

Activism Pressure and the Market for Corporate Assets

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Yifei Zhang Toulouse School of Economics

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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 increase divestitures and receive more merger bids. On balance, they also make fewer acquisitions, but this effect is entirely due to large firms. Activism targets and firms under hedge fund threats contribute about equally to the overall effect. We estimate that the increase in sales and reduction in purchases of assets reduces real asset liquidity by about 35% for asset sellers in industries with strong activist activity. The liquidity squeeze produces two effects: industry outsiders provide liquidity by purchasing more industry assets, and transaction prices are reduced. We find that activism positively affects the efficiency of divestitures and of acquisitions by small acquirers when firms are activism targets, but not when they act under activism threat.

Keywords: hedge fund activism, activism threat, divestitures, mergers, acquisitions, small acquirers, real asset liquidity, price pressure, acquisition efficiency

JEL Classifications: G23, G34

Ulrich Hege*

Professor Toulouse School of Economics, Research Faculty 21 allée de Brienne 31015 Toulouse Cedex 6, France phone: +33 561 128 601 e-mail: ulrich.hege@tse-fr.eu

Yifei Zhang

Researcher Toulouse School of Economics 21 All'ee de Brienne 31015 Toulouse Cedex 6, France e-mail: yifei.zhang@tse-fr.eu

*Corresponding Author

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Ulrich Hege[†] and Yifei Zhang[‡]

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ABSTRACT

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^{*}The authors are grateful to Alon Brav, Wei Jiang and Song Ma for sharing data and discussions. We alone are responsible for any errors.

[†]Toulouse School of Economics, University of Toulouse-Capitole, ulrich.hege@tse-fr.eu. Hege acknowledges funding from the European Research Council, ERC FP7 grant No. 312503-SolSys. Correspondence to Ulrich Hege, TSE, 21 allée de Brienne, 31015 Toulouse Cedex 6, phone: +33-5-6112-8601.

[‡]Toulouse School of Economics, University of Toulouse-Capitole, yifei.zhang@tse-fr.eu. Zhang thanks HEC Paris for its hospitality during his visit when this project was started.

1 Introduction

The rise of shareholder activism in the last two decades has spurred academics to analyze various aspects of activism, such as gains in value and economic performance following campaigns. But many of the real effects of activism campaigns remain largely unexplored, including effects on other firms, stakeholders, and markets.

This paper explores the impact of hedge fund activism on markets for corporate transactions. A small literature has analyzed the impact of activism on target firms' decisions to acquire and sell assets. Our paper extends the analysis beyond activism targets to firms that are not yet targeted by activists but indirectly exposed to activism threats, and looks at the impact on the supply and demand for corporate assets. We explore the effects of activism pressure on corporate asset markets by studying its impact on transaction volumes, real asset liquidity, transaction prices, and economic efficiency gains.

We try to answer the following questions: Does activism affect the acquisition and asset sale decisions of firms that are only indirectly affected by activists? Has activism grown sufficiently in importance that it influences the equilibrium in corporate asset markets, and what is its impact on the liquidity and efficiency of these markets? Our focus on the market externalities of activism is in contrast to most of the literature on shareholder activism that has mostly limited its investigation to effects on target firms. There is little literature on peer effects and spillovers beyond target firms. No earlier study has tried to estimate the effect of activism threats on acquisition behavior of firms, or the effect of activism on the equilibrium outcome in asset markets.

Our paper takes into account a wide range of corporate transactions: takeovers and mergers, divestitures, and acquisitions, including acquisitions of private targets. Confirming and extending earlier studies, we find that firms directly targeted in activist campaigns are more likely to receive merger bids, make more divestitures, and make fewer acquisitions. We show that the reduction in acquisition activity is due to larger firms, whereas smaller firms' frequency of making acquisitions shows no significant change.

We then consider firms' exposure to activism threats as a second channel of activism pressure and study its impact on firms' behavior in corporate asset markets. We first consider the threat impact for firms individually, by estimating their probability of becoming an activism target in the near future. However, since we want to study the effect of activism pressure on entire asset markets, our principal measures of the impact of activism threat are aggregated at the industry level (3-digit SIC codes). We use the frequency of recent activist campaigns in the industry as our main measure of changes in activism threats. We also use the jumps in activists hedge 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 following 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 fundactivist 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 and thus assuming that all firms in an industry face the same threat level, 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 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

Having established that activism pressure affects the behavior of both target firms as well as of firms under activism threat, we try to find out which of these two channels is more important for corporate transaction markets. 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 about 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% less 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.

¹The same instrument has been used in the previous studies looking at threat effects of hedge fund activism, Gantchev, Gredil, and Jotikasthira (2017), Feng, Xu, and Zhu (2017).

²The 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.

Indeed, we find that outside acquirers - private equity funds, private firms, and listed firms in other industries - 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 prize effect for activist target firms – thus, unlike other firms in industries under heavy activist pressure, activist target firms themselves are not affected.

Finally, we consider whether activism pressure improves the efficiency of corporate transactions, in the sense of transactions creating more long-run value. We look at accounting measures and Tobin's Q as a stock-based measure of long-run performance. We control for the documented impact of activism campaigns and of corporate transactions on long-run performance, and isolate the incremental effect of transactions done under activism influence. 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 findings on the effect of activism threats on firms' behavior in the market for corporate assets. Our paper also contributes to the analysis of strategic interactions between firms exposed to activism and rival firms. Aslan and Kumar (2016) show that following an activist campaign, rival firms of the campaign target lose market share and have reduced profitability, akin to competition in strategic substitutes. We find that rival firms adopt behavioral changes similar to those of that of activism targets, and that the overall impact on targets and rivals is sufficiently profound so as to affect the liquidity and valuation in real asset markets. A final contribution of the paper is to the literature on firm size and acquirer performance (see Moeller, Schlingemann, and Stulz (2004)); we show that activism further accentuates the difference in long-run acquisition performance between large and small acquirers. We also show that there is sharp distinction in acquisition activity, with small firms making more and large firms less acquisition under activism threats.

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, 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 a number of aspects to the analysis of real effects of activism, for example 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 firm seem to be able to 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.

³See 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)).

⁴There 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.

2 Literature and Hypotheses

There are theoretical and empirical papers supporting the view that hedge fund activism affects firms' decision-making in the market for corporate assets. 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 long-run performance.

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 that stipulates that takeover threats influence the decisions of companies that are not takeover targets (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 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 would lead firms under activism threat to adopt behavior similar to that of campaign targets. Firms might also simply mimic the behavior of closely watched rivals that are activist targets. Alternatively, they might react because of strategic interaction effects with activist targets in product or asset markets. Strategic interaction effects between activism targets and rivals, however, do not yield a clear prediction concerning the direction of rivals' adjustments; the optimal strategic response of rivals may have the opposite sign of the behavioral adjustment of activism targets, consistent with competition in strategic substitutes. Indeed, Aslan and Kumar (2016) study product market interactions of activism and find that activism targets increase their market share and profitability whereas product market rivals suffer reductions in market share and mark-ups. If rivals' reaction is in strategic substitutes, the strategic interaction effect would dampen rather than reinforce the impact of activism on corporate asset markets that we study.⁵ Throughout, we remain agnostic about the exact motives that lead to the behavioral change on acquisition markets.

The decrease in asset purchases and the increase in asset sales in affected industries should affect asset markets. When more assets are sold and fewer are bought, real asset liquidity for sellers is reduced. The effect 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.

The effect on real asset liquidity will change the industry equilibrium in the asset market. Following standard general equilibrium arguments, we expect a measurable effect both along the quantity and the price dimension. Specifically, with a high level of hedge fund activism, industry insiders that are listed firms and hence potentially also activism targets, will also feel pressure to sell assets and to curtail acquisitions. They are unlikely to be in a position to be providers of asset liquidity rather than liquidity seekers. This role should more fall to industry outsiders - private equity firms, private firms, and firms that operate predominantly in other industries - than industry insiders.

Finally, when studying the effect of activism on the efficiency of corporate transactions, the neoclassical view that corporate acquisitions serve the purpose of reallocating assets to more efficient uses has long dominated economics (Jovanovic and Rousseau (2002)), but 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.

The theoretical and empirical literature on the relationship between corporate governance and acquisition markets is also relevant in this context. The literature has considered empire building and value-destroying acquisitions as a prominent dimension of managerial

⁵From a theoretical point of view, the sign of the predicted rival reactions in response to the changed behavior of campaign targets is not unique; it depends on whether firms compete in strategic substitutes or strategic complements.

agency costs (Jensen (1986), Morck, Shleifer, and Vishny (1990)), and has emphasized the disciplining role of the market for corporate 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 acquisitions returns (Masulis, Wang, and Xie (2007)), but literature directly linking the governance role of active shareholders to ex post longterm merger performance is scant. There is also a literature 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 will execute more efficient transactions since they are co-governed by activist funds, but that the efficiency of transactions done by firms under activism threat improves less since they latter do not benefit from close monitoring by activist shareholders. It seems also plausible that the role of firm size in acquirer performance extends to the analysis of acquisitions done under activism pressure.

To summarize the hypotheses that we investigate, we first 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 reduce acquisitions 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.

Finally, we expect corporate transactions under activism pressure to show efficiency gains, and these gains potentially to be larger for activism targets than for firms under activism threat because of the stronger governance effect of an activism campaign.

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 Bray, Jiang, Partnoy, and Thomas (2008) that has been updated by Alon Brav and Wei Jiang to include the more recent time period⁶ and the FactSet SharkWatch database. The two databases are only partially 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'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-Computed Merged Database. This process yields a sample of 3,551 unique HFA campaigns in the U.S. (see Table 1, Panel A), and a list of 862 hedge funds that operate as activist hedge funds at least once in our sample and that will be used to distinguish between activist hedge funds and other institutional investors. The activism sample constructed in this way covers the period from 1994 - 2016. We use 1994 as the start date as the earliest possible year with significant hedge fund activism activity, consistent with earlier literature.

We use SDC Platinum for data on corporate transactions for our 1994-2016 sample

⁶We are grateful to Alon Brav and Wei Jiang for generously sharing their proprietary data with us.

 $^{^{7}}$ 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.

⁸We 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).

period and extract and construct three separate transaction samples, 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 corporate transactions, we use two identical filters: (*i*) we only retain transactions with an (attempted) control change, i.e. the acquirer owns less than 50% of shares before the bid and the percentage of shares sought is larger than 50%; (*ii*) we only include transactions with a (non-missing) transaction value of at least \$10 million.

For the merger sample (i.e., acquisitions of U.S. based listed firms), 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 as either "divestiture" or "division" in SDC Platinum, and for which there is no other information leading us to conclude that it is not a sale of a corporate unit or subsidiary. We exclude spinoffs and splitoffs, and require the transaction to be completed. For the acquisition sample, we start with the sample of all SDC M&A transactions of which targets are U.S. based listed firms, private firms, or subsidiaries, and the acquirer a listed firm included in the CRSP-Compustat Merged Database. We exclude transactions involving spinoffs, splitoffs, self-tenders and share repurchases.

B Firms and industries

We use the universe of U.S. firms in the CRSP-Compustat Merged Database as our baseline sample, both to identify the firms that operate under the impact of activism (the treated sample) as for 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. Our baseline sample contains 116,448 firm-year observations over the 23 years from 1994 to 2016. From CRSP-Compustat, we get financial and accounting data as well as CRSP stock price information.

We complement the data for our baseline sample with data on institutional ownership

⁹The first and second groups of transactions, mergers and divestitures, are mutually exclusive, but 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.

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)). Earlier work looking at the effects of activism threats also aggregates threats at the industry level (Gantchev, Gredil, and Jotikasthira (2017), Feng, Xu, and Zhu (2017)).

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 described in Section 3. We define a dummy variable that is equal to one when an activism event is recorded in our sample, and consider that the impact of this treatment lasts for a number of years, following earlier work that shows that there are long-run effects of HFA targeting even after the end of hedge fund campaigns (see Brav, Jiang, Partnoy, and Thomas (2008), Bebchuk, Brav, and Jiang (2015)). Boyson, Gantchev, and Shivdasani (2017) and Gantchev, Sevilir, and Shivdasani (2018) show that this persistent effect can also be observed for the acquisition behavior of activism targets. We use a two-year horizon for the impact on corporate transactions following Boyson, Gantchev, and Shivdasani (2017).

¹⁰Such 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.

For the second group, firms under activism threat, we begin with firm-level threat measures, recognizing that the HFA threat level is not the same for all firms in an industry. 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 also use large passive stakes of activist hedge funds as a second firm-level threat measure. Passive stakes by activists are deemed to capture threats 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 adopt this approach because of our focus on the impact on real asset markets that are best aggregated at the industry level, and because industry-level measures help to address concerns about selection bias.¹¹ Our main variable measuring industry-level activism threats is the fraction of recent HFA targets in the industry (at the 3 digit SIC level), that is the fraction of firms that have been targeted by activist hedge funds in last three years (year t-2, t-1, and year t).¹² 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, is constructed to measure 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 hedge funds increases during year tby more than 5%. We then aggregate this information at the industry level. The resulting

¹¹More 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.

¹²Specifically, we first define a dummy, D_HFA_2yr, equal to 1 if the firm is (was) targeted by activist hedge funds in the current year or in the past 2 years. Industry HFA Frequency is equal to the sum of D_HFA_2yr divided by the total number of firms in the industry.

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 plausible 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 decision in which industries 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

As Panel A of Table 1 shows, our sample of HFA events is fairly well distributed over the sample period of 23 years, albeit with a lower intensity in the first 2 years, a peak in 2006-2008, two marked slowdowns during stock market downturns (1999-2001 and 2009-2010), and a strong rebound in HFA activity after 2011. The number of firms in our baseline sample reaches a peak of 6,850 in 1996 and then steadily decreases to 3,990 firms in 2016, largely reflecting the intense M&A activity among listed U.S. corporations (see Doidge, Kahle, Karolyi, and Stulz (2018)).

¹³This 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).

Panel B of Table 1 presents summary statistics of our threat exposure variables. On average, 6.0% of firms in an industry are activism targets in the current year or in the past 2 years. 10.1% of firms in a given industry experience an increase in hedge funds ownership of more than 5% in at least one year of the current and past 2 years, with a median of 7.7%. There is substantial variance across industries and years in both of our main measures of activism threats, as well as in the variable FIFB that we will use as instrument.

Table 1 also reports in Panel C a large number of commonly used firm characteristics, breaking them down between our sample of HFA target firms (N = 3,551) and the remaining firm-year observations in the baseline sample (N = 112,897). This panel provides preliminary insight into the relationship between observable firm characteristics and target selection by activist hedge funds, and the magnitude of the possible selection bias. As expected and in accordance 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 discuss in Section E how these firm-level characteristics help to explain the selection of hedge fund targets, and we control for them in our regressions below.

In Panel D of Table 1, we present a similar comparison, but this time sort by activism threats. We sort observations into terciles according to our leading industry-level activism threat variable, Industry HFA Frequency. By construction, variations across columns reflect cross-industry differences by tercile of exposure to hedge fund pressure (industries may be assigned to different terciles in different years). Panel D reports quite a bit 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]

¹⁴There 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.

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 predicting the probability to become 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 others, and include all variables having been shown to have an impact on the target probability. We then include our industry-level variables of activism threat to see whether they significantly help to explain the probability of being targeted.

The results are presented in Table 2. Column (1) reports the benchmark in which we only include the known firm characteristics that help to explain the selection of activism targets. The known strong predictors are all confirmed, 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. These variables have some power predicting future hedge fund targeting (pseudo- $R^2 = 0.086$). The next three columns (2) to (4) look at our leading industry variables of activism threats sequentially. 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 that we use as our main 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 the second variable ($R^2 = 0.088$ for Industry HFStake Frequency). Even the variable FIFB that eliminates any effect of hedge funds shifting allocations across industry increases the predictive power (column (4)). These regressions confirm that our industry threat measures constitute a significant determinant of future target probabilities for individual firms in the affected industries. Importantly, the regressions show that a substantial fraction of hedge fund threats is driven by a common industry component, demonstrating that it is rational for firms to change their behavior in reaction to variations in industry threat levels, and providing microeconomic foundations for our investigation of the question whether activism pressure may affect entire corporate asset markets and not just individual firms.

[Insert Table 2 Here]

4 Deal Activity and Activism

We analyze univariate and multivariate findings of the impact of hedge fund activism on transaction frequencies for all three deal types.

A Deal frequencies

This section discusses the univariate evidence on the transaction frequencies for the three types of corporate transactions. We begin with the frequency of merger bids. 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. Following Boyson, Gantchev, and Shivdasani (2017), we define a merger bid to be an *activism merger* if it falls within a window of two calender years after the public announcement of the activist campaign (13D filing or announcement date).

Panel A of Table 3 shows year-by-year transaction frequencies for the full sample period. In any given year after 1995, between 3.75% and 8.16% of firms in the CRSP-Compustat sample are targets of a merger bid (including unsuccessful bids). The average frequency is 5.17%.¹⁵ 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]

In Panel B, we present the same breakdown for divestitures. On average, each year 5.19 % of listed firms divest business units with a transaction value of more than \$10m. This frequency rises by more than 50% to 7.81 % for *activism divestitures*, i.e. divestitures

 $^{^{15}\}mathrm{The}$ ratios of bids per firm (not reported) are higher since some firms receive multiple bids in a given year.

occurring in a two-year window after the start of an activist campaign.¹⁶ 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 of more than \$10m recorded is 15.06%, a percentage that decreases to 11.82% for firms with *activism acquisitions* (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) by firms in the baseline sample. We single out private acquisitions since they represent a deal flow without overlap with the previous panels.¹⁷ 45.8% of acquisitions in our sample are private acquisitions so their share is important. For the private acquisitions in Panel D, the (private) sellers are immune to hedge fund pressure, allowing us to isolate better fluctuations steming from the demand side. The annual rate of private acquisitions of more than \$10m. is 7.68%, which decreases by 28.5%, a higher relative decrease compared to Panel C, to 5.49% for activism acquisitions of private targets. 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, we consider campaign targets in this subsection, and the effects of activism threats in Sections C and D.

Table 4 shows logit regression results for our firm-year panel. 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

¹⁶(Gantchev, Sevilir, and Shivdasani (2018) also document an increase in activism divestitures.

¹⁷Since 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).

bid in Panel A, a divestiture in Panel B, etc.). In Panel A, the dependent variable is the probability of receiving a merger bid in year t.¹⁸ In all regressions, we use an extensive array of control variables, including variables known to contribute to the frequency of corporate transactions and/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 concentration (HHI), and real asset liquidity.¹⁹ We include industry and year fixed effects. As expected from earlier studies, the dummy D[Activist] has a very strong and robust effect on the probability of receiving a merger bid (p < 0.01), with t-values comprised between 8.37 and 12.99 and a change in predicted probabilities of 92 % (10.49 % vs. 5.45 %). There is no substantial difference whether when we distinguish between merger bids from strategic competitors, from financial buyer groups, or consider unsolicited bids (columns (2) to (4)).

In Panel B, we consider divestitures. We include the same array of control variables as in Panel A and industry and year fixed effects. The results are strong, with the variable of interest D[Activist] highly significant in all specification (t = 5.22). Regression (1) shows the baseline regression for all divestitures events. The predicted annual frequency of undertaking a divestiture increases by 41 % (6.44% vs. 4.57%) compared with the full sample. An even higher frequency of divestitures occurs among activist campaign target firms when the activists mention divestitures as an explicit campaign goal (11.63%, almost three times as high as the unconditional frequency). In regressions (3) and (4), we break the sample down by type of buyer, strategic buyer or private equity firm, and find no important difference. Regressions (5) and (6) split the sample between assets that are related to the seller firm's core activity (3-digit SIC code), and those that are unrelated. Both are highly significant (p < 0.01), but show no clear difference.

In Panel C, we turn to acquisitions. Again, we find a highly significant decrease in acquisitions in our benchmark specification in regression (1) (t = 3.56). However, 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

¹⁸D[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.

¹⁹We use the measure of Ortiz-Molina and Phillips (2014) that in turn is based on Schlingemann, Stulz, and Walkling (2002).

(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. In acquisitions, firm size matters, but we do not find similar effects for sales transactions (mergers and divestitures, not reported in tables). We will return repeatedly to this distinction. We 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 firms' selection as hedge fund target and their change of behavior in the market for corporate assets might be driven by omitted variable bias in the data, or another selection bias. To address these endogeneity concerns, we deploy in Panel D methodology first proposed by Bray, 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.²⁰ 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 $D[Post] \times D[13G$ 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 the selection of firms by hedge funds that explains the association between hedge fund exposure and acquisition behavior, dissipating substantially our concerns about endogeneity.

[Insert Table 4 Here]

 $^{^{20}}$ 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.

C Firm-level activism threats

Turning to the multivariate analysis of activism threats, we first investigate the impact of activism threat on firms asset market behavior using the company-specific threat measure. Since we focus on threat perceptions, we exclude activism events, i.e. for activism targets, we exclude the HFA event year and the three following years from our panel. We use two different measures of such threat levels that are idiosyncratic for each firm 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. In addition, we aggregate the two transaction types (mergers and divestitures) that correspond to corporate sales in regression (3), and separate between acquisitions of private targets and others in regression (5). Second, we use a dummy equal to 1 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. Panel B of Table 5 shows the results, again for all three types of corporate transactions. We find in both cases highly significant results showing an increase in merger bids and divestitures, and a small decrease in acquisition frequencies for large firms but not for small ones.²¹

[Insert Table 5 Here]

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 industryyear 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 consider our main threat variable, Industry HFA Frequency. Industry HFA Frequency leads to a significant increase in divestitures and

²¹Our two firm-level threat measures are subject to endogeneity concerns, that is our findings might be attributable to selection effects of targets by activists. We address this issue in the next subsection.

in sales (mergers and divestitures combined) (p < 0.05), but not in mergers. 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 an even 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 idiosyncratic large fund inflow shocks (> 5%), and most activist hedge funds are general investors in their passive investments, i.e. they invest in a diversified cross-section of industries and tend to invest quickly and in a mechanical manner 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 shocks or trends that could be associated with corporate transactions activity. In 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.²²

The results of our reduced form 2SLS approach are presented in Panel C of Table 6. Panel C shows that mergers, divestitures and sales become significantly more likely and acquisitions by large firms become less likely when using the FIFB instrument.

²²The 2SLS estimator gives us qualitatively similar results.

In conclusion, we find that firms under heightened activism threat divest more and are more frequently acquired. On average, they also make fewer acquisitions. These results extend findings by Gantchev, Sevilir, and Shivdasani (2018) and Boyson, Gantchev, and Shivdasani (2017) and show 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 when firms are 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.

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 relative importance of the two channels of activism pressure, the direct target impact and threat impact. We analyze logit regressions that investigate the joint impact of the two channels on the asset market behavior of firms. The main difference to our previous analyses is that the two groups of treated firms are now analyzed jointly, whereas they were analyzed separately in Table 4 and Table 6. Results are presented in Table 7. D[Activist] and D[High HFA Threat] are the variables of interest for the two disjoint groups of treated firms, and they are mutually exclusive: 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.

In Panel A of Table 7, 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 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 (p < 0.01).

[Insert Table 7 Here]

The most interesting insights of Table 7 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 1.²³ As reported in Panel A of Table 7, 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 activist, 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.

We next compare the relative importance of the two channels of activism pressure. 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. We focus 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%,²⁴, this means that corporate sales in industries under high activism pressure increase by 23.84% (= 2.47/10.36). On the acquisition side, we need to

²³Since 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.

 $^{^{24}}$ See Table 3: we add the average frequency for mergers of 5.17% (Panel A) and for divestitures of 5.19% (Panel B).

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 now turn to an assessment of the impact of activism on the asset market equilibrium of affected industries. We begin by investigating the impact on the industry equilibrium in terms of transaction activity. Firms in the industry with heightened hedge fund pressure tend to sell more assets and simultaneously are less willing to buy assets, as estimated in 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 to a lesser extent 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 8 presents the results of industryyear 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 each industry-year 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 8 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 8 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;²⁵ only publicly listed firms can be "insiders" since only listed firms can be affected by HFA pressure. All other sellers and acquirers are considered as "outsiders". Outsiders consist of three main categories includes types of buyers or sellers: (*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" the firms affected by hedge fund activism and activist threats in the corresponding industry.

In Panel B of Table 8, 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

²⁵There 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.

"insiders" in 8,279 out of total of 23,704 transactions. Consistent with our hypothesis, the results reveal that real asset liquidity provided by industry outsiders increases in topquintile industries by activism pressure (2.519% increase measured in frequency and 1.616% 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.

In Panel C of Table 8, 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 will significantly more frequently be 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 affected by the 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 8 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 9, we report the transaction-level regressions studying industry activism pressure, asset redeployability and type of outside buyers. Panel A of Table 9 shows that the dearth up of asset liquidity in industries with heightened activism pressure is mainly filled by one type of industry outsiders, private equity.²⁶ In Panel B, we present results interacting

 $^{^{26}}$ 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,

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. Panel B, Column (1) of Table 9 shows that outside provision of liquidity is stronger in industries under HFA pressure and with high asset redeployability. In Panel B, Column (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.²⁷ We find similarly significant results (not 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 9 Here]

D Price pressure

We also expect the squeeze in real asset liquidity to 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.²⁸ We look at the divestitures and mergers sample separately, using

where we show PE transaction waves are irrelevant or even negatively correlated with Industry HFA Freq. ²⁷Indeed, 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 10, Panel B).

²⁸The 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

the standard event windows in each case. 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 look at a long pre-announcement window of three months to account for pre-deal price run-ups in the target stock price, as well as the price premium (mark-up of offer price relative to stock price one month before).

Table 10 reports our findings for sellers in Panel A. 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].²⁹ We find a significant and robust negative effect for our transactions under high industry activism pressure but the seller recently is not under the HFA campaign (Industry HFA Freq × D[No 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 10).

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 10). 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 10 Here]

In Panel C, we look at the price pressure effects on buyers, using the same samples of

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.

²⁹D[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.

divestitures and mergers and regressions. The sample size shrinks because only about half of the transactions 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 hypothesis and our previous analysis of asset liquidity: as supply of corporate assets in affected industries increases and demand decreases, asset liquidity is affected. This leads to lower seller returns and also to (weakly) higher buyer returns. Weak price reactions are to be expected since, as Table 8 shows, outsiders step up and provide real asset liquidity and potentially mitigate the squeeze in asset prices.

6 Activism and the Efficiency of Corporate Transactions

A Evidence on post-transaction performance: asset sellers

Our final exploration addresses the question whether the involvement of activists in the corporate asset market leads to more efficient transactions. We first consider possible efficiency gains of asset sellers. We cannot analyze mergers because we cannot construct a satisfactory counterfactual allowing us to observe an independent time series of seller performance after the transaction, and we do not consider private acquisitions for the same reason (seller performance cannot be observed). Thus, we limit this analysis to divestitures, and to the long-run performance of the seller.

It is well-known that activism campaigns lead to long-run positive effects in stock market and accounting performance for seller firms (see Bebchuk, Brav, and Jiang (2015)). Thus, it is important to disentangle the long-run performance enhancing effect of activism campaign from that 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 report our findings in Table 11. We consider three different long-run performance measures, each for a period of two years after the divestiture event, to provide a crosssection of accounting-based and stock market based performance measures: Tobin's Q; ROA; and the ratio of Sales/Assets (Turnover) that is correlated with economic efficiency gains. Column (1) shows a positive effect on seller's Tobin's Q after divestitures (dummy D[Post Divestiture]),and after activist campaigns, the latter consistent with findings by Gantchev, Sevilir, and Shivdasani (2018). The key variable of interest is the interaction term D[Post Divestiture] × D[Activism Divestiture]. This variable shows a positive value effect over two years over and above the positive effect of having done divestitures, and having gone through an activism campaign. We find a positive and significant (p < 0.05) response to the interaction dummy D[Post Divestiture] × D[Activism Divestiture], for both Tobin's Q and for ROA. Only the sales/assets ratio does not show a significant long-run performance effect.

[Insert Table 11 Here]

Panel B repeats the analysis but looks at firms with elevated HFA threat (we look at 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 intersection term D[Post Divestiture] \times 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 done under the menace of HFA threats do not show any indication of a long-run efficiency gains captured by sellers, whereas columns (1) and (2) in Panel A show significant differences for activism divestitures. When it comes to long-run performance, there appears to be a clear difference between activism divestitures and divestitures done under elevated HFA threat: the magic of efficiency gains is limited to corporate sales of activism targets, and does not spread to other transactions in industries under activism pressure.

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

We finally analyze the long-run performance effect on the buyer side for acquisitions. A particular motivation for this investigation is the question whether our data can provide

a possible explanation to the puzzling observation that small firms, when acting under heightened HFA threat, appear to increase the frequency of acquisitions rather than decrease it, as large firms do and as activism targets do. Specifically, we ask: is there any hint that small firms under HFA threat make acquisitions as a restructuring tool (which might help to fend off activists)? We look for incomplete evidence consistent with such a possible explanation, by looking at the long-run performance effect of small firms that have undertaken an activism acquisitions of private targets.

Table 12 presents the findings. We are looking at the long-run performance effect for buyers of firms or assets. 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] × D[Activism Acquisition] × 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. 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 for Sales/Assets when we expand the subsample to the top tercile of firms under activism threat (not reported).

Measured by long-run efficiency, small firms seem to do well when undertaken 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 earlier observation (Table 6) that only large firms react to an increase in HFA threats with a reduction in their acquisition activity.

[Insert Table 12 Here]

7 Conclusions

The paper explores the impact of hedge fund activism on corporate asset markets. We find that activist target firms are more likely to receive merger bids, and make more divestitures and fewer acquisitions, in line with earlier studies. 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, and find that firms exposed to such threats change their behavior in similar ways, but with subtle differences: they divest more, but are only marginally more likely to be sold. 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 targets more important for corporate sales. We consider the impact on real asset liquidity: when firms in affected industries want to simultaneously sell more and buy less assets, then real asset liquidity shrinks by up to 35%, 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 liquidity, and more so in industries with high asset redeployability.

We find evidence that the squeeze on real asset liquidity also affects transaction prices: 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. The effect is stronger in industries with low redeployability. However, we find that divestitures done by activist targets resist the price pressure remarkably well.

Finally, we consider whether activist pressure leads to more efficient transactions. Isolating the incremental effect of transactions done under activism influence, we find positive long-run performance effects when corporate transactions are undertaken by activism targets; we do not find a similar effect for transactions undertaken under activism threat. Thus, the direct involvement of hedge fund activists seems necessary to create additional efficiency gains.

Our paper shows that activism creates important market externalities for firms not directly targeted, by changing the environment and behavior in acquisition markets. It is not clear that these changes are efficient, but at least small firms disciplined by activism threats seem to make better acquisitions. Our findings lead to new questions that go beyond the scope of this paper, for example whether activists reduce or magnify the cyclicality of real asset markets.

Appendix A: Definition of the Variables

Variables name	Data source	
Activism and threat va		
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 one 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 his 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 coau- thors
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 his coauthors
Industry HFA Freq	The fraction of firms in industry j and year t that have been targeted by activist hedge funds in last three years (year t -2, t -1, and year t)	
Industry HFStake Freq	The fraction of firms in industry j and year t that had at least one activist hedge funds' stake jump within last 3 years (year t -2, t -1, and year t).	Thomson Reuters 13f & SharkWatch
FIFB	The flow induced fund buy measure (FIFB) following Gantchev, Gredil and Jotikatshira (2017). The formula is as follows,	Thomson Reuters 13f,
	$\sum_{h} \left[Inflow 5_{h,t} \times \frac{TNA_{h,j,t-1}}{TNA_{h,t-1}} \right]$	and CRSP
	$FIF D_{j,t} =$	
	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 <i>Market Cap</i> 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).	
D[Industry HFA Freq P80]	Dummy equal to 1 if the Industry HFA Freq is in the top quintile of baseline industry-year sample.	
D[High HFA Threat]	Dummy equal to 1 if the 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 the Industry HFA Freq is in the second or third highest quintiles of baseline industry-year sample and $D[Activist] = 0$.	
Variables for transaction	ons of corporate assets	
Merger	Dummy equal to 1 if the firm receives merger bids in year t . We also 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 also 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
	Contir	iued on next page

Variable name	Appendix A continued from previous page 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 also 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 in similar way as TotM&A_3yr, but only include those transactions bought by private equity funds.	Thomson Reuters SDC M&A
D[Merger Wave]	Dummy equal to 1 if the industry j in year t is in the industry merger wave interval as defined in Harford (2005).	Thomson Reuters SDC M&A
Institution Owner- ship	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 the book value of assets (item AT_t) + the market value of common equity at fiscal year-end (item $CSHO_t \times$ item $PRCC_F_t$) – the book value of common equity (item CEQ_t) – balance sheet deferred taxes (item $TXDB_t$)	Compustat
Ln(age)	The natural logarithm of years since the firm first appears in CRSP	CRSP
Ln(MV)	The natural logarithm of the firm's market capitalization (item $CSHO_t \times \text{item} \ PRCC_F_t)$	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 pre- ferred (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	The Hirschman-Herfindahl index of sales in the industry Contir	Compustat ued on next page

	Appendix A continued from previous page	
Variable name	Definition and construction of variable	Data source
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 (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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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 firms targeted by activist hedge funds. 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 (year t-2, t-1, and year t). Industry HFStake Freq is defined as the fraction of firms in industry j and year t that had at least one activist hedge funds' stake jump within the previous three years (year t-2, t-1, and year 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-Computat 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 years [t, t+3].

Panel A: Frequency of HFA campaigns								
	(1)	(2)	(3)					
Calendar	Number of	Number of	Proportion of					
year	firms	HFA	firms targeted					
	(all)	$\operatorname{campaigns}$	by HFA					
1994	6176	12	0.19%					
1995	6372	33	0.52%					
1996	6850	90	1.31%					
1997	6847	170	2.48%					
1998	6408	131	2.04%					
1999	6226	90	1.45%					
2000	5986	86	1.44%					
2001	5296	79	1.49%					
2002	4911	121	2.46%					
2003	4635	118	2.55%					
2004	5066	128	2.53%					
2005	4977	211	4.24%					
2006	4888	273	5.59%					
2007	4758	319	6.70%					
2008	4487	256	5.71%					
2009	4252	134	3.15%					
2010	4125	149	3.61%					
2011	4002	172	4.30%					
2012	3940	174	4.42%					
2013	4001	197	4.92%					
2014	4152	236	5.68%					
2015	4103	203	4.95%					
2016	3990	169	4.24%					
Total	116,448	3,551	3.05%					

Panel B: Summary statistics of industry HFA threat variables

Tanci D. Summary statistics of industry in A uncet variables									
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^\dagger	0.064		

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

P	Panel	C:	Characteristics	of	activism	target firms	5
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	$\begin{array}{l} \text{HFA Target Firms} \\ (\text{N} = 3,551) \end{array}$			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 firm	ns under high, medium	and low threat	(Industry HFA Freq)

Tercile of Industry HFA Freq		ottom Terc $N = 42,908$	ile 3)	$\begin{array}{l} \text{Medium Tercile} \\ (\text{N} = 31,552) \end{array}$			Top Tercile $(N = 32,729)$		
	Mean	Median	S.D.	Mean	Median	S.D.	Mean	Median	S.D.
Institutional 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 [yearly]	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

This table reports the relationship between industry measures of activism threat and the HFA target probability. Columns (1) - (5) 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 i and year t that have been targeted by activist hedge funds in last three years (year t-2, t-1, and year t). Industry HFStake Freq is defined as the fraction of firms in industry j and year t that had at least one activist hedge funds' stake jump within last 3 years (year t-2, t-1, and year t). 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 (6) – (7) report OLS regressions for the industry-year sample; in this case all controls are industry-year medians. In these 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) - (5) and at the industry level in columns (6) - (7) (standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01).

Table 2: Industry activism threat and HFA target probability									
	(1)	(1) (2) (3) (4) (5) Firm-year regression				(6) Industry-ye	(7) ar regression		
	Logit D[HFA]	Logit D[HFA]	Logit D[HFA]	Logit D[HFA]	Logit D[HFA]	$\begin{array}{c} \hline \\ OLS \\ Industry HFA \\ Freq (year t) \end{array}$	$\begin{array}{c} \text{OLS} \\ \text{Industry HFA} \\ \text{Freq (year } t) \end{array}$		
Industry HFA Freq		$7.752^{***} \\ (0.304)$			$7.753^{***} \\ (0.305)$				
Industry HFStake Freq			$\begin{array}{c} 1.825^{***} \\ (0.220) \end{array}$						
FIFB (Percentile Rank)				0.363^{**} (0.141)		$\begin{array}{c} 0.0149^{***} \\ (0.00572) \end{array}$	$\begin{array}{c} 0.0151^{***} \\ (0.00572) \end{array}$		
TotM&A_3yr	$\begin{array}{c} 0.472 \\ (0.381) \end{array}$	$\begin{array}{c} 0.164 \\ (0.401) \end{array}$	$\begin{array}{c} 0.436 \\ (0.381) \end{array}$	$\begin{array}{c} 0.434 \\ (0.389) \end{array}$	$\begin{array}{c} 0.157 \\ (0.400) \end{array}$	$\begin{array}{c} 0.0192 \\ (0.0178) \end{array}$	$\begin{array}{c} 0.0200 \\ (0.0178) \end{array}$		
TotPE_3yr	$\begin{array}{c} 0.0721 \\ (0.660) \end{array}$	-0.00634 (0.764)	-0.155 (0.663)	$\begin{array}{c} 0.133 \\ (0.687) \end{array}$	$\begin{array}{c} 0.00598 \ (0.763) \end{array}$	-0.0591^{*} (0.0304)	-0.0601^{**} (0.0304)		
D[Merger Wave]					$\begin{array}{c} 0.0173 \ (0.0839) \end{array}$		-0.00491 (0.00487)		
Institutional Ownership	$\begin{array}{c} 1.459^{***} \\ (0.116) \end{array}$	$\begin{array}{c} 1.415^{***} \\ (0.118) \end{array}$	$\begin{array}{c} 1.419^{***} \\ (0.116) \end{array}$	$\begin{array}{c} 1.461^{***} \\ (0.117) \end{array}$	$\begin{array}{c} 1.416^{***} \\ (0.118) \end{array}$	$\begin{array}{c} 0.0136 \ (0.0124) \end{array}$	$\begin{array}{c} 0.0129 \\ (0.0124) \end{array}$		
Tobin's Q	-0.320^{***} (0.0353)	-0.312^{***} (0.0355)	-0.320^{***} (0.0354)	-0.321^{***} (0.0358)	-0.311^{***} (0.0356)	-0.00725^{**} (0.00345)	-0.00740^{**} (0.00345)		
$\ln(MV)$	-0.200^{***} (0.0208)	-0.194^{***} (0.0210)	-0.196^{***} (0.0208)	-0.199^{***} (0.0211)	-0.194^{***} (0.0210)	-0.00282 (0.00215)	-0.00273 (0.00215)		

Book Leverage	$\begin{array}{c} 0.325^{***} \\ (0.0920) \end{array}$	$\begin{array}{c} 0.342^{***} \\ (0.0942) \end{array}$	0.330^{***} (0.0919)	$\begin{array}{c} 0.319^{***} \\ (0.0934) \end{array}$	$\begin{array}{c} 0.342^{***} \\ (0.0942) \end{array}$	0.00987 (0.0115)	$0.0101 \\ (0.0115)$
Dividend Yield	-4.046^{***} (1.479)	-4.093^{***} (1.508)	-4.014^{***} (1.476)	-3.824^{**} (1.487)	-4.091^{***} (1.508)	-0.386^{***} (0.143)	-0.382^{***} (0.143)
Cash Flow	-0.285 (0.177)	-0.318^{*} (0.181)	-0.261 (0.177)	-0.296^{*} (0.179)	-0.317^{*} (0.181)	-0.0139 (0.0289)	-0.0138 (0.0289)
Sales Growth	-0.0642 (0.0689)	-0.0548 (0.0677)	-0.0537 (0.0684)	-0.0677 (0.0696)	-0.0552 (0.0677)	-0.00855 (0.0120)	-0.00834 (0.0120)
Asset Growth	-0.176^{*} (0.0907)	-0.135 (0.0904)	-0.167^{*} (0.0904)	-0.192^{**} (0.0926)	-0.135 (0.0904)	-0.0370^{***} (0.0142)	-0.0372^{***} (0.0142)
R&D	$\begin{array}{c} 0.516 \ (0.380) \end{array}$	$\begin{array}{c} 0.453 \\ (0.381) \end{array}$	$\begin{array}{c} 0.520 \ (0.379) \end{array}$	$\begin{array}{c} 0.520 \\ (0.382) \end{array}$	$\begin{array}{c} 0.451 \\ (0.382) \end{array}$	-0.298^{*} (0.171)	-0.291^{*} (0.171)
HHI	-0.388 (0.278)	-0.842^{***} (0.316)	-0.313 (0.280)	-0.471 (0.289)	-0.843^{***} (0.316)	0.0546^{**} (0.0262)	0.0543^{**} (0.0262)
Excess Cash	$\begin{array}{c} 0.620^{***} \\ (0.156) \end{array}$	$\begin{array}{c} 0.649^{***} \\ (0.157) \end{array}$	$\begin{array}{c} 0.613^{***} \\ (0.156) \end{array}$	$\begin{array}{c} 0.633^{***} \\ (0.157) \end{array}$	$\begin{array}{c} 0.648^{***} \\ (0.158) \end{array}$	0.0586^{**} (0.0282)	0.0592^{**} (0.0282)
CAR [Year t-1]	-0.125^{***} (0.0479)	-0.116^{**} (0.0489)	-0.124^{***} (0.0478)	-0.113^{**} (0.0484)	-0.116^{**} (0.0489)	$\begin{array}{c} -0.00319 \\ (0.00549) \end{array}$	-0.00319 (0.00549)
Year fixed effect Industry fixed effect N pseudo R^2 / adj. R^2	Yes Yes 68228 0.086	Yes Yes 68228 0.129	Yes Yes 68228 0.089	Yes Yes 66067 0.087	Yes Yes 68228 0.129	Yes Yes 4543 0.071	Yes Yes 4543 0.071

Standard errors in parentheses * p < 0.10, ** p < 0.05, *** p < 0.01

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: 1	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

		1 ani	er B: III II o	ampaigno and	arrestitutes		
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%

1	Faller C. IIFA campaigns and acquisitions of public, private, and subsidiary infins						
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
$\begin{array}{r} 1994-1995\\ 1996-2000\\ 2001-2005\\ 2006-2010\\ 2011-2016\\ \end{array}$	2,036 8,464 4,969 4,280 5,133	$11.53\% \\ 16.86\% \\ 14.66\% \\ 14.16\% \\ 15.65\%$	$\begin{array}{c} 4\\ 238\\ 117\\ 214\\ 265 \end{array}$	5.26% 16.54% 10.01% 9.49% 12.00%	$319 \\ 1,418 \\ 1,080 \\ 950 \\ 1,102$	$10.17\% \\ 14.87\% \\ 14.67\% \\ 14.58\% \\ 15.23\%$	$\begin{array}{c} 12.09\% \\ 17.21\% \\ 15.51\% \\ 15.60\% \\ 17.91\% \end{array}$
Total	24,882	15.06%	838	11.82%	4,869	14.51%	15.72%
Panel D: HFA campaigns and acquisitions of private firms							
	P	anel D: HFA	campaigns a	and acquisition	is of private f	hrms	
Calendar year	(1) Number of private acquisitions	(2) % of firms with private acquisitions	(3) Number of activism private acquisitions	and acquisition (4) % of firms with activism private acquisitions	(5) Number of private acquisitions under high HFA threat	hrms (6) % of firms with private acquisitions under high HFA threat	(7) % of firms with private acquisitions under low HFA threat
Calendar year 1994 – 1995 1996 – 2000 2001 – 2005 2006 – 2010 2011 – 2016	(1) Number of private acquisitions 794 3,989 2,154 2,043 2,417	anel D: HFA (2) % of firms with private acquisitions 5.10% 9.00% 7.16% 7.42% 7.97%	campaigns a (3) Number of activism private acquisitions 3 152 73 113 140	and acquisition (4) % of firms with activism private acquisitions 2.63% 6.38% 4.01% 4.82% 5.82%	s of private f (5) Number of private acquisitions under high HFA threat 131 733 529 530 588	hrms (6) % of firms with private acquisitions under high HFA threat 4.12% 7.64% 7.25% 8.09% 8.08%	(7) % of firms with private acquisitions under low HFA threat 5.26% 8.71% 7.29% 7.89% 9.06%

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

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 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 fillings 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:

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

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).

Pa	Panel A: Activism targets and mergers							
	(1) LOGIT Merger bids	(2) Logit Merger bids Strategic buyer	(3) Logit Merger bids Financial buyer	(4) Logit Merger bids Unsolicited bids				
D[Activist]	0.710^{***} (0.0550)	$\begin{array}{c} 0.611^{***} \\ (0.0620) \end{array}$	0.858^{***} (0.103)	1.206^{***} (0.160)				
Firm-level control variables Industry and Year fixed effect N pseudo R^2 Unconditional prob. Prob. conditional on HFA targets	Yes Yes 71879 0.051 5.45% 10.49%	Yes Yes 71534 0.049 4.43% 7.86%	Yes Yes 66332 0.107 0.79% 1.86%	Yes Yes 51167 0.088 0.33% 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]	$\begin{array}{c} 0.362^{***} \\ (0.0694) \end{array}$	0.259^{***} (0.0746)	$\begin{array}{c} 0.332^{***} \\ (0.0762) \end{array}$	$\begin{array}{c} 0.461^{***} \\ (0.139) \end{array}$	$\begin{array}{c} 0.294^{***} \\ (0.0967) \end{array}$	$\begin{array}{c} 0.414^{***} \\ (0.0921) \end{array}$		
D[Activist's Goal is Restructure]		$\begin{array}{c} 0.748^{***} \ (0.191) \end{array}$						
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%	$11.63\%^\dagger$	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^{***} (0.0584)		-0.335^{***} (0.0839)		-0.156 (0.122)	-0.187^{**} (0.0808)	-0.152^{**} (0.0756)
$D[Activist] \times D[Large]$		-0.252^{***} (0.0793)		-0.387^{***} (0.119)			
$D[Activist] \times D[Small]$		-0.0642 (0.0865)		-0.208^{*} (0.126)			
Firm-level controls Industry and Year fixed effect N	Yes Yes 69541	Yes Yes 66346	Yes Yes 69118	Yes Yes 66069	Yes Yes 67308	Yes Yes 68664	Yes Yes 69148
pseudo R^2 Unconditional prob. Prob. conditional on HFA targets	$0.124 \\ 14.42\% \\ 12.02\%$	0.125	$\begin{array}{c} 0.102 \\ 6.40\% \\ 4.66\% \end{array}$	0.104	$0.134 \\ 3.65\% \\ 2.51\%$	$\begin{array}{c} 0.129 \\ 6.46\% \\ 5.41\% \end{array}$	$\begin{array}{c} 0.126 \\ 7.33\% \\ 6.36\% \end{array}$

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

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

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. We report OLS regressions in all panels. 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, we use D[PassiveStake] to measure the activism threat, where D[PassiveStake] 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: Measuring the firm-level threat with Pr(Target)								
	(1) Merger	(2) Divestiture	(3) Sale	(4) Acquisition	(5) Acquire Private			
$\widehat{Pr(Target)}$	$\begin{array}{c} 0.622^{***} \\ (0.164) \end{array}$	0.536^{***} (0.140)	$\begin{array}{c} 1.149^{***} \\ (0.215) \end{array}$					
$Pr(Target) \times D[Small]$				-1.108^{***} (0.129)	-0.294^{***} (0.0955)			
$Pr(Target) \times D[Large]$				-2.011^{***} (0.183)	-0.527^{***} (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: Measuring the firm-level threat with D[PassiveStake]

	(1) Merger	(2) Divestiture	(3) Sale	(4) Acquisition	(5) Acquire Private
D[Passive Stake]	$\begin{array}{c} 0.0414^{***} \\ (0.00347) \end{array}$	$\begin{array}{c} 0.0131^{***} \\ (0.00330) \end{array}$	$\begin{array}{c} 0.0513^{***} \\ (0.00445) \end{array}$		
$D[Passive Stake] \times D[Small]$				-0.00469 (0.00553)	-0.00545 (0.00420)
$D[Passive Stake] \times D[Large]$				-0.0151^{*} (0.00795)	-0.0167^{***} (0.00561)
Firm-level control variables Industry and Year fixed effect N adj. R^2	Yes Yes 65430 0.021	Yes Yes 62935 0.069	Yes Yes 65430 0.047	Yes Yes 60602 0.086	Yes Yes 60602 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 HFS take 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	$\begin{array}{c} 0.00168 \\ (0.0140) \end{array}$	$\begin{array}{c} 0.0425^{***} \\ (0.0160) \end{array}$	0.0480^{**} (0.0213)				
Industry HFA Freq \times D[Small]				$\begin{array}{c} 0.0634^{**} \\ (0.0300) \end{array}$	0.0558^{**} (0.0227)		
Industry HFA Freq \times D[Large]				-0.0910^{**} (0.0366)	-0.0435^{*} (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

	8			1	
	(1) Merger	(2) Divestiture	(3)Sale	(4) Acquisition	(5) Acquire Private
Industry HFStake Freq	$\begin{array}{c} 0.0281^{**} \\ (0.0111) \end{array}$	0.0280^{**} (0.0125)	$\begin{array}{c} 0.0538^{***} \\ (0.0160) \end{array}$		
Industry HFStake Freq \times D[Small]				$\begin{array}{c} 0.0677^{***} \\ (0.0224) \end{array}$	0.0266^{*} (0.0161)
Industry HFStake Freq \times D[Large]				-0.0477^{**} (0.0223)	-0.0394^{***} (0.0151)
Firm lovel control variables	Voc	Voc	Voq	Vog	Voc
	Tes V	1es	1es V	1es V	Tes V
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

rater e. weasuring industry in it encar by the direction 2515 regression/								
	(1) Merger	(2) Divestiture	(3)Sale	(4) Acquisition	(5) Acquire Private			
FIFB (Percentile Rank)	$\begin{array}{c} 0.0114^{**} \\ (0.00556) \end{array}$	$\begin{array}{c} 0.0131^{**} \\ (0.00580) \end{array}$	$\begin{array}{c} 0.0233^{***} \\ (0.00769) \end{array}$					
$FIFB \times D[Small]$				$\begin{array}{c} 0.0107 \ (0.00933) \end{array}$	$\begin{array}{c} 0.000152 \\ (0.00688) \end{array}$			
$FIFB \times D[Large]$				-0.0438^{***} (0.0115)	-0.0153^{*} (0.00850)			
Firm-level control variables Industry-level control variables Industry and Year fixed effect N adj. R^2	Yes Yes Yes 58898 0.018	Yes Yes Yes 56659 0.074	Yes Yes 58898 0.046	Yes Yes Yes 54988 0.076	Yes Yes 54988 0.041			

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

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. 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 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).

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

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

I aner D. Logistic regressions and marginar enects	(acquisitions)
	(1)Logit Acquisition
$D[Activist] \times D[Small]$	-0.0610 (0.0956)
$D[High HFA Threat] \times D[Small]$	0.219^{***} (0.0646)
D[Medium HFA Threat] \times D[Small]	$\begin{array}{c} 0.0169 \ (0.0554) \end{array}$
$D[Activist] \times D[Large]$	-0.317^{***} (0.0901)
$D[High HFA Threat] \times D[Large]$	-0.128^{***} (0.0480)
D[Medium HFA Threat] \times D[Large]	$egin{array}{c} 0.00613 \ (0.0389) \end{array}$
Firm-level control variables Industry and Year fixed effect N pseudo R^2	Yes Yes 66896 0.111
<u>For Small Firms:</u> Marginal effect of Activist Prob. conditional on HFA targets	-0.40% 6.26%
Marginal effect of High HFA Threat Prob. conditional on High HFA Threat	$^{+1.50\%}_{8.22\%}$
For Large Firms: Marginal effect of Activist Prob. conditional on HFA targets	-4.55% 15.18%
Marginal effect of High HFA Threat Prob. conditional on High HFA Threat	$-2.16\%\ 20.29\%$

Panel B∙	Logistic regression	ons and	marginal	effects	(acquisitions)

Table 8: 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 i 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-vear 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 buver

Dependent Variable:	$\begin{array}{c} \text{Real As} \\ (1) \end{array}$	SET LIQUII (2)	DITY (RAI (3)	(4)
Buyer status:	Buyer =	Outsider	Buyer =	Insider
Measure of RAL:	Freq	Value	Freq	Value
D[Industry HFA Freq P80]	2.519^{*} (1.464)	$\begin{array}{c} 1.616^{**} \\ (0.720) \end{array}$	-0.0159 (0.467)	-0.0868 (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

Dependent Variable: Re	al Asset 1	Liquidity	(RAL)	
	(1)	(2)	(3)	(4)
Seller/buyer status:	Seller =	Insider	Seller =	Insider
	Buyer =	Outsider	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 $= 0$	Outsider	Seller =	Outsider
Seller/buyer status:	Seller = 0 Buyer =	Outsider Outsider	Seller = Buyer =	Outsider = Insider
Seller/buyer status: Measure of RAL:	Seller = 0 $Buyer = Freq$	Outsider Outsider Value	Seller = Buyer = Freq	Outsider = Insider Value
Seller/buyer status: Measure of RAL: D[Industry HFA Freq P80]	Seller = 0 $Buyer =$ $Freq$ 0.802	Outsider Outsider Value 0.175	$\overline{\begin{array}{c} \text{Seller} = \\ \text{Buyer} = \\ \text{Freq} \end{array}}$ -0.0619	Outsider = Insider Value -0.128*
Seller/buyer status: Measure of RAL: D[Industry HFA Freq P80]	$\overline{Seller} = 0$ $Buyer = Freq$ 0.802 (1.229)	Outsider Outsider Value 0.175 (0.420)	$\overline{Seller} = Buyer = Freq$ -0.0619 (0.445)	Outsider = Insider Value -0.128* (0.0749)
Seller/buyer status: Measure of RAL: D[Industry HFA Freq P80] Number of Industry-Year obs.	$\overline{Seller} = 0$ $Buyer = Freq$ 0.802 (1.229) 4783	Outsider Outsider Value 0.175 (0.420) 4783	$\overline{Seller} = Buyer = Freq$ -0.0619 (0.445) 4783	Outsider = Insider Value -0.128* (0.0749) 4783

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

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 9: Activism pressure, asset redeployability and outsider buyers

This table reports the 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 activism campaign(s) 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 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							
$\begin{array}{ccc} (1) & (2) & (3) \\ D[Outsider] & D[Outsider:PE] & D[Outsider:Second Second Sec$							
D[Industry HFA Freq P80]	0.0309^{**} (0.0134)	0.0290^{*} (0.0167)	$\begin{array}{c} 0.00137 \\ (0.0184) \end{array}$				
D[Activism on Seller]	$0.0173 \\ (0.0247)$	$\begin{array}{c} 0.0151 \\ (0.0192) \end{array}$	-0.000125 (0.0276)				
Firm-level control variables Industry and Year fixed effect N adj. R^2	Yes Yes 5824 0.089	Yes Yes 5824 0.094	Yes Yes 5824 0.053				

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

<u> </u>	0 I (1 0	/
	(1) D[Outsider]	(2) D[Outsider:PE]	(3) D[Outsider:SB]
D[Industry HFA Freq P80] \times High Redeploy Score	$\begin{array}{c} 0.148^{***} \\ (0.0486) \end{array}$	$\begin{array}{c} 0.0889^{***} \\ (0.0309) \end{array}$	$0.0553 \\ (0.0423)$
D[Industry HFA Freq P80] \times Low Redeploy Score	0.102^{**} (0.0395)	$0.0198 \\ (0.0262)$	0.0806^{*} (0.0454)
High Redeploy Score	$\begin{array}{c} 0.0119 \\ (0.0420) \end{array}$	0.0295^{*} (0.0173)	-0.0167 (0.0374)
Firm-level control variables Year fixed effect N adj. R^2	Yes Yes 5452 0.031	Yes Yes 5452 0.043	Yes Yes 5452 0.013

Table 10: 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 merger or 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).

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

	(1) (2)		(3)	(4)
	Sample of Divestitures		Sample	e of Mergers
	$\overline{\frac{\text{Seller's CAR}}{[-2d, +2d]}}$	$\begin{array}{c} \text{Seller's CAR} \\ [-5d, +5d] \end{array}$	Premium [1 month]	Target's CAR $[-43d, +1d]$
Industry HFA Freq \times D[Activism on Seller]	$0.00418 \\ (0.0448)$	$0.0325 \\ (0.0552)$	-0.151 (0.179)	-0.159 (0.135)
Industry HFA Freq \times D[No Activism] \times High Redeploy Score	-0.0257	-0.0434	-0.288^{*}	-0.262^{*}
	(0.0214)	(0.0268)	(0.168)	(0.156)
Industry HFA Freq \times D[No Activism] \times Low Redeploy Score	-0.0361^{**} (0.0171)	-0.0491^{**} (0.0233)	-0.350^{***} (0.123)	-0.276^{***} (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 B: Price pressure for sellers (interaction with Redeploy Score)

	Panel C:	Price press	ure for buy	vers				
	(1)	(2) Sample of 1	(3) Divestiture	(4) s	(5)	(6) Sample o	(7) f Mergers	(8)
	Buyer [-2d,	$rac{2}{ m s CAR}$ +2d]	Buyer ² [-5d,	$rac{2}{ m s CAR} + 5d$]	Acquire [-2d,	r's CAR +2d]	Acquire [-5d,	r's CAR +5d]
Industry HFA Freq \times D[No Activism]	-0.0240 (0.0254)		-0.0137 (0.0329)		$\begin{array}{c} 0.0299 \\ (0.0290) \end{array}$		$\begin{array}{c} 0.0659^{*} \\ (0.0396) \end{array}$	
Industry HFA Freq \times D[Activism on Seller]	$\begin{array}{c} 0.116^{*} \\ (0.0652) \end{array}$		$\begin{array}{c} 0.142^{*} \\ (0.0762) \end{array}$		-0.0540 (0.0505)		$\begin{array}{c} 0.00288 \\ (0.0583) \end{array}$	
Industry HFStake Freq \times D[No Activism]		$\begin{array}{c} 0.0370 \\ (0.0286) \end{array}$		$\begin{array}{c} 0.0758^{**} \\ (0.0354) \end{array}$		$\begin{array}{c} 0.0352\\ (0.0218) \end{array}$		$\begin{array}{c} 0.0644^{**} \\ (0.0263) \end{array}$
Industry HFStake Freq \times D[Activism on Seller]		$\begin{array}{c} 0.0573 \ (0.0570) \end{array}$		$\begin{array}{c} 0.0455 \\ (0.0648) \end{array}$		-0.0426 (0.0488)		$\begin{array}{c} 0.0371 \\ (0.0580) \end{array}$
Transaction-level controls Industry and Year fixed effect N adj. R^2	Yes Yes 2845 0.000	Yes Yes 2845 0.000	Yes Yes 2845 0.019	Yes Yes 2845 0.020	Yes Yes 2168 0.076	Yes Yes 2168 0.077	Yes Yes 2173 0.048	Yes Yes 2173 0.048

Table 11: 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 divestit	tures by HFA	. target firm	s
	(1) Tobin's Q	(2) ROA	(3) Sales/Assets(lag)
D[Post Divestiture]	$\begin{array}{c} 0.0629^{***} \\ (0.0186) \end{array}$	-0.00271 (0.00237)	-0.00664 (0.00915)
$D[Post Divestiture] \times D[Activism Divestiture]$	$\begin{array}{c} 0.147^{***} \\ (0.0561) \end{array}$	$\begin{array}{c} 0.0131^{**} \\ (0.00631) \end{array}$	$0.0430 \\ (0.0292)$
D[Post HFA]	$\begin{array}{c} 0.0933^{***} \\ (0.0344) \end{array}$	-0.00517 (0.00446)	-0.00953 (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]	$\begin{array}{c} 0.0621^{***} \\ (0.0202) \end{array}$	-0.00162 (0.00257)	$-0.00149 \\ (0.0102)$
$D[Post Divestiture] \times D[High HFA Threat]$	$\begin{array}{c} 0.0242 \\ (0.0295) \end{array}$	-0.00350 (0.00368)	-0.0152 (0.0161)
D[Post HFA]	$\begin{array}{c} 0.151^{***} \\ (0.0360) \end{array}$	-0.00102 (0.00457)	$\begin{array}{c} 0.0121 \\ (0.0173) \end{array}$
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 12: 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 acc	nuisitions	bv	HFA	target	firms
		· · · · · · · · · · · · · · · · · · ·			/			

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

	(1)Tobin's Q	$\binom{(2)}{\text{ROA}}$	(3) Sales/Assets(lag)
D[Post Acquisition]	-0.185^{***} (0.0331)	$\begin{array}{c} -0.0170^{***} \\ (0.00326) \end{array}$	-0.0931^{***} (0.0125)
$D[Post Acquisition] \times D[Small]$	$\begin{array}{c} 0.195^{***} \\ (0.0597) \end{array}$	$\begin{array}{c} 0.0125^{**} \\ (0.00635) \end{array}$	$\begin{array}{c} 0.0401^{*} \ (0.0235) \end{array}$
$D[Post Acquisition] \times D[High HFA Threat]$	$\begin{array}{c} 0.000568 \\ (0.0518) \end{array}$	$\begin{array}{c} -0.000647 \\ (0.00494) \end{array}$	-0.0115 (0.0214)
D[Post Acquisition] \times D[High HFA Threat] \times D[Small]	-0.0133 (0.114)	$\begin{array}{c} 0.0133 \ (0.0142) \end{array}$	$\begin{array}{c} 0.0962 \\ (0.0600) \end{array}$
D[Post HFA]	$\begin{array}{c} 0.0566 \\ (0.0507) \end{array}$	-0.00698 (0.00590)	-0.0345^{*} (0.0190)
Firm-level controls Year and Firm fixed effect N	Yes Yes 49293	Yes Yes 46525 0.620	Yes Yes 49110 0.800
aul. n	0.000	0.020	0.800

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