Activism Waves and the Market for Corporate Assets

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Abstract

We show that the majority of hedge fund activism campaigns occur in clusters by industry and time. Activism waves are explained by poor and deteriorating industry conditions and magnified by the herd behavior of inexperienced funds, but they are not driven by asset liquidity. Activism waves lead to a large increase in the threat to become an activism target. They strongly impact the market for corporate assets as targets as well as peer firms receive more merger bids, increase divestitures and make fewer acquisitions. We estimate that the simultaneous increase in asset sales and decrease in acquisitions in activism waves reduce real asset liquidity for asset sellers by about 35%. The liquidity squeeze produces two effects: transaction prices are reduced, and industry outsiders provide liquidity by purchasing more industry assets. Looking at short-term price pressure and long-run performance, we present evidence that transactions by activist targets are less affected by the reduced asset liquidity than those of other firms.

Keywords: activism waves, hedge fund activism, real asset liquidity, fire sales, divestitures, mergers, acquisitions, small acquirers.

JEL Classifications: G23, G34

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ABSTRACT

We show that the majority of hedge fund activism campaigns occur in clusters by industry and time. Activism waves are explained by poor and deteriorating industry conditions and magnified by the herd behavior of inexperienced funds, but they are not driven by asset liquidity. Activism waves lead to a large increase in the threat to become an activism target. They strongly impact the market for corporate assets as targets as well as peer firms receive more merger bids, increase divestitures and make fewer acquisitions. We estimate that the simultaneous increase in asset sales and decrease in acquisitions in activism waves reduce real asset liquidity for asset sellers by about 35%. The liquidity squeeze produces two effects: transaction prices are reduced, and industry outsiders provide liquidity by purchasing more industry assets. Looking at short-term price pressure and long-run performance, we present evidence that transactions by activist targets are less affected by the reduced asset liquidity than those of other firms.

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1. Introduction

The rise of shareholder activism over more than two decades has spurred research into its effects on target firms, including their performance and behavior. Studies typically explore the impact on individual firms, thus implicitly treating campaigns as firm-specific events. But conditions that lead to underperformance and to activist involvement are unlikely to be randomly distributed: shocks that trigger campaigns are frequently common shocks, generated by technology or macro shocks, regulation or changing consumer attitudes, and clustered by industry.

In this paper, we explore whether activism events are in fact clustered by industry and time, and if this is the case, whether it is possible to identify the determinants of such activism waves, related to factors such as industry performance, asset markets, and herd behavior. Activism waves are likely to create economic spillover effects. Such effects could be manifold, but corporate transactions are a natural starting point to look for such externalities, considering earlier findings that activists tend to influence target firms' M&A behavior and to increase their probability to be taken over. Therefore, we explore whether the uniform direction and the concentration of the change in acquisition behavior in activism waves is sufficiently strong to dislocate the equilibrium in corporate asset markets. Specifically, we explore whether activism waves reduce the real asset liquidity in affected industries and squeeze asset prices. By doing so, we contribute to the analysis of real asset market spillovers and of fire sales triggered by common shocks to firms' financial conditions.

Our main findings are as follows. We document that hedge fund activism is highly concentrated. The majority of activism campaigns can be attributed to activism waves that we define as the top quintile of industry-years (at the 3-digit SIC level) by frequency of targeted firms: in activism waves, a quarter of firms in the industry on average is targeted by activists, and 52% of all activist campaigns occur in these waves. On the other hand, only 13% of industry-years are classified as activism waves. We find similar results for different measures of activism clusters. Moreover, we show that the risk of being targeted in the near future increases sharply for peer firms during activism waves, by 37% for a one standard increase in campaign frequency. Thus, activism waves presumably have a substantial impact not only on target firms, but also on their industry peers.

Exploring the determinants of activism waves, we show that they arise in industries with low and deteriorating performance, using an array of performance measures. They are more likely in cash-rich industries and in industries hosting smaller firms on average. They are magnified by herd behavior among hedge funds, with relatively inexperienced hedge funds imitating the industry picks of their more experienced peers. By contrast, activism clusters are not explained by a high level of asset liquidity or heightened industry activity in corporate transactions. The last findings show that activists do not select industries that offer favorable conditions to conduct corporate transactions that they tend to initiate.

Turning to the impact on transaction behavior, we confirm that activist target firms are more likely to receive merger bids, make more divestitures, and make fewer acquisitions, with the last effect due to larger firms. The strong increase in the threat level for industry peers during activism waves leads us to investigate their reaction as a second channel of the impact on corporate asset markets. We show that industry peers also adjust their behavior in the same direction, by selling more assets, acquiring less on average, and being more likely to be acquired. The latter effect, however, is nuanced: only large firms make fewer acquisitions, whereas small firms maintain or increase their acquisitions activity. Activist targets change their behavior more dramatically but only a few firms in an industry are targeted at any given time, and many more firms are peers. We provide estimates for the relative importance of the two channels of imbalances in transaction behavior, for target and for peer firms, and find that the overall impact attributed to the peer firm channel is nearly the same as that of the target channel, with a larger relative effect on the demand side (acquisitions), and a smaller effect on the supply side (mergers and divestitures).

We estimate that during activism waves, firms sell on average about 23% more assets, and make close to 12% fewer acquisitions, leading to a combined shift in the relation between demand and supply for corporate assets of roughly 35%.

Such a squeeze in real asset liquidity is likely to have an effect both on transaction volume and on transaction prices. Hence, we consider whether during activism waves, when real asset liquidity dries up, there is a role for outside liquidity providers. Indeed, we find that outsider acquirers - private equity funds, private firms, and listed firms in other industries - provide liquidity and that their acquisition volume increases in affected industries. We find that outside asset liquidity provision is stronger in industries with high asset redeployability, and show that this effect is predominantly due to private equity being more willing to provide asset liquidity.

We then explore whether the squeeze in real asset liquidity affects transaction prices. We find that 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 price pressure is stronger in industries with low asset redeployability, the flipside of our result that outsiders are less willing to provide asset liquidity when assets are not redeployable. We do not find evidence for a similar price effect for activist target firms: unlike other firms in industries under heavy activist pressure, activist target firms themselves appear little affected.

Finally, we consider whether the negative externalities of industry clustering affect the long-run performance of corporate transactions undertaken under activism pressure. Looking at accounting measures and Tobin's Q, we isolate the incremental long-run effect of transactions done under activism influence from the documented performance boost of activism campaigns and of corporate transactions. We find positive long-run performance effects for corporate transactions undertaken by activism targets. We do not find similar effects for transactions undertaken by peer firms. The direct involvement of activists appears to be necessary for activism pressure to produce additional efficiency gains in corporate transactions. Overall, transactions by targets are relatively efficient and immune to the squeeze in real asset liquidity, providing a rationale why hedge funds are not more actively fleeing activism waves.

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. Our study addresses these concerns in various ways. First, for target firms (for which such concerns are particularly important), we follow Brav, Jiang, and Kim (2015a) and look at the effect when a hedge fund, for a given hedge fund-activist pair, switches from a sizable passive stake in a given firm (Schedule 13G filing) to an activist stance (Schedule 13D filing). We show that such switches produce a significant change in firms' corporate transactions in the same direction we found earlier, providing a "clean identification of intervention beyond stock picking" (Brav et al., 2015a).

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

Third, therefore, we deploy an instrumental variable built on the idiosyncratic fund inflow shock of each activist hedge fund that hypothetically reassigns new fund inflows according to the previous industry holding structure of each hedge fund and hence dissociates the increase in activist's targeting from their selection of industries.[1] We find that our results on corporate asset markets remain in place when we use this instrument.

[1] The instrument is similar to the well-known instrument of mutual fund fire sales (Coval and Stafford, 2007; Edmans, Goldstein, and Jiang, 2012) and has been used in the activism literature, see Section 2.2.

Finally, we carefully investigate whether the emergence of activism clusters could be related to industry asset liquidity or recent merger waves. We find no association between merger waves and hedge fund target selection[2] and find no evidence that differences in asset liquidity or transaction frequency play a role in determining activism waves.

Our paper is related to various strands of the literatures on activism, takeovers, and on corporate asset markets. In the activism literature, our paper contributes to the large body of earlier work on the real effects and the financial performance of hedge fund activism. This literature[3] analyzes in particular value gains following campaigns (Brav, Jiang, Partnoy, and Thomas, 2008; Greenwood and Schor, 2009; Becht et al., 2017), improvements in operations and profitability of targets (Bebchuk, Brav, and Jiang, 2015; Brav et al., 2015a),[4] their competitive position in product markets (Aslan and Kumar, 2016), and the quality of their innovation effort (Brav, Jiang, Ma, and Tian, 2018). Our paper contributes several new aspects to this literature, notably by showing that post-activism corporate transactions improve the economic efficiency of sellers, but less for firms acting under activism threat, and that only smaller firms generate performance gains from activism acquisitions.

Our paper is also related to earlier work on predicting activism targets (Brav et al., 2008; Klein and Zur, 2009). We contribute to this approach the importance of industrywide shocks and determinants.

A number of reasons can explain why industry peers in activism clusters adopt behavior similar to that of campaign targets. The idea of a disciplinary effect of activism is related to the literature on the disciplining effect of the market for corporate control (see Grossman and Hart (1980) and Bertrand and Mullainathan (2003) for evidence). On the theory side, Edmans and Manso (2011) and Fos and Kahn (2016) develop models that imply that managers proactively adjust their behavior in anticipation of activism risk. Other possible explanations include strategic interaction effects in product or asset markets[5] and mimicking behavior. There is also a small empirical literature on threat effects of activism (Gantchev, Gredil, and Jotikasthira, 2019; Feng, Xu, and Zhu, 2021; Bourveau and Schoenfeld, 2017) to which our investigation is

[2]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.

[3]See Denes, Karpoff, and McWilliams (2017) and Brav, Jiang, and Kim (2015b) for surveys. The international expansion of activism is analyzed in Becht, Franks, Grant, and Wagner (2017).

[4]There is some controversy concerning the improvement in long-term performance, see deHaan, Larcker, and McClure (2019) for size effects and Grennan (2019) for evidence on short-termism.

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

related. We contribute to this literature insights about the importance of activism waves and the presence of activism threat peer effects in transaction behavior.

Concerning the literature on merger waves, our paper builds on earlier work pointing to the role of industry shocks (Mitchell and Mulherin, 1996; Andrade, Mitchell, and Stafford, 2001) as well as of policy shocks in their emergence.[6] Our exploration whether activism clusters can be traced to industry conditions is inspired by this literature, as is the choice of our measures (in particular (Harford, 2005). Herd behavior among fund managers can also contribute to clusters, a classic theme in investments going back to Scharfstein and Stein (1990).

Our focus on the spillover effects of activism waves on the market for corporate assets is motivated by theoretical models that explain why activism targets frequently become takeover targets. Burkart and Lee (2022) show that activists reduce ex ante and ex post free-riding in takeovers, and Corum and Levit (2019) 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 et al., 2017; Becht et al., 2017). Gantchev, Sevilir, and Shivdasani (2020) find that activism campaigns reduce firm's propensity to make acquisitions, increase the frequency of divestiture, and improve the quality of transactions.

Finally, our paper is related to earlier literature on corporate asset markets. The squeeze in real asset liquidity when more assets are sold and fewer are bought is related to the argument by Shleifer and Vishny (1992) that industry peers are the highest-value acquirer of any assets in an industry that is for sale. There is a substantial theoretical and empirical literature on asset fire sales[7] that guides our expectation that the effect on real asset liquidity be measurable both along the quantity and the price dimension, following the discussion on asset fire sales since Pulvino (1998). The market imbalance for corporate assets in our study, however, is driven by coincident hedge fund strategies and hence by factors that are markedly different from those typically associated with fire sales, in particular industry financial distress (see Shleifer and Vishny, 1992; Franks, Seth, Sussman, and Vig, 2021) and stress in intermediary balance sheets (e.g., Campbell, Giglio, and Pathak, 2011). 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.

When studying the effect of activism on the efficiency of corporate transactions, two lit-

[6]Deregulation was found to be a particularly salient shock in the 1980s and 1990s (Andrade et al., 2001). Other determinants of merger waves include industry fluctuations in valuations (e.g., Rhodes-Kropf, Robinson, and Viswanathan, 2005).

[7]See Shleifer and Vishny (2011) for a survey.

eratures are relevant: the neoclassical view that corporate acquisitions serve the purpose of reallocate assets efficiently[8] and the literature on the relationship between corporate governance and acquisition markets that considers value-destroying acquisitions as a prominent dimension of managerial agency costs (Jensen, 1986; Morck, Shleifer, and Vishny, 1990) and emphasizes the disciplining role of the market for corporate control on acquisition behavior (Mitchell and Lehn, 1990).[9] We add to this literature the findings that transaction efficiency achieved by activism targets exceeds that of peer firms and increases in the intensity of the activism-led governance shock, findings that are in line with the literature on the governance-transaction performance link since activism is generally viewed as a positive governance shock. Our paper is also related to earlier work showing that acquirer returns and long-term post-acquisition performance are significantly higher for smaller acquirers (Moeller, Schlingemann, and Stulz, 2004; Gorton, Kahl, and Rosen, 2009); we show that this relationship extends to activism.

To summarize the ideas that guide our analysis, we expect activism to be clustered when poor and deteriorating performance is explained by common industry shocks. Activism targets as well as peer firms in activism waves should be more likely to be sold or to make divestitures, and to make fewer acquisitions. We expect that during activism waves, the supply of real assets increases and the demand for real assets decreases, and that these common trends create imbalances in corporate asset markets. The ensuing squeeze in real asset liquidity should depress transaction prices and create a role for outside asset liquidity provision.

To the best of our knowledge, no earlier paper has investigated activism waves (clusters of activism campaigns) and its causes and consequences. There is also no earlier work on the effect of activism on the equilibrium outcome in asset markets and on the impact of activism on the acquisition and asset sales behavior of peer firms.

The paper is organized as follows. We explain our sample construction and methodology in Section 2. Section 3 studies the clustering of activism in waves and its origins. Section 4 analyzes the impact of activism waves on mergers, divestitures, and acquisitions. In Section 5, we investigate how activism waves alter 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.

[8] While long dominating economics (Jovanovic and Rousseau, 2002), the evidence is mixed: Maksimovic and Phillips (2001) find that mergers improve plant-level efficiency, but studies based on Tobin's Q do not yield a consensus.

[9] The empirical evidence is mostly supportive as it shows that acquirers with better corporate governance have higher acquisition returns (Masulis, Wang, and Xie, 2007) and that the ex post performance of mergers and acquisitions is generally positive (Andrade et al., 2001) though acquirer returns in acquisitions of public targets are low.

2. Data and Measures of Activism Intensity

2.1 Data on activism, transactions and firms

Our comprehensive sample of hedge fund activism (HFA) combines two data sources: the sample originally studied in Brav et al. (2008) and updated by Alon Brav, Wei Jiang and Song Ma to include the more recent time period[10] and the FactSet SharkWatch database. The two databases are only partially overlapping as they use complementary sampling strategies.[11] When combining the two samples, we carefully screen the data, remove duplicates and merge multiple campaigns targeting a single firm.[12] The merger of multiple activism campaigns targeting a single firm in any calendar year as a single activism observation, starting at the first recorded announcement date, follows Boyson et al. (2017). We obtain a total sample of 4,380 HFA events. We further limit the sample to HFA events that target firms incorporated in the U.S. and included in the CRSP-Compustat Merged Database. This process yields a sample of 3,551 unique HFA campaigns in the U.S. (see Table 1, Panel A), and of 862 hedge funds that operate as activist hedge funds at least once in our sample and that we use to distinguish between activist hedge funds and other institutional investors. The activism sample covers the period from 1994 - 2016. We fix 1994 as the start date, the earliest year with significant activity by hedge fund activists, consistent with earlier literature.

We use SDC Platinum to construct three separate samples of corporate transactions during the 1994-2016 period, covering respectively (1) mergers (U.S. listed firms being acquired), (2) divestitures (sellers are U.S. listed firms), and (3) acquisitions (acquirers are U.S. listed firms). We only retain transactions with a control change[13] and with a (non-missing) transaction value of at least $10 million, and apply standard filters for each transaction type[14] and apply otherwise

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

[11] Brav and Jiang identify hedge fund activism campaigns mainly through the first Schedule 13D filing with the Securities and Exchange Commission (SEC) whereas FactSet SharkWatch focuses on public campaigns and identifies them from various sources, such as press releases, financial news, 13D fillings and proxy statements, and tracks public campaigns also when activists have ownership below 5%. 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 and intends to influence management, corporate policy or fs control.

[12] We find that 1,728 of 3,537 campaigns in Brav, Jiang and Ma's extended sample are also recorded in FactSet SharkWatch. We only retain HFA events from SharkWatch if at least one of the activists is a hedge fund and if the campaign target is not a fund (such as a closed end or real estate fund). We also drop 292 activist campaigns involving risk arbitrage as in Boyson et al. (2017).

[13] The acquirer owns less than 50% of shares before the bid and seeks to own more than 50% afterwards.

[14] For the merger sample, we exclude divestitures, spinoffs, recapitalizations, self-tender offers, repurchases, partial equity stakes, acquisitions of remaining interest, privatizations, as well as deals in which the target or the acquirer is a government agency. For the divestiture sample, we only retain transactions that are marked in SDC Platinum as either "divestiture" or "division" and are completed, for which no other information leads us to conclude that it is not a sale of a corporate unit or subsidiary, and we exclude spinoffs and splitoffs. For

identical filters for all three transaction types.[15]

The universe of U.S. firms in the CRSP-Compustat Merged Database serves as our baseline sample. We exclude all firms that are not incorporated and headquartered in the U.S., and exclude firm-years with missing SIC codes and with missing or negative total sales, yielding a baseline sample of 116,448 firm-year observations from 1994 to 2016. We complement the financial and stock price data with data on institutional ownership from 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.

Based on the idea that real assets, in particular intangible assets, are often industry-specific (Shleifer and Vishny, 1992), we study activism waves and 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. Data for patent applications by US public firms from 1994 to 2009 are from the sample of Kogan et. al. (2017).

2.2 Measuring activism intensity

Using our sample of 3,551 HFA events, we define a dummy variable for HFA targets, D(Activist), that is equal to one in the year when an activism event is recorded and for a two-year period afterwards.[16] The two-year horizon is taken from Boyson et al. (2017) and it builds on earlier work on long-run effects of HFA targeting on target behavior in asset markets (Gantchev et al., 2020).

We focus on industry-level measures of activism intensity. Our main measure of activism intensity is the fraction of recent HFA targets in the industry (at the 3 digit SIC level), i.e. firms that have been targeted by activist hedge funds in the last three years. The resulting industry-level metric, Industry HFA Frequency, exhibits strong patterns of cross-sectional and year-to-year fluctuations that capture changes in the industry-wide involvement of activists.[17]

We construct an alternative measure of activism intensity, Industry HFStake Frequency, by aggregating the quarterly total active and passive ownership by activist hedge funds from 13F

the acquisition sample, we include all SDC M&A transactions where targets are U.S. based listed firms, private firms, or subsidiaries, and the acquirer a listed firm in the CRSP-Compustat Merged Database.

[15] We exclude transactions involving spinoffs, splitoffs, self-tenders and share repurchases.

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

[17] See Table 1, Panel C.

filings (using the Refinitiv 13F database). We only include 13F filings of hedge funds in our list of 832 activist funds. We define a dummy for each firm-year that is equal to one if the total ownership of hedge funds increases in that year by more than 5%. We aggregate this dummy variable at the industry level and obtain Industry HFStake Frequency, the fraction of industry firms with one or several HF stake jumps of more than 5% within the last 3 years.

The focus on industry-level measures of activism should address concerns about possible selection biases in our sample of activism targets that arise due to firm-level characteristics. It still leaves open the possibility that hedge funds select target firms based on common industry characteristics. We study potential determinants of such selection effects based on observable industry characteristics in Section 3.3. To address selection effects based on unobservable industry characteristics and similar endogeneity concerns, we construct an additional, plausibly exogenous measure of changes in activism intensity. Inspired by Edmans et al. (2012) and reproducing the exact definitions and procedure used by Gantchev et al. (2019) who apply the concept to activism, we construct the variable Flow Induced Fund Buy (FIFB) that removes the hedge funds' possibly endogenous choice of industries in which they increase their holdings. 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 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. 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.[18]

2.3 Summary statistics

Our sample of HFA events is fairly well distributed over the sample period, as Table 1 shows (Panel A), with a peak in 2006-2008, two slowdowns during stock market downturns (1999-2001 and 2009-2010), and a strong rebound after 2011. The number of firms in the baseline sample peaks at 6,850 in 1996 and then steadily declines to 3,990 firms in 2016, largely reflecting the

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

intense M&A activity among listed U.S. firms (Doidge, Kahle, Karolyi, and Stulz, 2018).

Table 1 reports in Panel B commonly used firm characteristics, splitting our sample in HFA target firms (N = 3,551) and the remaining firm-year observations in the baseline sample (N = 112,897). In line with earlier papers (starting with Brav et al. (2008)), we find that the differences in institutional ownership, Tobin's Q, market capitalization (in logs), as well as those in dividend yield, cash flow, ROA, sales growth, asset growth, recent stock performance (one-year CAR) and industry concentration are all significant. We control for these and other firm-level characteristics in our regressions, and discuss below how they help to explain the selection of hedge fund targets (Section 3.2).

Panel C presents summary statistics of the distribution of our activism intensity measures by industry-year. On average, 6.0% of firms in an industry are recent or current activism targets, and 10.2% of firms experience a recent or current increase in hedge funds ownership of more than 5%. Both values are about 50% higher at the 75% percentile, sorted by industry-year.

[Insert Table 1 Here]

3. Activism Waves

3.1 Identifying activism waves

To shed light on the question whether activism campaigns are concentrated by industry and time period, we consider the top quintile in the distribution of Industry HFA Frequency, reported by industry-year. Some 3-digit SIC industries are thin and contain only a small number of firms, and hence we define as *activism waves* only industry-years in the top quintile of observations by Industry HFA Frequency in which at least two activism campaigns occur. Table 2 shows in column (3) that a majority of activist campaigns, 52% (1,829 out of 3,551), occur in activism waves using this definition. On the other hand, activism waves account for only 13% of all industry-years (770 out of 6,028), a much smaller fraction. Without the condition of at least two campaigns in any given year, top-quintile industry-years account for 57% of all campaigns but only 16% of industry-years, see column (2). When we consider a wider measure of clustering, industry-years in the top tercile by Industry HFA Frequency with at least two campaigns, we find that 78% of campaigns are taking place in such clusters. In column (4), we consider a more selective criterion of clustering that we call Harford waves, developed by adapting Harford (2005)'s method for merger waves and determining the equivalent top segment of the distribution of Industry HFA Frequency with at least two campaigns.[19] Even for this restrictive cluster measure, we still find that Harford waves comprise 37% of all campaigns (1,310 of 3,551) while they cover only 6% of all industry-years in our sample.

Thus, whichever criterion is used to slice the data, the distribution of campaigns over industry-years is very uneven and highly concentrated.

Panel B of Table 2 documents the year-by-year evolution of industries that we classify as activism waves, and their persistence and importance: in every year after 2004 (with 2010 the only exception), more than 50% of campaigns occur in activism waves.

[Insert Table 2 Here]

Overall, our descriptive evidence suggests that activism campaigns are highly concentrated in industry waves. Table IA.1 in the Online Appendix lists the industries in which activism clusters occur most and least frequently during the 23-year period 1994-2016. The top industries (retail-department stores, hotels & motels) are theaters of activism waves in more than 40% of industry-years. Activism clusters seem to concentrate in service and communication industries.

We find little differences in firm characteristics when we split the sample in industry-year quantiles by activism intensities. While there is substantial variation across quantile means and medians, the percentage differences are small, with the exception of dividends and cash holdings, and there is hardly any monotonic trend in the variables.[20] Only a handful of differences in mean firm characteristics emerge between industries exposed to activism waves and those that are not, and as we discuss next, they are in line with established determinants of target selection.[21]

3.2 Activism waves and threat levels

Do industry measures of activism intensity predict changes in the probability of individual firms to become activism targets? This question is important to understand firm behavior in affected industries. To answer the question, we look at the predicted probability of a firm to

[19]Our measure Harford wave (column (4)) adapts Harford (2005)'s simulation method as follows. If there are n HFA events in an industry in our sample, we simulate 1000 times the distribution of n HFA events and record the max number of campaigns in any two consecutive years in each simulation. We identify an industry-year in the real data as a Harford wave if the number of HFA events within two consecutive years is in the top quintile of the simulated max number of HFA events.

[20]See Table IA.2 in the Online Appendix where we split the full sample by terciles of Industry HFA Frequency. Differences between the bottom and the middle quantile tend to revert back when moving to the top quantile.

[21]They concern four variables predicting higher frequencies of hedge fund targeting, consistent with earlier work and documented in Table 3: hedge funds are more likely to be active in industries with smaller firms, more institutional ownership, lower dividends and larger cash reserves.

become a hedge fund activism target in the following year, following the methodology pioneered by Brav et al. (2008) and Klein and Zur (2009). Our logit model includes only firms that were not HFA targets in the last two years. We add all variables that the literature has shown to affect target probabilities. The results are presented in Table 3, Panel A. Column (1) confirms all the known robust predictors for the benchmark, in particular small size, low Tobin's Q, institutional ownership, low dividends and cash flows or ROA, large cash holdings, and underperforming recent stock returns, with reasonable combined predictive power (pseudo-$R^2 = 0.086$).

We then add our industry-level variable of activism intensity, Industry HFA Frequency, in columns (2) and (5). We find that the probability of becoming a HFA target sharply increases. A one-standard deviation increase in Industry HFA Frequency translates into an approximately 37% increase in the probability of becoming a target in the next 2 years. Importantly, the model's power to predict whether an individual firm will be targeted relative to the known determinants strongly increases by 52% ($R^2 = 0.129$).

[Insert Table 3 Here]

Considering Industry HFStake Frequency, our second activism intensity measure (see Section 2.2), we find that the increase in the predictive power is again highly significant at the 1% level (columns (3) and (6)), but with a smaller contribution to combined predictive power.

To ensure that these results are not driven by endogenous relationships, we use our variable FIFB that captures exogenous variations in likely activist engagement. The regressions in columns (4) and (7) show that our industry-level activism measures significantly determine future target probabilities and hence, express threat levels for firm managers, again at the 1% level. FIFB also strongly predicts future activism frequency in the industry (columns (8) and (9)).

To sum up, our estimates all show that the probability to become an activism target sharply increases in the activism intensity of the industry. A substantial fraction of hedge fund threats is driven by a common industry component captured by current activism intensity. Thus, it appears rational for firms to change their behavior when they observe that activism intensity in their industry is heating up.

3.3 Origins of activism waves

Is it possible to identify observable characteristics of industries that attract fund activists and hence expose industries to activism waves? We explore this question, which can be compared to the search for determinants of merger waves,[22] by running panel regressions that analyze the role of industry conditions in the emergence of activism waves. We expect that activism clusters emerge in industries with conditions that entice activist interest, for example after exposure to negative performance shocks. We look at two sets of variables, industry performance metrics and industry measures of corporate restructuring and asset liquidity.

[Insert Table 4 Here]

In Panel A of Table 4, we document our findings for standard performance metrics at the industry level: aggregate industry valuation (Tobin's Q), aggregate 12-month stock market performance (aggregate CAR in a Fama-French 5-factor model) and industry cash flows. Importantly, we look at the recent change in each of these variables as well (one-year change lagged by one year), since a recent deterioration should indicate that an industry becomes more attractive for hedge funds. Panel A shows that both the level and recent deteriorations in these variables indicate that the industry is more likely to face an activism wave. We also look at the firm size distribution since activists tend to target smaller firms, and find that there is substantial variation in the firm size distribution across industries. We find that industries with lower average market capitalizations are more likely to experience an activism wave, again consistent with firm-level findings.[23] These findings hold for our main measure of activism waves, the top quintile of industry-years by Industry HFA Frequency, as well as for the more restrictive criterion that follows Harford's (2005) method.

The second pass of our investigation looks at transaction activity and asset liquidity as possible explanations of activism waves. Facilitating and intensifying corporate restructuring through transactions is a major objective of hedge fund activists; hence industries with higher asset liquidity and more asset turnover could look more attractive to activists. We use two standard measures of transaction activity and two for asset market liquidity. For transaction activity, we use the volume of corporate transactions in an industry (scaled by market capitalization) introduced by Schlingemann et al. (2002)[24] and Harford's (2005) measure of merger waves. For

[22]Characteristics that expose industries to an increased incidence of merger waves include valuations, cash overhang, or deregulation, see Harford (2005).

[23]By contrast, industries with high leverage, high excess cash, high institutional ownership or low dividend yields do not have a higher probability of activism waves (results not reported). These variables help predict in firm-level regressions the probability of becoming activism targets, when measured as differences from the industry average or with industry×year fixed effects. Since by definition these differences disappear in industry-level regressions, it is entirely consistent that they are not significant in regressions of industry aggregates.

[24]We deploy the version of Ortiz-Molina and Phillips (2014) and cumulate transactions over three years. We also use the same variable based purely on Private Equity transactions, with the same (insignificant) result. We recognize that transaction activity and asset liquidity are to some extent overlapping concepts that cannot be perfectly separated. For example, Schlingemann et al. (2002) refer to their measure as asset liquidity.

asset liquidity, we use the asset redeployability score of Kim and Kung (2017) (see Section 5.3) and the weighted asset liquidity score of Gopalan, Kadan, and Pevzner (2012).[25]

Our findings, summarized in Panel B of Table 4, do not show any evidence that the emergence of activism waves is linked to industry characteristics with regard to transaction activity or asset liquidity, or by changes in firms' proclivity to initiate restructuring transactions. The latter finding is also reflected in our earlier regressions in Table 3 that show that merger waves do not explain an increase in Industry HFA Frequency, regardless whether we consider firm-level regressions (columns (5) to (7)) or their industry-level counterpart (column (9)).

In addition to looking at industry-level characteristics, we investigate the relationship (or absence thereof) between hedge fund targeting and transaction fluidity at the firm level. Specifically, we investigate whether hedge funds select target firms because of their propensity to engage in corporate transactions. We explore whether changes in firm-level propensities to undertake corporate transactions explain whether a firm will be targeted by hedge fund activists. We follow recent takeover prediction models (Cremers, Nair, and John, 2009; Karpoff, Schonlau, and Wehrly, 2017) for the estimation of the probability of a company to become a merger target, and use the same comprehensive set of explanatory variables and controls in models predicting the other transaction types, divestitures and acquisitions. Our main variable of interest is the change from year $t-1$ to t in the estimated probability to engage in any of the three transaction types. In Panel C of Table 4, we successively include these estimated innovations in transaction probabilities in our model predicting the likelihood of a firm to become a HFA campaign target (see Table 3). We find that the variables of interest, the innovations in transaction probabilities, are not significant (only the change in merger bids is weakly significant at the 10% level, but exhibits the wrong sign).

Overall, the lack of evidence for a relationship between activism intensity and asset liquidity,at the firm level and at the industry level, should go some way to address the possible endogeneity concern - which is about reverse causality - that the observed pattern in corporate transactions might not be the consequence of activism pressure, but on the contrary of activists picking industries because of the liquidity of their transaction market.

To summarize, activism waves are more likely in industries that experience low and deteriorating performance, and are more likely when firms are smaller on average. By contrast, we do not find evidence that the emergence of hedge fund activism clusters is driven by the industry's transaction activity or asset liquidity, or that firm-level target probabilities are driven by consideration of transaction frequency or liquidity.

[25] Specifically, we use the WAL 3 measure of Gopalan et al. (2012).

3.4 Activist herd behavior

Another possible determinant of activism clustering is behavioral: hedge funds might flock to the same industries because they mimic each other's behavior. Herd behavior in financial markets can have many causes and motives, ranging from fads, risk aversion to incentives that foster mimicking and discourage contrarian stances. We focus on one possible motive of mimicking behavior, that of less experienced hedge fund managers following the lead of more experienced peers. We follow the implementation of Koch (2017) who studies herd behavior among mutual funds to explore whether the portfolios of industry leaders are imitated with a lag by non-leaders.

We define leading funds as the top 20% of activist hedge funds by number of past active campaigns, updated annually (alternatively, the top 20% of activist hedge funds by number of past *hostile* campaigns[26]). We then implement a McFadden discrete choice model (McFadden, 1981) to predict in which of the SIC-3 industries in our sample any non-leading funds will launch its next activist campaign. The unit of observation is non-leading fund $\times$ industry $\times$ year. The variable of interest is Num(Leading Funds), the number of leading funds that targeted the same industry in a campaign in year $t-1$ (in campaigns or past hostile campaigns). D(Target Last Year) is a dummy that is equal to one if the fund has already targeted the industry in year $t-1$.

Table 5 shows the results. Column (1) shows that a non-leading fund's probability to choose any of the 3-digit SIC industries (there are 248 industries in this test) strongly increases when more leading funds undertook campaigns in the same industry in the past year; column (3) shows the same relationship by considering only hostile campaigns. We control for the number of firms in the industry since the dependent variable should increase in their number. We also control for all industry variables used in Table 4 Panel A. Further confirmation comes when we split the sample of non-leading funds at the median into novice and experienced funds in columns (2) and (4). We find that the mimicking effect is entirely due to the behavior of novice funds, in line with the idea that younger funds take cues from more experienced managers.

In conclusion, herd behavior of less experienced funds appears to contribute to the strong industry clustering of activism campaigns that we document, in addition to a variety of industry characteristics that capture low and deteriorating industry performance and smaller firm size. By contrast, activism clustering seems to be unrelated to the existing propensity and liquidity of corporate transactions.

[Insert Table 5 Here]

[26]Hostile campaigns are campaigns implying proxy fights or law suits according to the SharkWatch data.

4. Deal Activity and Activism Waves

4.1 Transaction behavior and activism: univariate evidence

We define an *activism merger* as a merger bid that falls within a two-year window after the public announcement of an activist campaign (13D filing or announcement date), following Boyson et al. (2017). We define *activism divestitures* and *activism acquisitions* similarly, using the same two-year window. Panel A of Table 6 shows univariate evidence on the relationship between activism and transaction frequencies for all three types of transactions. 5.17% of firms in the full CRSP-Compustat sample are targets of a merger bid each year (including unsuccessful bids), but the bid frequency rises to 10.19% for HFA target firms, almost twice as high, and it is substantially higher in every single year (Table IA.4 in the Online Appendix). The annual frequency of divestitures rises for activist targets by more than 50% in the two-year window after the campaign launch, from 5.19% to 7.81%. For acquisitions, including acquisitions of private firms and business units, the average annual frequency decreases by 22%, from 15.06% for the full sample to 11.82% for activism targets. These findings confirm earlier work.[27]

The last two columns tabulate the transaction frequencies for firms under high (low) HFA threat, defined as industries in the top (bottom) tercile by Industry HFA Frequency. We only tabulate the effect of peer firms, excluding firms targeted by activists in the current or previous two years. The average annual merger bid rate for firms under High HFA Threat is 24% higher than for the firms under low HFA threat (5.38% vs. 4.34%), the divestiture frequency for firms under high HFA threat is 13% higher, and the acquisition frequency is 7.7% lower for firms under high HFA compared to firms under low HFA threat (14.51% vs. 15.72%).

[Insert Table 6 Here]

4.2 Transaction behavior of activism targets: multivariate evidence

Turning to multivariate regressions, Panel B of Table 6 shows logit regressions for our firm-year panel where the variable of interest is D(Activist), the dummy variable tracking whether the firm is an activist campaign target in the 2 years prior to a transaction. We include an extensive list of control variables known to alter the frequency of activism campaigns or of corporate transactions.[28] We find a very strong effect of D(Activist), implying an estimated

[27] Gantchev et al. (2020) for acquisitions and divestitures, and Becht et al. (2017) and Boyson et al. (2017) for mergers.

[28] They include Tobin's Q, size, leverage, institutional ownership, cash, dividends, cash flow, asset and sales growth, recent stock market return, industry concentration (HHI), real asset liquidity (specified as in Ortiz-

increase in the probability of receiving a merger bid of 92% (10.49% vs. 5.45%) (t-value 12.9). The type of buyer does not seem to matter since the results are similar when we consider merger bids from strategic competitors, from financial buyer groups, or unsolicited bids separately (not reported in tables).

For divestitures, the results are again strong and highly significant, with HFA campaign targets having a 41% higher annual frequency of undertaking a divestiture (6.44% vs. 4.57%) compared with all firms ($t = 5.22$).[29]

When we turn to acquisitions, we find a highly significant decrease in acquisitions in our benchmark specification in regression (1) ($t = 3.56$). In regression (5), we split the variable of interest D(Activist) by firm size, inspired by the literature on firm size and acquirer performance (Moeller et al., 2004); we find that only firms with above-median size (market capitalization) significantly cut back on acquisitions, whereas the variable is insignificant for firms of below-median size. This result is robust when we use a more granular sample split by firm size (Table IA.5, Panel A, in the Online Appendix).[30] Unreported regressions show that the effect is driven by acquisitions of private targets, whereas acquisitions of public targets show no significant coefficient, and that there is no difference between acquisitions of related and unrelated assets.

We are concerned about endogeneity affecting the regression set-up of Panel B in Table 6, in particular about selection bias in activists' selection of target firms and the subsequent change of behavior in the market for corporate assets by target firms. To address these concerns, we deploy in Panel C methodology first proposed by Brav et al. (2015a) and distinguish between passive (13G filing) and active stakes (13D filing switched from 13G) by the same activist hedge funds in our sample.[31] The results in Panel C 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

Molina and Phillips (2014)), and industry and year fixed effects.

[29]Unreported regressions show that the frequency of divestitures is even higher when the activists mention divestitures as an explicit campaign goal. They also show that there is no important difference when we split the sample by type of buyer (strategic buyer or private equity), or by related vs. unrelated assets (related assets are assets that share the same 3-digit SIC code as the seller firm's core activity.)

[30]We do not find similar size effects for mergers and divestitures.

[31]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. We are grateful to Alon Brav and Song Ma for data.

significantly less likely. These findings are reassuring with regard to possible selection biases affecting the association between hedge fund exposure and acquisition behavior.

4.3 Activism waves and the pressure on transaction behavior

We explore whether peer firms acting under the disciplinary effect of activism waves change their transaction behavior, thus magnifying the impact of activism on the market for corporate assets. Since we focus exclusively on peer firms acting under perceived threats, we exclude target firms in the following multivariate analysis.[32]

In a preliminary test, we look at firm-level evidence. We use two different measures of firm-specific threat levels. First, we use the predicted probability of becoming an activism target, obtained from regression (1) in Table 3. Second, we use a dummy equal to one if the combined passive ownership by activist hedge funds is at least 5% for the firm in year t. Panel A of Table 7 shows the results for all three types of corporate transactions, and in addition for a fourth aggregate variable "corporate sales" that combines mergers and divestitures into a single variable (column (3)). We find highly significant results showing an increase in merger bids and divestitures, and a decrease in acquisition frequencies for large firms but not for small ones (see column (5)).

[Insert Table 7 Here]

We then turn to the impact of activism waves on industry transaction activity. As before, we only consider peer firms that act under heightened activism threat (D(Activist) = 0) and exclude firms that are current or recent activism targets (D(Activist) = 1). In order to control for industry shocks, we add the industry-level controls proposed by Harford (2005), such as industry-year median absolute change of ROA, Sales Growth, Employee Growth, and Turnover (sales scaled by lagged assets). We also add the full set of firm-level controls used in Table 3.

Panel B of Table 7 presents the results. Industry HFA Frequency, our main clustering variable, leads to a significant increase in divestitures and in sales (mergers and divestitures combined) ($p < 0.05$), but not in mergers.[33] 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 size, there is a highly significant *positive* effect

[32] Specifically, we exclude firms in the HFA event-year and the three subsequent years from our panel.

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

($p < 0.01$) on acquisitions and private acquisitions. We return to this puzzling finding below (see Section 5.5).

Panel B also shows strong results for our alternative measure of industry activism threats, Industry HFStake Frequency, the proportion of firms with a more than 5% increase in (active and passive) exposure to activist hedge funds. Divestitures and mergers both increase significantly, and the effect is stronger when we combine them again to sales of assets ($p < 0.01$). The findings confirm a negative reaction of acquisitions to heightened hedge fund threats only for large firms, whereas the sign is positive and significant for small firms.

Unobserved industry characteristics may bias our analysis. To address this concern, we use the instrument FIFB introduced in Section 2 that is based on large idiosyncratic fund inflow shocks ($> 5\%$). Most activist hedge funds are general investors in their passive investments and tend to invest quickly and in a mechanical manner in a diversified cross-section of industries when experiencing large inflows Coval and Stafford (2007). Therefore, it is reasonable to assume they will not allocate these inflows to industries according to unobserved industry trends that could be associated with corporate transactions activity. In Table 3, columns (4) 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.[34] The results, presented in Panel C of Table 7, show that mergers, divestitures and sales become significantly more likely and acquisitions by large firms less likely when using the FIFB instrument.

In conclusion, we find that both the target firm channel and the peer firm channel are active and lead firms during activism waves to divest more, to make fewer acquisitions, and to be more frequently targeted by merger bids. Peer firms make similar changes in their behavior compared with target firms, but there are two subtle differences: first, the effect on merger bids is strong for target firms, but weaker for firms acting under threat. Second, the discrepancy in acquisition behavior by firm size is even stronger for firms acting under activism threat compared with target firms, with large firms making fewer acquisitions as expected, and small firms under activism threat making *more* acquisitions.

[34] Gantchev et al. (2019) use the same approach for the analysis of FIFB. To check robustness, we also use a standard 2SLS estimator and find qualitatively similar, but less robust results.

5. Activism Waves and the Market for Corporate Assets

5.1 The impact of activism waves on real asset markets

Our next step is to gain perspective on the imbalance in corporate asset markets generated by activism waves. We consider the direct impact on targets and the indirect impact on peer firms caught in activism waves separately to get a gauge of the relative importance of both transmission channels. We use logit regressions to jointly analyze their respective impact, measured by D(Activist) and D(High HFA Threat), two variables that are mutually exclusive.[35]

Results are presented in Table 8. In Panel A, we find that both dummies, D(Activist) and D(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.

[Insert Table 8 Here]

The most interesting insights of Table 8 can be gleaned from the model's estimate of conditional probabilities of corporate transactions and marginal effects. After estimating the logit model, we calculate conditional probabilities of transactions by fixing all other controls at the mean values of the treated group. We define the marginal effect as the estimated increase in the probability of a transaction when the HFA exposure dummy (either D(Activist) or D(High HFA Threat)) is switched from 0 to 1.[36] As reported in Panel A of Table 8, the probability of receiving merger bids for activism targets increases by 5.31%, and for firms under High HFA Threat it increases by 0.28%. Concerning corporate sales, activism targets are 7.44% more likely to sell corporate assets, and firms under High HFA Threat are 0.81% more likely. Concerning acquisitions in Panel B, large activism targets are 4.55% less likely to undertake acquisitions, and large firms under High HFA Threat 2.16% less likely.

[35] D(Activist) is defined in Section 2.2 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.

[36] Since we estimate two different transmission channels, for target and for peer firms with High HFA Threat, we estimate the probability of transactions conditional on being HFA target 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 acting under 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.

Activism targets exhibit a much stronger reaction but are less frequent, compared with firms under HFA threat that show a weaker reaction but are more numerous. This observation suggests that it is interesting to size up the relative importance of the two channels of activism pressure. We propose a simple method to do so. During activism waves, the mean value of Industry HFA Frequency is around 0.25, i.e. in 25% of firms in industry-years classified as activism waves are activism targets in the current or in the preceding two years; 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 firms in activism waves will on average increase their 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%,[37] this means that corporate sales in activism waves increase by 23.84%(= 2.47/10.36). On the acquisition side, we need to distinguish between small and large firms since activism pressure affects them in opposite directions. For large firms (above median in size), the overall impact of high HFA pressure is equal to $(0.25 \times -4.55\% + 0.75 \times -2.16\%) = -2.76\%$ less acquisitions; for small firms, the overall increase in acquisitions is $(0.25 \times -0.40\% + 0.75 \times +1.50\%) = 1.03\%$. Thus, the overall activism pressure effect on acquisitions in activism waves is 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 6, Panel A), this means that firms in activism waves decrease their frequency of acquisitions by $-1.76/15.06 = -11.69\%$ on average.

We can also estimate the combined impact of activism waves on the equilibrium in corporate asset markets: in industry-years classified as activism waves, firms undertake on average 23.84% more corporate sales and 11.69% less acquisitions, meaning that activism waves create an imbalance of more than 35% between the supply and the demand for corporate assets.

5.2 Activism waves and real asset liquidity

We next assess the impact of activism waves on the asset market equilibrium in affected industries. In an activism wave, firms tend to sell more assets and simultaneously are less willing to buy assets, as estimated in the last subsection, hence they are less likely to appear as liquidity providers in corporate asset markets. We stipulate that "outsider buyers", that is buyers that are not affected by the industry-specific activism pressure, should be a possible source of asset liquidity. By outsider buyers, we have in mind firms outside the affected industry, but also financial acquirers and private firms located in the industry itself.

Our measure of real asset liquidity (RAL) records the total value of transactions of industry

[37] See Table 6 (Panel A): we add the average frequency for mergers of 5.17% and for divestitures of 5.19%.

assets in a given industry-year, that is the sum of *completed* merger bids, divestitures, and acquisitions, but counts each transaction only once, and scaling the sum of transaction value by the sum of market value of public firms, following Ortiz-Molina and Phillips (2014) and Schlingemann et al. (2002).

How much of the imbalance in corporate asset markets created by hedge fund activism is absorbed by insiders, and how much by outsiders? Table 9 presents the results of industry-year regressions to answer this question. The main explanatory variable is D(Activism Wave), a dummy that is equal to one for activism waves (top quintile of industry-years by Industry HFA Frequency). Alternatively, we use a dummy for Harford waves (see Section 3.1). We require that industry-years have at least 3 public firms to be included in our regression analysis. We first investigate the overall impact on real asset liquidity. The analysis is not obvious since activism leads to opposite shifts in supply and demand (an increase in supply and decrease in demand) for corporate assets, and we only observe transactions where prospective buyers and sellers find a match. Does the frequency of asset transactions rise or decline when industries experience an activism wave? Panel A of Table 9 provides an answer: we find an increase in transaction activity (measured by transaction value) in activism waves. This observation is intriguing: why does the supply-demand imbalance lead to an increase and not to a drop in asset liquidity?

[Insert Table 9 Here]

To address this question, 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 and their primary SIC 3-digit code is identical to that of the transaction since only listed firms are affected by activism pressure.[38] All other sellers and acquirers are "outsiders", comprising listed firms in other industries or countries, private firms, and financial buyers, in particular private equity firms. That is, the notion of "insiders" attempts to identify the firms that are affected by hedge fund activism in the corresponding industry.

In Panel B of Table 9, we distinguish between insider buyers and outsider buyers, but do not yet sort transactions by seller category. We calculate the real asset liquidity absorbed by insider buyers and outsider buyers, respectively. Buyers are insiders in 8,279 out of a total of

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

23,704 transactions. Consistent with our hypothesis, the results reveal that real asset liquidity provided by industry outsiders shows a significant increase during activism waves (the effect is almost as strong in Harford waves). By contrast, the RAL provided by industry insiders does not increase.

In Panel C of Table 9, we sort buyers *and* sellers by insider/outsider category. We run separate regressions for each possible pairing of seller and buyer according to their status as insiders and outsiders. That is, we calculate the sub-sample RAL for each of the four possible buyer-seller pairings, outsider-outsider, outsider-insider, insider-outsider, and insider-insider, respectively. Panel C shows that assets sold by insiders are significantly more frequently acquired by outsiders when the industry is in an activism wave (columns (1) and (2)). By contrast, we find no such increase when we look at the liquidity provision by insiders, consistent with the idea that insiders are reluctant to buy since they are subject to activism 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.

In addition, when the seller is an outsider, then there is no significant impact of activism waves on the frequency of asset transactions by outsiders (columns (5) and (6) in Panel C) and by insiders (columns (7) and (8)).

To conclude, Table 9 provides clear evidence for a shift from insider buyers to outsider buyers in activism waves, confirming the hypothesis that when hedge fund pressure increases in an industry, inside real asset liquidity is drying up. As a consequence, outsider acquirers step up as providers of real asset liquidity.

5.3 Asset redeployability and activism waves

In Table 10, we report transaction-level regressions studying activism waves and asset redeployability. We present results interacting with Kim and Kung (2017)'s asset redeployability score that measures how many industry real assets are sold in secondary markets, using a median split. Panels (3) and (4) shows that outside provision of liquidity is stronger during activism waves in industries with high asset redeployability. 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 10 Here]

5.4 Price pressure

We expect the squeeze in real asset liquidity to also have an impact on deal pricing. We use regressions to look at the seller price reactions for the two transaction samples, mergers and divestitures, that allow us to observe price reactions (we need to leave out the remaining category, sales of private targets, as we cannot observe seller CARs in this case). We use the measure for transactions price effects most frequently used in the literature, cumulative abnormal returns (CAR) around the deal announcement. For mergers, we also consider deal premiums (deal premiums are not observed in divestitures).

We regress CARs and deal premiums on 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 use standard event windows around the deal announcement: for divestitures, we look at the symmetric event windows (CAR[-2, +2] and CAR[-5, +5]); for mergers, we use a long pre-announcement window of three months to account for pre-deal price run-ups, and for the deal premium, the offer price relative to stock price one month before. We include relevant transaction level controls that are known to affect seller announcement returns.[39]

Table 11 reports our findings. Panel A looking at the effect on sellers, both for divestitures and mergers. We look at HFA targets and peer firms separately, and hence interact the measures of industry level activism pressure with the dummy D(Activism on Seller)(for HFA targets) and its complement, D(No Activism) (for peer firms). We find a robust negative effect on seller announcement returns when Industry HFA Frequency increases, but only for sellers that are peer firms (D(No Activism) = 1), significant at least at 5% in all regressions. For mergers, the results are robust for shorter run-up periods or symmetric CAR windows (not reported in tables), and the significance rises to 1% in the case of deal premiums. The effects are weaker but consistently negative for Industry HFStake Frequency.

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

Panel B shows that the negative price pressure effect is clearly more pronounced in industries

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

with low asset redeployability. This finding complements our result in the previous section that outsider buyers, and in particular private equity, provide real asset liquidity only in industries with highly redeployable or liquid assets (Table 11). Consequently, the price pressure effect is essentially driven by low asset liquidity industries in which private equity firms do not act as liquidity providers.

[Insert Table 11 Here]

In Panel C, we look at the price pressure effect on buyers, using the same set-up as in Panel A. The sample size shrinks because only about half of the assets are bought by listed acquirers. We find the expected positive effect for activism waves, 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 the idea that asset liquidity is affected when supply of corporate assets increases and demand decreases during activism waves. This leads to lower seller returns and also (weakly) higher buyer returns. Weak price reactions are to be expected since, as Table 9 shows, outsiders step up and provide real asset liquidity, mitigating the squeeze on asset prices.

5.5 Are acquisitions by smaller firms different?

Our analysis has revealed an intriguing size difference in the change in acquisition behavior, with small activism targets not reducing acquisitions as much as large firms do (Table 6, Panel B), and an even stronger difference for small firms acting under activism threat (Table 7). This size discrepancy deserves further examination. We explore three possible explanations: first, small acquirers may feel less pressure to refrain from acquisitions if activists show a less hostile reaction to their acquisitions compared with acquisitions by large firms. Second, small firms might trigger a less hostile response by activists to the extent that they acquire higher-value targets. Finally, they might continue or even intensify acquisitions in the hope that hedge funds view such acquisitions as value accretive.

Relevant for the first possible explanation, Gantchev et al. (2020) show that activists are more likely to target firms that have historically been busy acquirers, particularly firms with poor past acquisition performance. We define a new variable, NumAcq, that counts the number of acquisitions undertaken in the past three years, and include NumAcq in our regressions predicting whether firms become activist targets (introduced in Table 3), in order to explore whether the activism threat increases in the frequency of recent acquisitions during activism waves. Hence we focus on the interaction of NumAcq with our proxies for activism pressure, Industry HFA Frequency and Industry HFStake Frequency, and measures for firm size. As reported in Panel A of Table 12, we find that the probability of becoming an activist target increases in the number of recent acquisitions and in industry activism pressure for large firms, but not for small firms (median split by market capitalization). That is, when large firms undertake acquisitions while their industry is under activism pressure, their activism threat level increases, but there is no corresponding effect for small firms. We find no difference between large and small firms when we do not interact with industry activism pressure (not reported in tables). These differences suggest that large firms act rationally when curtailing acquisitive behavior under strong activism pressure, and small firms act equally rationally when they do not, since there is no equivalent disciplinary pressure on them. When we partition firms by size quantiles of finer granularity, we find that the effect is robust and monotonic (Table IA.6 in the Online Appendix).

[Insert Table 12 Here]

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

We discuss the third possible explanation, that small firms might be less pressed to reduce acquisitions because their acquisitions tend to create better long-run value for shareholders, in the next section that collects our evidence on post-transaction performance.

6. Do Activism-Led Transactions Suffer from Activism Waves?

A natural follow-on question is whether the imbalance in asset markets during activism waves negatively affects the long-run performance of corporate transactions, for example through the initial price pressure. This question seems important in view of the prominent role of corporate transactions for the performance of activists (Greenwood and Schor, 2009; Becht et al., 2017).

6.1 Evidence on post-transaction performance: asset sellers

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

It is well-known that activism campaigns lead to long-run positive effects in market and accounting performance for target firms (see Bebchuk et al., 2015). Thus, it is important to disentangle the long-run performance enhancing effect of activism campaigns from the additional effect of activism divestitures. Gantchev et al. (2020) document the positive long-run stock market performance of seller firms in corporate activism divestitures, but do not address the likely overlap with the long-run performance-enhancing effect of the post-activism period.

We consider three different long-run performance measures providing a cross-section of accounting-based and stock market based performance metrics: Tobin's Q, ROA, and the Sales/Assets ratio (Turnover) that is correlated with economic efficiency. In each case, we look at a period of two years after the divestiture event.[40] We report our findings in Table 13, looking in Panel A at divestitures by activism targets. The key variable of interest is the inter-

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

action term D(Post Divestiture) $\times$ D(Activism Divestiture). We find a positive and significant response to this interaction variable, for both Tobin's Q and for ROA. Only the Sales/Assets ratio does not show a significant long-run performance effect. Thus, we are able to uncover a positive value effect over two years, in addition to the positive effects (documented in regression (1)) of having undertaken divestitures and having gone through an activism campaign that are accounted for by D(Post Divestiture) and D(Activism Divestiture), respectively.

[Insert Table 13 Here]

Panel B repeats the analysis for peer firms acting under activism threat during activism waves. We do not find evidence that divestitures undertaken under HFA threat are performance-enhancing: the interaction 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 undertaken under the disciplinary effect of HFA threats do not create long-run efficiency gains for sellers, in contrast to columns (1) and (2) in Panel A that show significant differences for activism divestitures. Taken together, the two panels show a clear difference between divestitures by activism targets and divestitures by peer firms acting under HFA threat, with efficiency gains limited to the first group.

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

In addition, we find that activist targets less often announce campaign goals related to corporate sales, and reduce transactions in industries that might be adversely affected by an activism-induced reduction in real asset liquidity (see Panel C and D of Table IA.7 in the Online Appendix). These findings are consistent with those on price pressure effects reported earlier (Table 11). Taken together, these results suggest that the benefits for activists of seeking to pursue a contrarian target selection strategy by diversifying away from activism waves are limited.

6.2 Post-transaction performance of asset buyers and the role of firm size

We conclude by analyzing the long-run performance effect on the buyer side of transactions. Specifically, we are interested to find out whether there is any measurable impact of acquirer size.[41] As discussed earlier (Section 5.5), this could possibly provide an additional explanation for the observation that small peer firms acting under activism threat do not reduce the frequency of acquisitions in the same way as large firms and activism targets do.

Table 14 presents the findings when we differentiate by buyer size. We find in Panel A a strong performance-enhancing effect for activism acquisitions by small firms ($p < 0.05$) for two out of three measures of long-run performance, ROA and Sales/Assets, 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 peer firms during activism waves. We split the sample again at the median by size. The triple interaction term D(Post Acquisition) × D(Activism Acquisition) × D(Small) is positive. While it is not significant, we find a significant reaction for ROA and Sales/Assets when we widen the measure of activism clustering to the top tercile of industry-years instead of the top-quintile (Table IA.7 in the Online Appendix).

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

[Insert Table 14 Here]

7. Conclusion

In this paper, we demonstrate that a majority of activist campaigns cluster in activism waves, and we explore the impact of this concentration on corporate asset markets. We find that in

[41] The literature has noted before that small acquirers differ substantially in their short- and long-run acquisition performance (Moeller et al., 2004; Gorton et al., 2009) but satisfactory explanations are largely missing.

activism waves, the threat for firms to become activism targets in the near future increases significantly, with a one-standard-deviation increase in campaign frequency raising the target probability by about 50%. We establish that peer firms react proactively to activism pressure and adjust their behavior in corporate asset markets in the same direction as target firms. Target and peer firms in activism waves receive more merger bids, make fewer acquisitions and divest more. There are subtle differences: peer firms divest more, but are only marginally more likely to be sold entirely, and only large peer firms reduce their acquisition activity.

We explore the behavior change of target firms and of peer firms as two parallel channels of hedge fund pressure, and estimate that they contribute about equally to the change in asset liquidity in activism waves. We consider the impact on real asset liquidity: when firms in affected industries push in the same direction of simultaneously selling more and buying less assets, then real asset liquidity is reduced by more than a third, creating a role for outside liquidity providers. We find that acquirers outside the industry - private equity funds and firms in other industries - provide real asset liquidity, and more so in industries with high asset redeployability.

We find evidence that the squeeze on real asset liquidity also affects transaction prices. The effect is stronger in industries with low redeployability. We find that transactions undertaken by activist targets resist the price pressure remarkably well. Finally, we consider whether the negative market externalities of activism pressure affects the efficiency of activism-led transactions. We find positive long-run performance effects for corporate transactions undertaken by activism targets, but not for transactions undertaken by peer firms. Thus, hedge fund activists seem to be able to partially shield target firms from the negative market externalities of activism clusters, which could help to understand why they are not more actively trying to diversify away from activism waves when selecting targets.

Overall, our paper shows that the clustering of activism is important and that it creates spillovers that affect the equilibrium in real asset markets. The substantial supply overhang for corporate assets arises for reasons that are distinct from those typically associated with fire sale environments, namely financial stress of industry firms or of intermediaries.

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Appendix A: Definition of the Variables

Variables name	Definition and construction of variables	Data source
Activism and threat variables		
D(Activist)	Indicator variable tracking whether the firm is an HFA campaign target in the 2 years prior to each type of transaction; D(Activist) is equal to 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 coauthors
D(13G to 13D Switcher)	Indicator variable equal to 1 if activists switch from the 13G filling to 13D against the targeted firm.	Brav and 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	
Industry HFStake Freq	The fraction of firms in industry j and year t that have experienced at least one activist hedge fund's stake jump within last 3 years	Thomson Reuters 13F & SharkWatch
FIFB	The flow induced fund buy measure (FIFB) following Gantchev, Gredil and Jotikatshira (2017). The formula is as follows, $$FIFB_{j,t} = \frac{\sum_h \left[Inflow5_{h,t} \times \frac{TNA_{h,j,t-1}}{TNA_{h,t-1}} \right]}{Market\ Cap_{j,t}}$$ where $Inflow5$ is the fund specific inflow shock measured in million dollars (shock is defined as the increase of hedge fund's inflow which is larger than 5% of its total net assets in the start of year t), $\frac{TNA_{h,j,t-1}}{TNA_{h,t-1}}$ is the distribution of assets the hedge fund h invested in year *t-1* across industries, and $Market\ Cap$ is the sum of market capitalization of firms in the industry. We assign the idiosyncratic fund-level shock according to the past (year *t-1*) distribution of its total net assets in the stock market and sum up the measure at the industry-year level. See the details in Gantchev, Gredil and Jotikatshira (2017).	Thomson Reuters 13F, SharkWatch, and CRSP
D(Activism Wave)	Dummy equal to 1 if Industry HFA Freq is in the top quintile of the baseline industry-year sample.	
D(Harford Wave)	Dummy equal to 1 if Industry HFA Freq is in the top segment of the simulated distribution of the baseline industry-year sample, adapting Harford (2005)'s method to activism waves.	
D(High HFA Threat)	Dummy equal to 1 if Industry HFA Freq is in the top quintile of the baseline industry-year sample and D(Activist) = 0.	
D(Medium HFA Threat)	Dummy equal to 1 if Industry HFA Freq is in the second or third highest quintiles of the baseline industry-year sample and D(Activist) = 0.	
Variables for transactions 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).	Refinitiv SDC M&A

Continued on next page

Variable name	Definition and construction of variable	Data source
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).	Refinitiv SDC M&A
Sale	Dummy equal to 1 if either the firm divests assets or receives merger bids in year t	Refinitiv 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).	Refinitiv 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).	Refinitiv 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.	Refinitiv 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).	Refinitiv SDC M&A
Institution Ownership	Total ownership (as % of shares outstanding) of institutional investors that file 13F reports	Refinitiv 13F
Tobin's Q	Market-to-book ratio in assets. Market value equals book value of assets (item AT_t) + market value of common equity at fiscal year-end ($CSHO_t \times PRCC\_F_t$) − book value of common equity (CEQ_t) − balance sheet deferred taxes ($TXDB_t$)	Compustat
Ln(age)	Natural log of years since the firm first appears in CRSP	Compustat
Ln(MV)	Natural log of the firm's market capitalization ($CSHO_t \times PRCC\_F_t$)	Compustat
Book Leverage	Defined as debt including long-term debt ($DLTT_t$) plus debt in current liabilities (DLC_t) divided by the sum of debt and book value of common equity (CEQ_t)	Compustat
Dividend Yield	Defined as [common dividend (DVC_t) + preferred dividends (DVP_t)]/[market value of common stocks + book value of preferred (item $PSTK_t$)]	Compustat
Cash Flow	Defined as [net income (NI_t) + depreciation and amortization (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 ($SALE_t$) over previous year	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 (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 (CHE_t) scaled by lagged book assets	Compustat
HHI	The Hirschman-Herfindahl index of sales in the industry	Compustat
CAR[Year t-1]	Cumulative abnormal return in year $t-1$ (applying monthly data and market model)	CRSP

Appendix B: Details about Industry and Insider/Outsider 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 measures for activism intensity and activism waves are overwhelmingly constructed based on Compustat SIC-3 classifications.

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

Table 1: Hedge fund activism and characteristics of activist target firms

This table reports annual frequencies of HFA events (Panel A), characteristics of firms under HFA target (Panel B), and summary statistics of variables measuring industry HFA threats (Panel C). Panel A reports the annual number of firms and of HFA campaigns in the CRSP-Compustat universe. Panel B reports characteristics of firms in the year in which they are targeted by activist hedge funds (HFA Target Firms). Variables are measured in the year prior to the HFA event. The Remaining Sample is the CRSP-Compustat universe excluding the HFA Target Firms sample. We report the differences in mean and median values between the target and non-target sample of firm-years, and conduct t tests for differences in means and Wilcoxon tests for differences in medians (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). Panel C presents the summary statistics of three industry HFA threat variables. Industry HFA Freq is defined as the fraction of firms in industry j and year t that have been targeted by activist hedge funds in the previous three years. Industry HFStake Freq is defined as the fraction of firms in industry j and year t that had experienced at least one activist hedge funds' stake jump within the previous three years. 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 A: Number and frequency of HFA campaigns

Calendar Year	(1) Number of firms (all)	(2) Number of HFA campaigns	(3) Proportion of firms targeted by HFA
1994	6,176	12	0.19%
1995	6,372	33	0.52%
1996	6,850	90	1.31%
1997	6,847	170	2.48%
1998	6,408	131	2.04%
1999	6,226	90	1.45%
2000	5,986	86	1.44%
2001	5,296	79	1.49%
2002	4,911	121	2.46%
2003	4,635	118	2.55%
2004	5,066	128	2.53%
2005	4,977	211	4.24%
2006	4,888	273	5.59%
2007	4,758	319	6.70%
2008	4,487	256	5.71%
2009	4,252	134	3.15%
2010	4,125	149	3.61%
2011	4,002	172	4.30%
2012	3,940	174	4.42%
2013	4,001	197	4.92%
2014	4,152	236	5.68%
2015	4,103	203	4.95%
2016	3,990	169	4.24%
Total	116,448	3,551	3.05%

Panel B: Characteristics of activism target firms

	HFA Target Firms (N = 3,551)			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 C: Summary statistics of activism intensity measures (firm-year sample)

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

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

Table 2: Frequency of activism clusters

This table presents summary statistics of activism cluster measures. Panel A presents frequencies for five measures of activism clusters, and Panel B breaks down the frequencies by year for the same measures. Column (1) shows the total number of HFA campaigns and of industry-year observations in our CRSP-Compustat sample. The measure Top Quintile in Column (2) is defined as industry-years in the top-quintile by Industry HFA Freq where 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 (t, t-1, and t-2). Our main measure, Activism Wave, further requires at least two campaigns in the period of the wave and is reported in column (3). Harford Wave (column (4)) adapts Harford (2005)'s simulation method to identify HFA waves, with details of the estimation procedure as follows. If there are n HFA events in the SIC-3 industry k in our sample, we simulate 1000 times the distribution of n HFA events and record the max number of campaigns in any two consecutive years in each simulation. We identify an industry-year in the real data as the Harford Wave if the number of HFA events within two consecutive years is in the top quintile of simulated max number of HFA events. Ind HFStake Frequency (column (5)) are industry-years in the top-quintile by Industry HFStake Freq where Industry HFStake Freq is the fraction of firms in industry j and year t that have experienced at least one activist hedge fund's stake jump within last 3 years. In column (6), the method in column (2) is used but expanded to the top tercile of industry-years.

Panel A: Summary statistics: Frequency of activism clusters

	(1)	(2)	(3)	(4)	(5)	(6)
Measure of activism cluster	Full Sample†	Top Quintile	Activism Wave	Harford Wave	Ind. HFStake Freq.	Top Tercile
Definition of measure	all	Top Quintile	Top Quintile	Harford Method	Top Quintile	Top Tercile
Min. num. of campaigns required for measure	–	≥ 1	≥ 2	≥ 2	≥ 2	≥ 2
Num. of HFA campaigns (present in clusters)	3,551	2,035	1,829	1,310	1,624	2,789
Num. of industry-years (counted as clusters)	6,028	976	770	372	695	1,115
Num. of hedge funds active in clusters	862	559	527	407	501	675

† Column (1): total number of HFA campaigns and industry-years in our CRSP-Compustat sample.

Panel B: Frequency of activism clusters, by year

Number of HFA campaigns in activism waves by years						
	(1)	(2)	(3)	(4)	(5)	(6)
Measure of activism cluster	Full Sample†	Top Quintile	Activism Wave	Harford Wave	Ind. HFStake Freq.	Top Tercile
Definition of measure	all	Top Quintile	Top Quintile	Harford Method	Top Quintile	Top Tercile
Min. num. of campaigns required for measure	–	≥ 1	≥ 2	≥ 2	≥ 2	≥ 2
Num. of HFA campaigns (present in clusters)						
1994	12	1	1	0	0	2
1995	33	2	0	1	7	5
1996	90	26	19	8	1	45
1997	170	39	32	34	9	94
1998	131	35	26	18	7	72
1999	90	30	27	15	4	49
2000	86	26	20	10	6	51
2001	79	17	16	12	10	53
2002	121	34	27	13	17	85
2003	118	47	39	13	49	83
2004	128	75	63	29	70	110
2005	211	143	129	93	139	177
2006	273	198	186	187	198	236
2007	319	230	216	226	231	285
2008	256	186	170	135	181	220
2009	134	86	77	47	66	109
2010	149	77	67	31	70	122
2011	172	118	107	43	73	143
2012	174	118	105	60	70	147
2013	197	139	132	88	136	180
2014	236	172	163	116	146	213
2015	203	132	120	82	103	172
2016	169	101	85	50	37	134
Total	3,551	2035	1829	1310	1624	2789

† Column (1): total number of HFA campaigns and industry-years in our CRSP-Compustat sample.

Table 3: Activism intensity and target probability

This table reports the relationship between industry measures of activism intensity and the HFA target probability. Columns (1) – (7) report logit regressions for our firm-year sample. The left-hand side variable D(HFA) is a dummy that is equal to one if activists initiate a new campaign against the firm in year t. We use 3 variables to measure industry HFA intensity. Industry HFA Freq is defined as fraction of firms in industry j and year t that have been targeted by activist hedge funds within last three years. Industry HFStake Freq is defined as the fraction of firms in industry j and year t that had experienced at least one activist hedge fund stake jump in the last 3 years. FIFB hypothetically assigns the fund inflow shock of activist hedge fund k to industry j and in year t according to industry weight of j in k's portfolio in year t-1. Columns (8) – (9) report OLS regressions for the industry-year sample; in this case all controls are industry-year medians. TotM&A_3yr is Ortiz-Molina and Phillips (2014)'s measure of real asset liquidity, the average ratio of transaction volume of public companies over the past 3 years scaled by assets, TotPE_3yr the same limited to PE deals, D(Merger Wave) a dummy for merger waves following Harford (2005). All firm-level control variables are one year lagged except for industry threat measures, TotM&A_3yr, TotPE_3yr, and D(Merger Wave). All regressions include year and industry fixed effects. Standard errors are clustered at the firm level in columns (1) - (7) and at the industry level in columns (8) – (9) (standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

	Firm-year regressions							Industry-year regressions	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Logit D(HFA)	Logit D(HFA)	Logit D(HFA)	Logit D(HFA)	Logit D(HFA)	Logit D(HFA)	Logit D(HFA)	OLS Ind. HFA Freq	OLS Ind. HFA Freq
Industry HFA Freq		7.752***			7.753***				
		(0.304)			(0.305)				
Industry HFStake Freq			1.825***			1.825***			
			(0.220)			(0.220)			
FIFB (Percentile Rank)				0.366***			0.366***	0.0149***	0.0151***
				(0.140)			(0.140)	(0.00570)	(0.00570)
D(Merger Wave)					0.0173	-0.0166	-0.0417		-0.00485
					(0.0839)	(0.0860)	(0.0896)		(0.00486)
TotM&A_3yr	0.472	0.164	0.436	0.458	0.157	0.442	0.473	0.0199	0.0207
	(0.381)	(0.401)	(0.381)	(0.389)	(0.400)	(0.380)	(0.389)	(0.0179)	(0.0179)
TotPE_3yr	0.0721	-0.00634	-0.155	0.0841	0.00598	-0.163	0.0598	-0.0629**	-0.0639**
	(0.660)	(0.764)	(0.663)	(0.696)	(0.763)	(0.662)	(0.696)	(0.0306)	(0.0306)
Institutional Ownership	1.459***	1.415***	1.419***	1.466***	1.416***	1.419***	1.465***	0.0178	0.0171
	(0.116)	(0.118)	(0.116)	(0.117)	(0.118)	(0.116)	(0.118)	(0.0124)	(0.0125)
Tobin's Q	-0.320***	-0.312***	-0.320***	-0.321***	-0.311***	-0.321***	-0.321***	-0.00676*	-0.00690**
	(0.0353)	(0.0355)	(0.0354)	(0.0358)	(0.0356)	(0.0355)	(0.0359)	(0.00346)	(0.00347)
ln(MV)	-0.200***	-0.194***	-0.196***	-0.200***	-0.194***	-0.196***	-0.199***	-0.00329	-0.00320
	(0.0208)	(0.0210)	(0.0208)	(0.0211)	(0.0210)	(0.0208)	(0.0211)	(0.00216)	(0.00216)

Book Leverage	0.325***	0.342***	0.330***	0.316***	0.342***	0.330***	0.316***	0.00796	0.00821
	(0.0920)	(0.0942)	(0.0919)	(0.0935)	(0.0942)	(0.0919)	(0.0935)	(0.0115)	(0.0115)
Dividend Yield	-4.046***	-4.093***	-4.014***	-3.753**	-4.091***	-4.015***	-3.757**	-0.383***	-0.379***
	(1.479)	(1.508)	(1.476)	(1.484)	(1.508)	(1.475)	(1.483)	(0.143)	(0.143)
Cash Flow	-0.285	-0.318*	-0.261	-0.303*	-0.317*	-0.262	-0.305*	-0.0226	-0.0225
	(0.177)	(0.181)	(0.177)	(0.179)	(0.181)	(0.177)	(0.179)	(0.0291)	(0.0291)
Sales Growth	-0.0642	-0.0548	-0.0537	-0.0700	-0.0552	-0.0533	-0.0690	-0.0108	-0.0105
	(0.0689)	(0.0677)	(0.0684)	(0.0698)	(0.0677)	(0.0683)	(0.0697)	(0.0121)	(0.0121)
Asset Growth	-0.176*	-0.135	-0.167*	-0.190**	-0.135	-0.167*	-0.191**	-0.0359**	-0.0361**
	(0.0907)	(0.0904)	(0.0904)	(0.0926)	(0.0904)	(0.0904)	(0.0926)	(0.0146)	(0.0146)
R&D	0.516	0.453	0.520	0.519	0.451	0.522	0.525	-0.308*	-0.301*
	(0.380)	(0.381)	(0.379)	(0.382)	(0.382)	(0.380)	(0.382)	(0.171)	(0.171)
HHI	-0.388	-0.842***	-0.313	-0.476	-0.843***	-0.311	-0.470	0.0550**	0.0547**
	(0.278)	(0.316)	(0.280)	(0.291)	(0.316)	(0.280)	(0.291)	(0.0261)	(0.0261)
Excess Cash	0.620***	0.649***	0.613***	0.631***	0.648***	0.614***	0.633***	0.0580**	0.0586**
	(0.156)	(0.157)	(0.156)	(0.157)	(0.158)	(0.156)	(0.157)	(0.0283)	(0.0283)
CAR [12 months]	-0.125***	-0.116**	-0.124***	-0.113**	-0.116**	-0.124***	-0.113**	-0.00280	-0.00281
	(0.0479)	(0.0489)	(0.0478)	(0.0485)	(0.0489)	(0.0479)	(0.0485)	(0.00552)	(0.00552)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. Obs.	68228	68228	68228	65934	68228	68228	65934	4517	4517
Pseudo R^2 / Adj. R^2	0.086	0.129	0.089	0.087	0.129	0.089	0.087	0.071	0.071

Table 4: Determinants of activism waves

This table presents evidence on possible determinants of activism waves. Panel A reports the role of industry characteristics in generating activism waves. Panel B explores the possible role of asset liquidity conditions in the industry. We consider two measures of activism clustering: Activism Wave denotes industry-years in the top-quintile by Industry HFA Frequency, the fraction of firms in industry j and year t targeted by activist hedge funds within the last three years. Harford Wave, a more restrictive criterion (see Table 2), adapts the method introduced by Harford (2005) for merger waves and determines the equivalent top segment of the distribution by Industry HFA Frequency with at least two campaigns; see Table 2 for details of the estimation procedure. All reported explanatory variables use the (value-weighted) SIC3 industry average. In Panel A, the first 3 and the last row consider values in year t - 1, the remaining rows the change from year t - 2 to year t - 1. Tobin's Q is the market-to-book ratio, CAR the annual cumulative abnormal return, and cash flow the sum of net income and depreciation and amortization. In Panel B, WAL3 is the weighted asset liquidity score (WAL 3) of Gopalan et al. (2012), TotM&A_3yr is Ortiz-Molina and Phillips (2014)'s measure of real asset liquidity, the average ratio of dollar transaction volume of public companies over the past 3 years scaled by assets, and D(Merger Wave) a dummy for years classified as merger waves using Harford (2005)'s method. Panel C reports logit regressions of HFA target probabilities including predicted probability of corporate transactions. The regression setup follows that of Table 3. We estimate the probability of the three transaction types (receiving a merger bid, divesting assets, and acquisitions) in (unreported) first stage logit regressions where all controls are as in Table 3, Column (1). Δ Pr(Transaction type) is defined as the estimated probability in this first-stage regression minus the estimated probability in year t -1. We then include Δ Pr(Transaction type) as independent variable in a regression that follows Table 3, Column (1). All regressions include year and industry fixed effects. Standard errors are clustered at the firm level (standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Industry characteristics and activism waves

Measure of activism wave	(1) Activism Wave	(2) Harford Wave	(3) Activism Wave	(4) Harford Wave	(5) Activism Wave	(6) Harford Wave	(7) Activism Wave	(8) Harford Wave	(9) Activism Wave	(10) Harford Wave	(11) Activism Wave	(12) Harford Wave	(13) Activism Wave	(14) Harford Wave
Ind Tobin's Q (t-1)	-0.036***	-0.011**												
	(0.012)	(0.005)												
Ind CAR (t-1)			-0.021*	-0.027***										
			(0.013)	(0.007)										
Ind Cash Flow (t-1)					-0.17*	-0.051								
					(0.095)	(0.040)								
Ind Δ Tobin's Q							-0.0009	-0.012**						
							(0.008)	(0.005)						
Ind Δ CAR									-0.002	-0.014***				
									(0.008)	(0.005)				
Ind Δ Cash Flow											-0.12*	-0.13***		
											(0.073)	(0.041)		
Ind LnMV (t-1)													-0.042***	-0.015***
													(0.006)	(0.003)
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. Obs.	5688	5688	5709	5709	5434	5434	5376	5376	5414	5414	5127	5127	4404	4404
Adj. R^2	0.193	0.064	0.191	0.061	0.188	0.058	0.189	0.062	0.186	0.058	0.188	0.057	0.228	0.129

Panel B: Asset liquidity and activism waves

Measure of activism wave	(1) Activism Wave	(2) Harford Wave	(3) Activism Wave	(4) Harford Wave	(5) Activism Wave	(6) Harford Wave	(7) Activism Wave	(8) Harford Wave	(9) Activism Wave	(10) Harford Wave
Ind Redeploy Score	-0.105	-0.00986								
	(0.102)	(0.0449)								
Ind. WAL3			0.00316	-0.00561						
			(0.0151)	(0.00929)						
Ind. TotM&A_3yr					0.0903	-0.0472				
					(0.0824)	(0.0317)				
Ind. D(Merger Wave)							-0.00883	0.0107		
							(0.0199)	(0.0132)		
Ind. HHI									-0.0294	-0.0843*
									(0.141)	(0.0498)
Industry F.E.	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. Obs.	4848	4848	5389	5389	5488	5488	5758	5758	6026	6026
Adj. R^2	0.095	0.046	0.187	0.059	0.188	0.058	0.191	0.059	0.195	0.060

Panel C: Target probability and prior changes in transaction frequency

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

Table 5: Herd behavior of non-leading hedge funds

This table investigates the herd behavior of hedge fund managers in selecting HFA targets. We estimate a standard McFadden discrete choice model in a hedge fund × year × industry sample. A hedge fund enters our sample in a year if it participates in at least one activism campaign in that year. Each hedge fund has in each year 248 industries to choose from for the choice of its campaign target. Industries are defined at the SIC-3 level. We allow an activist hedge fund to choose more than one industry. Lead activist hedge funds are funds with a reputation score in the top quintile. We apply two methods to calculate the reputation score: (1) the cumulative number of HFA campaigns launched by the fund prior to year t; and (2) the cumulative number of hostile HFA campaigns launched by the fund prior to year t. We estimate the discrete choice model using conditional logit and group the data at the fund-by-year level (called the decision node). Robust standard errors are clustered at the fund level. (standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Discrete choice model with decision node: Fund-Year (only non-leading funds) Set of alternatives: 248 SIC-3 industries				
	(1)	(2)	(3)	(4)
Lead funds determined by ranking	Num. Past Campaigns		Num. Hostile Campaigns	
Dependent Var.	D(Target)	D(Target)	D(Target)	D(Target)
Num(Leading Funds) (Year t-1)	0.0973**		0.142***	
	(0.0495)		(0.0489)	
Num(Leading Funds) (Year t-1) × D(Young Fund)		0.159***		0.212***
		(0.0581)		(0.0597)
Num(Leading Funds) (Year t-1) × D(Old Fund)		0.00546		0.0594
		(0.0603)		(0.0614)
D(Target Last Year)	1.882***	1.899***	1.700***	1.716***
	(0.122)	(0.122)	(0.111)	(0.111)
Num. Firms (SIC-3)	0.857***	0.856***	0.841***	0.841***
	(0.0239)	(0.0239)	(0.0211)	(0.0211)
Include Industry-Median Characteristics	Yes	Yes	Yes	Yes
Include Industry-Median Δ Characteristics	Yes	Yes	Yes	Yes
Grouped by	Fund-Year	Fund-Year	Fund-Year	Fund-Year
Num. Obs.	365,375	365,375	378,110	378,110
Pseudo R^2	0.174	0.175	0.177	0.177

Table 6: Activism targets and acquisition behaviour

This table studies the relationship between firms being activism targets and their acquisition behavior. We study three types of corporate asset transactions: (1) target firms being acquired (merger bids); (2) target firms divesting assets (divestitures); and (3) target firms acquiring other firms (including both private and public firms). Panel A provides the summary statistics of transactions by years. Activism transactions (Column (3)) are defined as transactions that take place within two years following an HFA campaign. Panel B tabulates logistic regressions. The left-hand side variable is a dummy that takes the value one if the firm undertakes a transaction in year t (a merger bid, divestiture, etc.) D(Activist) is equal to one in year t if activists launch a campaign against the firm during the 730 calendar days prior to the transaction event, or, if there is no transaction event for the firm in year t, during the 730 calendar days prior to the median date of all transaction events of other firms in year t. All panels include the following firm-level control variables: TotM&A_3yr, Institutional Ownership, Tobin's Q, ln(MV), Book Leverage, Dividend Yield, Cash Flow, Sales Growth, Asset Growth, R&D, Excess Cash, HHI, CAR[Year t-1]. All firm-level controls are one-year lagged. D(Large) (D(Small)) is a dummy equal to one if the firm's size is larger (smaller) than the industry-year median size of firms in year t-1. In Panel C, we merge the data of 13G fillings and 13G-to-13D switchers with the CRSP-Compustat universe. The dataset includes 4,488 13G filings and 227 13G-to-13D switchers. The regression sample includes firm-year observations from 5 years prior to and 5 years post the 13G filling or 13D switcher filling. Following Brav, Jiang, Ma, and Tian (2016)'s setting, we apply the following difference in difference specification:

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

where $D[Post]$ is a dummy variable equal to 1 if the firm-year observation is within $[t+1, t+5]$ years post the event year. The event year is the year of the filing of Schedule 13G for non-switchers or the year of the switch for the switcher sub-sample. $D[13G\ to\ 13D\ Switcher]$ is a dummy variable equal to one if there is a 13-G to-13D switch for a firm during the event year (as opposed to remaining with Schedule 13G status).

Panel A: Summary statistics of transactions by years

Calendar year	(1) Number of transactions	(2) % of firms conducting transactions	(3) Number of activism transactions	(4) % of firms with transactions among HFA targets	(5) Number of transactions under high HFA threat	(6) % of firms with transactions under high HFA threat	(7) % of firms with transactions under low HFA threat
Transaction type: Merger bids							
1994–2000	2,587	5.53%	91	7.26%	748	5.24%	5.55%
2001–2010	2,509	5.10%	325	11.29%	822	5.51%	3.75%
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%
Transaction type: Divestiture							
1994–2000	2,812	4.85%	66	5.97%	586	5.13%	5.00%
2001–2010	3,299	5.34%	283	7.68%	782	5.80%	5.30%
2011–2016	1,741	5.52%	225	8.60%	361	5.19%	4.43%
Total	7,852	5.19%	574	7.81%	1,729	5.16%	4.58%
Transaction type: Acquisition							
1994–2000	10,500	15.34%	242	13.32%	1,737	13.53%	15.75%
2001–2010	9,249	14.41%	331	9.75%	2,030	14.63%	15.55%
2011–2016	5,133	15.65%	265	12.00%	1,102	15.23%	17.91%
Total	24,882	15.06%	838	11.82%	4,869	14.51%	15.72%

Panel B: Activism targets and probability of conducting transactions

	(1) Logit Merger	(2) Logit Divestiture	(3) Logit Sale	(4) Logit Acquisition	(5) Logit Acquisition
D(Activist)	0.710***	0.362***	0.622***	-0.210***	
	(0.0550)	(0.0694)	(0.0472)	(0.0584)	
D(Activist) × D(Large)					-0.252***
					(0.0793)
D(Activist) × D(Small)					-0.0642
					(0.0865)
Firm-level controls included	Yes	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes	Yes
Num. Obs.	71,879	68,772	7,0951	69,541	66,346
Pseudo R^2	0.051	0.183	0.170	0.124	0.125
Unconditional prob.	5.45%	4.57%	9.37%	14.42%	–
Prob. conditional on HFA targets	10.49%	6.44%	16.02%	12.02%	–

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

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

Table 7: Activism threat and corporate transactions

This table provides evidence on the relationship between threats of hedge fund activism and asset transaction activities of firms not (yet) targeted by activists. In Panel A, we use $Pr(Target)$ and D(Passive Stake) 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 3. We use the post estimation probability as $Pr(Target)$. D(Passive Stake) is a dummy equal to 1 if the combined ownership by activist hedge funds is at least 5% in year t. In Panel B, we use the industry-level threat variables. In Panel C, we use FIFB, our industry-level threat variable that is plausibly exogenous since it hypothetically assigns the fund inflow shock of activist hedge fund k to industry j and in year t according to the industry weight of j in k's portfolio 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: Firm-level threat measure

	(1) Merger	(2) Divestiture	(3) Sale	(4) Acquisition	(5) Merger	(6) Divestiture	(7) Sale	(8) Acquisition
$Pr(\widehat{Target})$	0.622***	0.536***	1.149***					
	(0.164)	(0.140)	(0.215)					
$Pr(\widehat{Target})$ × D(Small)				-1.108***				
				(0.129)				
$Pr(\widehat{Target})$ × D(Large)				-2.011***				
				(0.183)				
D(Passive Stake)					0.0414***	0.0131***	0.0513***	
					(0.00347)	(0.00330)	(0.00445)	
D(Passive Stake) × D(Small)								-0.00469
								(0.00553)
D(Passive Stake) × D(Large)								-0.0151*
								(0.00795)
Firm-level control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	65429	62934	65429	60601	65429	62934	65429	60601
adj. R^2	0.018	0.073	0.045	0.079	0.021	0.069	0.047	0.086

Panel B: Industry-level threat measure

	(1) Merger	(2) Divestiture	(3) Sale	(4) Acquisition	(5) Merger	(6) Divestiture	(7) Sale	(8) Acquisition
Industry HFA Freq	0.00168	0.0425***	0.0480**					
	(0.0140)	(0.0160)	(0.0213)					
Industry HFA Freq × D(Small)				0.0634**				
				(0.0300)				
Industry HFA Freq × D(Large)				-0.0910**				
				(0.0366)				
Industry HFStake Freq					0.0281**	0.0280**	0.0538***	
					(0.0111)	(0.0125)	(0.0160)	
Industry HFStake Freq× D(Small)								0.0677***
								(0.0224)
Industry HFStake Freq× D(Large)								-0.0477**
								(0.0223)
Firm-level control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-level control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	60618	58307	60618	56512	60618	58307	60618	56512
adj. R^2	0.018	0.074	0.045	0.075	0.018	0.074	0.046	0.076

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

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

Table 8: Combined impact of activism pressure on transaction activity

This table reports logit regressions investigating the overall impact of HFA pressure on corporate transactions. We estimate the HFA target effect (separately analyzed in Table 6) and the industry HFA threat effect (separately analyzed in Table 7) in one combined framework. D(Activist) is defined as in Table 6. D(High HFA Threat) is a dummy for high industry HFA threat, which is equal to one if the industry-year is in an activism wave but the firm is not an activism target ((D(Activist) = 0). D(Medium HFA Threat) is a dummy for medium-level industry HFA threat, which is equal to one if the industry-year is in the second and third highest quintile of Industry HFA Freq and the firm is not an activism target ((D(Activist) = 0). Prob. conditional on HFA targets is the estimated probability when we fix 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 probability conditional on HFA exposure minus the conditional probability if the exposed firms were not exposed. Firm-level control variables are the same as in Table 6. Industry fixed effects and year fixed effects are always included. Standard errors are clustered at the firm level (standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

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

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

Panel B: Logistic regressions and marginal effects (acquisitions)

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

Table 9: Activism waves and industry asset liquidity

This table reports industry-year regressions linking activism waves 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). For each industry-year to be included in the regression sample, we require that at least 3 public firms be present. We define our dependent variable, real asset liquidity, as the total value of transactions divided by the total market value of public firms in industry j and year t, similar to Ortiz-Molina and Phillips (2014). 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. D(Activism Wave) is a dummy for industry-years in the top quintile of Industry HFA Freq. D(Harford Wave) is a dummy of activism waves following Harford (2005)'s method (see Table 2). 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 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 outsider buyers, where the dependent variable is the percentage of transactions acquired by outsider buyers in industry j and in year t; regressions in Panel D only use the sample of transactions with insider sellers. Industry-year control variables, including HHI, Industry-year median of Tobin's Q, Leverage, Cash Flow, Sales Growth, Cash, R&D, and Assets Growth, and the Industry-year S.D. of Tobin's Q, are included in all regressions. 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)
D(Activism Wave)	1.426**	
	(0.667)	
D(Harford Wave)		1.431*
		(0.851)
Industry-level control variables	Yes	Yes
Industry and Year fixed effect	Yes	Yes
Number of Industry-Year obs.	4783	4783
adj. R^2	0.232	0.231
Number of transactions	23,704	23,704

Panel B: Real asset liquidity sorted by outside/inside buyer

Dependent Variable: Real Asset Liquidity (RAL)	(1)	(2)	(3)	(4)
Buyer status:	Buyer = Outsider		Buyer = Insider	
D(Activism Wave)	1.376**		0.0502	
	(0.654)		(0.134)	
D(Harford Wave)		1.220**		0.211
		(0.622)		(0.261)
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	0.223	0.223	0.151	0.151
Number of transactions	15,425	15,425	8,279	8,279

Panel C: Real asset liquidity sorted by outside/inside buyer and seller

Dependent Variable: Real Asset Liquidity (RAL)	(1)	(2)	(3)	(4)
Seller/buyer status:	Seller = Insider Buyer = Outsider		Seller = Insider Buyer = Insider	
D(Activism Wave)	1.189**		0.186	
	(0.591)		(0.386)	
D(Harford Wave)		1.614**		-0.394*
		(0.817)		(0.209)
Number of Industry-Year obs.	4783	4783	4783	4783
Number of transactions	5,776	5,776	2,579	2,579
	(5)	(6)	(7)	(8)
Seller/buyer status:	Seller = Outsider Buyer = Outsider		Seller = Outsider Buyer = Insider	
D(Activism Wave)	0.155		-0.104	
	(0.115)		(0.0705)	
D(Harford Wave)		0.228		-0.0173
		(0.246)		(0.110)
Number of Industry-Year obs.	4783	4783	4783	4783
Number of transactions	9,649	9,649	5,700	5,700

Panel D: Regression of outsider buyer's ratio

Dependent Variable: Outside Buyer's Ratio	(1)	(2)
D(Activism Wave)	4.337*	
	(2.241)	
D(Harford Wave)		4.729
		(3.349)
Industry-level control variables	Yes	Yes
Industry and Year fixed effect	Yes	Yes
Number of Industry-Year obs.	2267	2267
adj. R^2	0.145	0.144

Table 10: Activism pressure and asset redeployability

This table reports transaction-level regressions investigating the relation between activism waves and asset redeployability. We only include transactions with assets sold by industry insiders. The definition of industry insiders follows Table 9. The dependent variable is a dummy equal to 1 if the buyer in the transaction is an industry outsider. D(Activism Wave) is a dummy for industry-years in the top quintile of Industry_HFA_Freq. D(Harford Wave) is a dummy of activism waves following Harford (2005)'s method (see Table 2). Redeploy High (Low) is a dummy equal to 1 if the asset redeployability score in that industry is above the sample median. We measure the redeployability score using Kim and Kung (2017)'s asset redeployability score. Standard errors are clustered at the industry level (standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

	(1)	(2)	(3)	(4)
	D(Outside Buyer)			
D(Activism Wave)	0.0564**			
	(0.0225)			
D(Harford Wave)		0.0574**		
		(0.0226)		
D(Activism Wave)*Redeploy High			0.0836***	
			(0.0301)	
D(Activism Wave)*Redeploy Low			0.0309	
			(0.0292)	
D(Harford Wave)*Redeploy High				0.0776**
				(0.0337)
D(Harford Wave)*Redeploy Low				0.0381
				(0.0302)
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	5502	5502	5150	5150
adj. R^2	0.140	0.140	0.135	0.135

Table 11: Price pressure under HFA impact

This table reports transaction-level regressions investigating the price pressure hypothesis. We only include transactions that occur in industry-years with at least 3 public firms in the baseline sample. Panel A reports the regressions of Seller CARs and premiums. Panel B reports regressions of Buyer CARs. D(Activism Wave) is a dummy for industry-years in the top quintile of Industry_HFA_Freq. D(Harford Wave) is a dummy of activism waves following Harford (2005)'s method (see Table 2). The transaction level controls are a dummy for payment by stock, TotM&A_3yr (measured in the industry of the transaction), Institutional Ownership, Tobin's Q, ln(MV), Book Leverage, Dividend Yield, Cash Flow, Sales Growth, Asset Growth, R&D, and Excess Cash. All left-hand side variables are winsorized at the 1% and 99% level. All CARs are estimated with a market model using daily stock prices data in CRSP. Asset industry fixed effects and year fixed effects are always included. Standard errors are clustered at the firm level (standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Price pressure for sellers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sample of Divestitures				Sample of Mergers			
	Seller's CAR [-2d, +2d]		Seller's CAR [-5d, +5d]		Premium [1 month]		Target's CAR [-43d, +1d]	
D(Activism Wave)	-0.00477**		-0.00845**		-0.0476**		-0.0333*	
	(0.00235)		(0.00415)		(0.0230)		(0.0176)	
D(Harford Wave)		-0.00192		-0.00591*		-0.0460***		-0.00948
		(0.00271)		(0.00354)		(0.0152)		(0.0126)
Transaction-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5420	5420	5422	5422	4100	4100	4024	4024
adj. R^2	0.034	0.034	0.024	0.023	0.118	0.117	0.162	0.161

Panel B: Price pressure for buyers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sample of Divestitures				Sample of Mergers			
	Buyer's CAR [-2d, +2d]		Buyer's CAR [-5d, +5d]		Acquirer's CAR [-2d, +2d]		Acquirer's CAR [-5d, +5d]	
D(Activism Wave)	0.00337		0.0108*		0.00470		0.0158*	
	(0.00561)		(0.00575)		(0.00622)		(0.00817)	
D(Harford Wave)		0.0203***		0.0248***		0.00352		0.0130**
		(0.00737)		(0.00844)		(0.00492)		(0.00600)
Transaction-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2845	2845	2845	2845	2168	2168	2173	2173
adj. R^2	0.000	0.000	0.019	0.020	0.076	0.077	0.048	0.048

Panel C: Price pressure for sellers (distinguish asset redeployability)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sample of Divestitures				Sample of Mergers			
	Seller's CAR [-2d, +2d]		Seller's CAR [-5d, +5d]		Premium [1 month]		Target's CAR [-43d, +1d]	
D(Activism Wave)*Redeploy High	-0.00287		-0.00744		-0.0439		-0.0392*	
	(0.00402)		(0.00583)		(0.0309)		(0.0221)	
D(Activism Wave)*Redeploy Low	-0.00593**		-0.00985**		-0.0623**		-0.0402**	
	(0.00262)		(0.00499)		(0.0272)		(0.0202)	
D(Harford Wave)*Redeploy High		-0.000873		-0.00178		-0.0180		0.0114
		(0.00477)		(0.00528)		(0.0177)		(0.0174)
D(Harford Wave)*Redeploy Low		-0.000628		-0.00474*		-0.0830***		-0.0332**
		(0.00311)		(0.00323)		(0.0187)		(0.0146)
Transaction-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5176	5176	5179	5179	3911	3911	3853	3853
adj. R^2	0.035	0.035	0.025	0.024	0.120	0.120	0.164	0.163

Panel D: Price pressure for buyers (distinguish asset redeployability)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sample of Divestitures				Sample of Mergers			
	Buyer's CAR [-2d, +2d]		Buyer's CAR [-5d, +5d]		Acquirer's CAR [-2d, +2d]		Acquirer's CAR [-5d, +5d]	
D(Activism Wave)*Redeploy High	-0.00953		-0.00573		0.00527		0.0152	
	(0.00950)		(0.0125)		(0.00717)		(0.00982)	
D(Activism Wave)*Redeploy Low	0.0107		0.0192*		0.00420		0.0220**	
	(0.0102)		(0.0111)		(0.00770)		(0.00893)	
D(Harford Wave)*Redeploy High		0.0105		0.0139		-0.00173		0.0107
		(0.00840)		(0.0110)		(0.00423)		(0.00683)
D(Harford Wave)*Redeploy Low		0.0265**		0.0334***		0.00466		0.0185**
		(0.0122)		(0.0126)		(0.00679)		(0.00772)
Transaction-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2179	2179	2179	2179	2015	2015	2019	2019
adj. R^2	-0.002	0.001	0.023	0.026	0.068	0.068	0.049	0.049

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

This table investigates acquirer and target characteristics in acquisitions by small and large acquirers. Regressions are in transaction levels. We require both the acquirer and target to be publicly listed firms and their Tobin's Q and ROA information not to be missing. Panel A considers the interaction of industry activism intensity and the number of firm-level past acquisitions as determinants of the activism target probability (following the model in Table 3). Panel B shows quality characteristics of acquisition targets relative to that of the acquirer, and Panel C shows the same relationship as a function of the industry-level activism threat. The dependent variable is equal to the difference between the target's attribute and the acquirer's, for each of the attributes in columns (1) to (5). All characteristics are measured in the year preceding the bidding year. NumPats, NumCites, and PatValue denote number of patents, number of citations, and Kogan et. al. (2017)'s estimated value of the patent in nominal dollars, respectively. Patent data are from Kogan et. al. (2017). Standard errors are clustered at the firm level (standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Past acquisition behavior and HFA target probability

	(1)	(2)
	OLS	OLS
Dependent Var.	D(HFA)	D(HFA)
Industry HFA Freq × NumAcq × D(Large)	0.0753***	
	(0.0275)	
Industry HFA Freq × NumAcq × D(Small)	0.0225	
	(0.0544)	
Industry HFStake Freq × NumAcq × D(Large)		0.0420***
		(0.0161)
Industry HFStake Freq × NumAcq × D(Small)		0.00219
		(0.0324)
Year F.E.	Yes	Yes
Industry F.E.	Yes	Yes
Num. Obs.	61187	61187
Adj. R^2	0.023	0.027

Panel B: Target quality of small acquirers

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

Panel C: Target quality of small acquirers and industry activism threat

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

Table 13: HFA impact on the efficiency of divestitures

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

Panel A: Efficiency of divestitures by HFA target firms

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

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

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

Table 14: Activism 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 in the five-year period $[t+1, t+5]$ after the acquisition announcement. D(Post HFA) is a dummy variable equal equal to one in the five-year period $[t+1, t+5]$ after the HFA event. Panel B investigates the ex-post operating performance of acquirers acting under high industry HFA threat that are not current or recent (past two years) activism targets. In this panel, we drop all activism acquisitions from the sample. We use Industry HFA Freq as our measure of the industry HFA threat. D(Activism Wave) is a dummy equal to one if the industry-year is in the top quintile by Industry HFA Freq in the year when the acquisition is announced. D(Small) is a dummy equal to one if the firm's size is smaller than the industry-year median size of firms in the year before the announcement of acquisition. Following Bebchuk, Brav, and Jiang (2015), we include ln(MV) and ln(Age) as controls in each regression. Year fixed effects and firm fixed effects are always included. Standard errors are clustered at the firm level (standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Efficiency of acquisitions by HFA target firms

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

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

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

Online Appendix for
Activism Waves and the Market for Corporate Assets

Contents not for Publication

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Table IA.1: Industries with highest and lowest frequency of activism waves

This table lists all industries (3-digit SIC code) with activism waves occurring in at least 40% of all 23 years. An activism wave is defined as an industry-year in the top quintile of the industry-year sample by Industry HFA Freq, the fraction of firms targeted within the past 3 years (t-2, t-1, or t) and with at least 2 activist campaigns (D(Activism Wave) = 1). Frequency in % is calculated as the fraction of years in the whole sample of Compustat.

Panel A: Industries with highest frequency of activism waves

Industry (SIC-3)	Industry description	Frequency in % years
731	SERVICES-ADVERTISING	73.91%
533	RETAIL-VARIETY STORES	60.87%
489	COMMUNICATIONS SERVICES, NEC	60.87%
701	HOTELS & MOTELS	52.17%
596	RETAIL-NONSTORE RETAILERS	52.17%
799	SERVICES-MISCELLANEOUS AMUSEMENT & RECREATION	52.17%
483	RADIO BROADCASTING STATIONS	52.17%
581	RETAIL-EATING & DRINKING PLACES	52.17%
603	SAVINGS INSTITUTION, FEDERALLY CHARTERED	47.83%
738	SERVICES-MISCELLANEOUS BUSINESS SERVICES	47.83%
481	TELEPHONE COMMUNICATIONS	43.48%
369	MISCELLANEOUS ELECTRICAL MACHINERY, EQUIPMENT & SUPPLIES	43.48%
737	SERVICES-COMPUTER PROGRAMMING, DATA PROCESSING, ETC.	43.48%
594	RETAIL-MISCELLANEOUS SHOPPING GOODS STORES	43.48%
562	RETAIL-WOMEN'S CLOTHING STORES	43.48%
808	SERVICES-HOME HEALTH CARE SERVICES	43.48%
508	WHOLESALE-MACHINERY, EQUIPMENT & SUPPLIES	43.48%
651	REAL ESTATE OPERATORS (NO DEVELOPERS) & LESSORS	43.48%

Panel B: Industries with lowest frequency of activism waves (some examples)

Industry (SIC-3)	Industry description	Frequency in % years
20	AGRICULTURAL PROD-LIVESTOCK & ANIMAL SPECIALTIES	0.00%
80	FORESTRY	0.00%
154	GENERAL BLDG CONTRACTORS - NONRESIDENTIAL BLDGS	0.00%
210	TOBACCO PRODUCTS	0.00%
222	BROADWOVEN FABRIC MILLS, MAN MADE FIBER & SILK	0.00%
234	WOMEN'S, MISSES', CHILDREN'S & INFANTS' UNDERGARMENTS	0.00%
240	LUMBER & WOOD PRODUCTS (NO FURNITURE)	0.00%
243	MILLWOOD, VENEER, PLYWOOD, & STRUCTURAL WOOD MEMBERS	0.00%
261	PULP MILLS	0.00%
277	GREETING CARDS	0.00%
279	SERVICE INDUSTRIES FOR THE PRINTING TRADE	0.00%
325	STRUCTURAL CLAY PRODUCTS	0.00%
328	CUT STONE & STONE PRODUCTS	0.00%
339	MISCELLANEOUS PRIMARY METAL PRODUCTS	0.00%
343	HEATING EQUIP, EXCEPT ELEC & WARM AIR; & PLUMBING FIXTURES	0.00%
345	SCREW MACHINE PRODUCTS	0.00%
387	WATCHES, CLOCKS, CLOCKWORK OPERATED DEVICES/PARTS	0.00%
396	COSTUME JEWELRY & NOVELTIES	0.00%

Table IA.2: Characteristics of firms under high, medium and low activism threat (Industry HFA Frequency)

This table reports firm characteristics, sorted by terciles of industry-years according to the distribution of Industry HFA Frequency which 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). Each value (mean, median and standard deviations) reports the aggregate value of all firms in the associated tercile of industry-years. The tabulation excludes observations of the 3,551 firms that are HFA targets in year t for the years $[t, t+3]$.

Tercile of Industry HFA Freq	Bottom Tercile (N = 42,908)			Medium Tercile (N = 31,552)			Top Tercile (N = 32,729)		
	Mean	Median	S.D.	Mean	Median	S.D.	Mean	Median	S.D.
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

Table IA.3: Campaign goals, firm characteristics, and activism waves

This table reports HFA campaign goals and their relationship with firm characteristics and activism waves. Panel A reports descriptive statistics for 5 different goals. Information about campaign goals is from Factset SharkWatch database. In Panel A, the aggregate number of stated campaign goals exceeds the number of campaigns with stated goals since campaigns announce multiple goals quite frequently. Panel B reports logit regressions for each of these HFA campaign goals separately. The regressions are based on our sample of 3,551 HFA campaigns. The dependent variable is a dummy equal to one if activists pursue the indicated goal (such as Board Seat) in the campaign and 0 if not. Panel C repeats the same regressions but includes a dummy for activism waves in the previous logit regressions, in the top-quintile of top-decile of industry-years by campaign frequency. D(Activism Wave) is a dummy equal to one in industry-years in the top quintile by Industry HFA Frequency and with at least two campaigns. D(Activism Wave P90) is a identically constructed dummy but defined for a more restrictive set of activism waves: D(Activism Wave P90) is equal to one in industry-years in the top-decile (instead of top-quintile) of the distribution by Industry HFA Frequency and with at least two campaigns. Panel D conducts logit regressions of corporate transactions with our main firm-year sample and includes the two activism wave dummies sequentially.

Panel A: Classification of campaign goals

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

Panel B: Campaign goals and firm characteristics

	(1) Board Seat	(2) Governance	(3) Payout	(4) Seek Sale	(5) Restructure
Institutional Ownership	0.498**	0.237	0.108	0.401	0.00834
	(0.243)	(0.302)	(0.350)	(0.283)	(0.393)
Tobin's Q	-0.214***	-0.120	-0.165	-0.0761	-0.304**
	(0.0743)	(0.0938)	(0.110)	(0.0911)	(0.136)
ln(MV)	-0.0362	-0.0109	0.0732	-0.0984**	0.353***
	(0.0411)	(0.0519)	(0.0534)	(0.0468)	(0.0571)
Book Leverage	-0.402**	-0.00483	0.282	-0.00603	-0.0489
	(0.195)	(0.253)	(0.271)	(0.231)	(0.320)

Dividend Yield	1.428	-3.198	-0.746	1.434	-3.058
	(2.394)	(3.528)	(4.286)	(3.429)	(4.435)
Cash Flow	1.058**	0.857	1.451*	1.631***	0.564
	(0.443)	(0.612)	(0.743)	(0.504)	(0.988)
Sales Growth	-0.369*	-0.200	0.00170	-0.0137	0.205
	(0.191)	(0.264)	(0.285)	(0.237)	(0.360)
Asset Growth	-0.0841	0.235	-0.573	-0.312	-0.0534
	(0.202)	(0.246)	(0.350)	(0.255)	(0.364)
R&D	1.937**	-0.988	-1.894	1.215	1.975
	(0.800)	(1.185)	(1.460)	(0.965)	(1.318)
HHI	-0.0494	-0.102	0.168	-0.662*	-0.392
	(0.289)	(0.359)	(0.390)	(0.396)	(0.501)
Excess Cash	-0.0882	0.637	1.581***	0.108	-0.387
	(0.325)	(0.405)	(0.451)	(0.378)	(0.623)
CAR [12 Months]	-0.168	-0.00207	0.0796	-0.0242	-0.409*
	(0.115)	(0.142)	(0.159)	(0.120)	(0.219)
Industry and Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
N	2325	2010	2061	2415	2051
pseudo R^2	0.133	0.058	0.080	0.084	0.111

Panel C: Campaign goals and activism waves

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

Panel D: Corporate transactions and activism waves

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

Table IA.4: Summary statistics of corporate transactions by year

This table reports descriptive statistics of corporate transaction activities by calendar year. Definitions of all variables and the structure follow that of Table 6 (Panel A). Table 6 reports cumulative values for five-year periods and this table reports annual data by calendar year.

Panel A: Activism campaigns and merger bids

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

Panel B: Activism campaigns and divestitures

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

Panel C: Activism campaigns and all acquisitions

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

Panel D: Activism campaigns and acquisitions of private targets

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

Table IA.5: Robustness checks for Table 6 and Table 7

This table reports robustness checks for our finding that firms' acquisition behavior under HFA pressure differs according to firm size (Table 6 for HFA targets and Table 7 for firms under HFA threats). Instead of a median split as in Table 6 and Table 7, we sort firms into firm size terciles in this table. Definitions of all variables follow the corresponding tables (Table 6 and Table 7) in the paper.

Panel A: Replicate Table 6 – Panel B

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

Panel B: Replicate Table 7 – Panel B

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

Panel C: Replicate Table 7 – Panel B

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

Panel D: Replicate Table 7 – Panel C

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

Table IA.6: Robustness checks for Table 12

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

Panel A: Replicate Table 12 – Panel A

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

Panel B: Replicate Table 12 – Panel A

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

Table IA.7: Robustness checks for Table 13 and Table 14

This table reports robustness checks for our findings in Table 13 and Table 14 of the paper. In this table, we use a wider definition of D(High HFA Threat): D(High HFA Threat P66) is a dummy equal to one if the industry is in the top tercile (instead of top quintile in Table 13 and 14) of Industry HFA Freq in the year when the acquisition is announced and if the firm (seller of an asset in Panel A, buyer in Panel B) is not currently an activism target. The rest of the regression setup follows Table 13 and 14, respectively.

Panel A: Replicate Table 13 – Panel B

	(1) Tobin's Q	(2) ROA	(3) Sales/Assets(lag)
D(Post Divestiture)	0.0630***	-0.00179	0.00199
	(0.0204)	(0.00268)	(0.0105)
D(Post Divestiture) × D(High HFA Threat P66)	0.0116	-0.00154	-0.0212
	(0.0260)	(0.00320)	(0.0133)
D(Post HFA)	0.151***	-0.00109	0.0127
	(0.0359)	(0.00458)	(0.0173)
Firm-level controls	Yes	Yes	Yes
Year and Firm fixed effect	Yes	Yes	Yes
N	22839	21537	23261
adj. R^2	0.562	0.636	0.817

Panel B: Replicate Table 14 – Panel B

	(1) Tobin's Q	(2) ROA	(3) Sales/Assets(lag)
D(Post Acquisition)	-0.317***	-0.0115***	-0.0971***
	(0.0229)	(0.00218)	(0.00880)
D(Post Acquisition) × D(Small]	0.218***	0.0126***	0.0457***
	(0.0309)	(0.00356)	(0.0141)
D(Post Acquisition) × D(High HFA Threat P66)	-0.0293	-0.00606**	-0.0356***
	(0.0267)	(0.00258)	(0.0104)
D(Post Acquisition) × D(High HFA Threat P66) × D[Small]	0.0359	0.0122**	0.0352
	(0.0448)	(0.00499)	(0.0232)
D(Post HFA)	0.123***	0.000801	0.0181
	(0.0288)	(0.00312)	(0.0133)
Firm-level controls	Yes	Yes	Yes
Year and Firm fixed effect	Yes	Yes	Yes
N	49293	46525	49110
adj. R^2	0.556	0.620	0.800

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