIT Acquire Private firms
D[Activist] × D[Large]	-0.296***	-0.395***
	(0.0949)	(0.142)
D[Activist] × D[Medium]	-0.129	-0.206*
	(0.0907)	(0.123)
D[Activist] × D[Small]	0.0147	-0.287
	(0.121)	(0.185)
Firm-level controls	Yes	Yes
Industry and Year fixed effect	Yes	Yes
N	66346	66069
pseudo R^2	0.125	0.104

Panel B: Replicate Table 6 – Panel A

Explained Var.	(1) OLS Acquisition	(2) OLS Acquire Private firms
Industry HFA Freq × D[Large]	-0.112***	-0.0675**
	(0.0385)	(0.0265)
Industry HFA Freq × D[Medium]	0.0493	0.0540*
	(0.0380)	(0.0295)
Industry HFA Freq × D[Small]	0.139***	0.0791***
	(0.0322)	(0.0233)
Firm-level controls	Yes	Yes
Industry and Year fixed effect	Yes	Yes
N	56512	56512
adj. R^2	0.075	0.041

Panel C: Replicate Table 6 – Panel B

Explained Var.	(1) OLS Acquisition	(2) OLS Acquire Private firms
Industry HFStake Freq × D[Large]	-0.0805***	-0.0434**
	(0.0282)	(0.0193)
Industry HFStake Freq × D[Medium]	0.0346	0.00872
	(0.0275)	(0.0207)
Industry HFStake Freq × D[Small]	0.0950***	0.0421**
	(0.0244)	(0.0184)
Firm-level controls	Yes	Yes
Industry and Year fixed effect	Yes	Yes
N	56512	56512
adj. R^2	0.076	0.041

Panel D: Replicate Table 6 – Panel C

Explained Var.	(1) OLS Acquisition	(2) OLS Acquire Private firms
FIFB × D[Large]	-0.0550***	-0.0166*
	(0.0135)	(0.00993)
FIFB × D[Medium]	0.0118	0.00183
	(0.0119)	(0.00892)
FIFB × D[Small]	0.0244**	0.00755
	(0.00951)	(0.00705)
Firm-level controls	Yes	Yes
Industry and Year fixed effect	Yes	Yes
N	54988	54988
adj. R^2	0.076	0.041

Table IA.4: Robustness checks for Table 12

This table reports robustness checks for Table 12. In the triple interaction, we sort firms into terciles by firm size instead of performing a median split in as Table 12. All double interactions are included but, for simplicity, not reported in the table. Definitions of all variables follow Table 12 in the paper.

Panel A: Replicate Table 12 – Panel A

	(1)	(2)
	OLS	OLS
Explained var.	D(HFA)	D(HFA)
NumAcq (past 3 years) includes	All acquisitions	Private acquisitions
Industry HFA Freq × NumAcq × D(Large)	0.128***	0.219***
	(0.0421)	(0.0531)
Industry HFA Freq × NumAcq × D(Medium)	0.0416	0.0739
	(0.0324)	(0.0450)
Industry HFA Freq × NumAcq × D(Small)	-0.0312	-0.0500
	(0.0793)	(0.105)
Industry and Year fixed effect	Yes	Yes
Num. Obs.	61187	61187
Adj. R^2	0.027	0.027

Panel B: Replicate Table 12 – Panel B

	(1)	(2)
	OLS	OLS
Explained var.	D(HFA)	D(HFA)
NumAcq (past 3 years) includes	All acquisitions	Private acquisitions
Industry HFStake Freq × NumAcq × D(Large)	0.104***	0.132***
	(0.0187)	(0.0266)
Industry HFStake Freq × NumAcq × D(Medium)	0.00940	0.0179
	(0.0260)	(0.0330)
Industry HFStake Freq × NumAcq × D(Small)	-0.0697	-0.102*
	(0.0489)	(0.0609)
Industry and Year fixed effect	Yes	Yes
Num. Obs.	61187	61187
Adj. R^2	0.027	0.027

Table IA.5: Robustness checks for Table 13 and Table 14

This table reports robustness checks for our findings in Table 13 and Table 14 of the paper. In this table, we use a different definition of D[High HFA Threat]. D[High HFA Threat] is a dummy equal to one if the industry is in the top tercile (instead of top quintile in Table 13 and 14) of Industry HFA Freq in the year when the acquisition is announced and if the firm (seller of an asset in Panel A, buyer in Panel B) is not currently an activism target. The rest of the regression setup follows Table 13 and 14, respectively.

Panel A: Replicate Table 13 – Panel B

	(1) Tobin's Q	(2) ROA	(3) Sales/Assets(lag)
D[Post Divestiture]	0.0630***	-0.00179	0.00199
	(0.0204)	(0.00268)	(0.0105)
D[Post Divestiture] × D[High HFA Threat]	0.0116	-0.00154	-0.0212
	(0.0260)	(0.00320)	(0.0133)
D[Post HFA]	0.151***	-0.00109	0.0127
	(0.0359)	(0.00458)	(0.0173)
Firm-level controls	Yes	Yes	Yes
Year and Firm fixed effect	Yes	Yes	Yes
N	22839	21537	23261
adj. R^2	0.562	0.636	0.817

Panel B: Replicate Table 14 – Panel B

	(1) Tobin's Q	(2) ROA	(3) Sales/Assets(lag)
D[Post Acquisition]	-0.317***	-0.0115***	-0.0971***
	(0.0229)	(0.00218)	(0.00880)
D[Post Acquisition] × D[Small]	0.218***	0.0126***	0.0457***
	(0.0309)	(0.00356)	(0.0141)
D[Post Acquisition] × D[High HFA Threat]	-0.0293	-0.00606**	-0.0356***
	(0.0267)	(0.00258)	(0.0104)
D[Post Acquisition] × D[High HFA Threat] × D[Small]	0.0359	0.0122**	0.0352
	(0.0448)	(0.00499)	(0.0232)
D[Post HFA]	0.123***	0.000801	0.0181
	(0.0288)	(0.00312)	(0.0133)
Firm-level controls	Yes	Yes	Yes
Year and Firm fixed effect	Yes	Yes	Yes
N	49293	46525	49110
adj. R^2	0.556	0.620	0.800

Table IA.6: Campaign goals, firm characteristics, and industry HFA clustering

This table reports HFA campaign goals and their relationship with firm characteristics and industry HFA clustering. Panel A reports descriptive statistics for 5 different goals. Information about campaign goals is from Factset SharkWatch database. In Panel A, the aggregate number of stated campaign goals exceeds the number of campaigns with stated goals since campaigns announce multiple goals quite frequently. Panel B reports logit regressions for each of these HFA campaign goals separately. The regressions are based on our sample of 3,551 HFA campaigns. The dependent variable is a dummy equal to one if activists pursue the indicated goal (such as Board Seat) in the campaign and 0 if not. Panel C repeats the same regressions but includes a dummy for industry HFA clusters in the previous logit regressions, either by looking at industry-years in the top quintile by Industry HFA Frequency and with at least two campaigns (D(Industry HFA Cluster P80) = 1) or at industry-years in the top decile by Industry HFA Frequency and with at least two campaigns (D(Industry HFA Cluster P80) = 1). Panel D conducts logit regressions of corporate transactions with our main firm-year sample and includes the two industry HFA cluster dummies sequentially.

Panel A: Goals classification

Goals Classification	Details	Num. Campaigns
Seek Sale	Activists urge firms to seek sale or directly buyout the company	501
Restructure	Activists push firms for divesting assets, spinning off or blocking new acquisitions	226
Board Seat	Activists try to seek board seats for themselves or add new independent directors	883
Payout	Activists demand share repurchase, increasing dividends payment and other capital structure related goals	376
Governance	Remove CEO, CEO compensation related, remove anti-takeover defense, and other governance related goals	413
No specific goals	No specific goals in 13D fillings and media source	2,200
Total Campaigns		3,551

Panel B: Campaign goals and firm characteristics

	(1) Board Seat	(2) Governance	(3) Payout	(4) Seek Sale	(5) Restructure
Institutional Ownership	0.498**	0.237	0.108	0.401	0.00834
	(0.243)	(0.302)	(0.350)	(0.283)	(0.393)
Tobin's Q	-0.214***	-0.120	-0.165	-0.0761	-0.304**
	(0.0743)	(0.0938)	(0.110)	(0.0911)	(0.136)
ln(MV)	-0.0362	-0.0109	0.0732	-0.0984**	0.353***
	(0.0411)	(0.0519)	(0.0534)	(0.0468)	(0.0571)
Book Leverage	-0.402**	-0.00483	0.282	-0.00603	-0.0489
	(0.195)	(0.253)	(0.271)	(0.231)	(0.320)
Dividend Yield	1.428	-3.198	-0.746	1.434	-3.058
	(2.394)	(3.528)	(4.286)	(3.429)	(4.435)
Cash Flow	1.058**	0.857	1.451*	1.631***	0.564
	(0.443)	(0.612)	(0.743)	(0.504)	(0.988)

	(1)	(2)	(3)	(4)	(5)
Sales Growth	-0.369*	-0.200	0.00170	-0.0137	0.205
	(0.191)	(0.264)	(0.285)	(0.237)	(0.360)
Asset Growth	-0.0841	0.235	-0.573	-0.312	-0.0534
	(0.202)	(0.246)	(0.350)	(0.255)	(0.364)
R&D	1.937**	-0.988	-1.894	1.215	1.975
	(0.800)	(1.185)	(1.460)	(0.965)	(1.318)
HHI	-0.0494	-0.102	0.168	-0.662*	-0.392
	(0.289)	(0.359)	(0.390)	(0.396)	(0.501)
Excess Cash	-0.0882	0.637	1.581***	0.108	-0.387
	(0.325)	(0.405)	(0.451)	(0.378)	(0.623)
CAR [12 Months]	-0.168	-0.00207	0.0796	-0.0242	-0.409*
	(0.115)	(0.142)	(0.159)	(0.120)	(0.219)
Industry and Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
N	2325	2010	2061	2415	2051
pseudo R^2	0.133	0.058	0.080	0.084	0.111

Panel C: Campaign goals and Industry HFA Clustering

Dependent Var.	(1) Seek Sale	(2) Restr.	(3) Sale/ Restr.	(4) Seek Sale	(5) Restr.	(6) Sale/ Restr.
D(Industry HFA Cluster P80)	0.148	-0.0756	0.125			
	(0.126)	(0.169)	(0.116)			
D(Industry HFA Cluster P90)				0.0669	-0.396*	-0.0455
				(0.162)	(0.234)	(0.152)
Firm-level Controls Included	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	2427	2062	2427	2427	2062	2427
pseudo R^2	0.085	0.112	0.103	0.085	0.112	0.103

Panel D: Corporate transactions and Industry HFA Clustering

Dependent Var.	(1) Merger	(2) Divestiture	(3) Sale	(4) Merger	(5) Divestiture	(6) Sale
D(Industry HFA Cluster P80) × D(Activist)	-0.240**	-0.335**	-0.221**			
	(0.116)	(0.147)	(0.0978)			
D(Industry HFA Cluster P90) × D(Activist)				-0.477**	-0.420**	-0.416***
				(0.191)	(0.204)	(0.152)
D(Activist)	0.795***	0.507***	0.682***	0.761***	0.451***	0.658***
	(0.0660)	(0.0887)	(0.0573)	(0.0570)	(0.0772)	(0.0493)
Firm-level Controls Included	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	71879	68772	72357	71879	68772	72357
pseudo R^2	0.052	0.173	0.072	0.052	0.173	0.072