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To cite this article:

Nickolay Gantchev, Chotibhak Jotikasthira (2018) Institutional Trading and Hedge Fund Activism. Management Science 64(6):2930-2950. <https://doi.org/10.1287/mnsc.2016.2654>

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Institutional Trading and Hedge Fund Activism

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Received: November 3, 2015

Revised: April 4, 2016

Accepted: July 5, 2016

Published Online in Articles in Advance:
February 23, 2017

<https://doi.org/10.1287/mnsc.2016.2654>

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Abstract. This paper investigates the role of institutional trading in the emergence of hedge fund activism—an important corporate governance mechanism. We demonstrate that institutional sales raise a firm’s probability of becoming an activist target. Furthermore, by exploiting the funding circumstances of individual institutions, we establish that such effects occur through a liquidity channel, i.e., the activist camouflages his purchases among other institutions’ liquidity sales. Additional evidence supports our conclusion. First, activist purchases closely track institutional sales at the daily frequency. Second, such synchronicity is stronger among targets with lower expected monitoring benefits, suggesting that gains from trading with other institutions supplement these benefits in the activist’s targeting decision. Finally, we find that institutional sales accelerate the timing of a campaign at firms already followed by activists rather than attract attention to unlikely targets. Taken together, our findings offer a novel empirical perspective on the liquidity theories of activism; while activists screen firms on the basis of fundamentals, they pick specific targets at a particular time by exploiting institutional liquidity shocks.

History: Accepted by Amit Seru, finance.

Supplemental Material: The Internet appendix is available at <https://doi.org/10.1287/mnsc.2016.2654>.

Keywords: shareholder activism • corporate governance • institutional investors • hedge funds

1. Introduction

Hedge fund activism is an important governance mechanism associated with significant improvements in the performance and governance of targeted firms (see Brav et al. 2008, 2015; Becht et al. 2008; Clifford 2008; Klein and Zur 2009).¹ Prior literature has established that activists target firms with particular fundamentals, such as low payout and leverage (see survey by Brav et al. 2010), and market characteristics, such as high institutional ownership and stock liquidity (Edmans et al. 2013, Norli et al. 2014). However, these characteristics alone cannot explain why certain firms are targeted at certain times while others that fit the same profile are not.² In this paper, we provide new evidence that institutional trading is critical in determining an activist’s specific target choice and time of entry, and ultimately the scale of activism.

We start with the observation that institutions sell an unusually large fraction of their ownership in target firms in the months leading up to the activist campaigns. Institutional selling appears to be positively associated with a firm’s probability of becoming an activist target, even after controlling for firm characteristics shown in the literature to impact targeting, including general stock liquidity. In economic terms, a one standard deviation increase in institutional selling volume is associated with a 0.45% increase in the probability of being targeted (one-fifth of the unconditional probability of 2.33%). This effect is larger than that of

most fundamentals (e.g., leverage) and stronger among firms with characteristics conducive to activism.

To investigate the economic mechanism, we rely primarily on the theoretical model of Maug (1998) and other similar *liquidity* theories (Kahn and Winton 1998, Kyle and Vila 1991, Back et al. 2015, and others). Though different in their assumptions and (in some cases) predictions, these theories share the premise that nonactivist shareholders are noise traders whose liquidity trades allow the activist to camouflage his purchases and gain on his newly acquired shares after declaring his activist intentions.³ These (expected) trading gains are critical in covering the activist’s monitoring costs, making a campaign financially viable, and hence, raising the probability of an intervention.

In testing the liquidity theories, we capture institutional liquidity trades by using fire-sale based instrumental variables (see Coval and Stafford 2007, Edmans et al. 2012). Specifically, we extract each institution’s trades that are driven by institution-specific funding constraints, unrelated to information about any particular firm or the activist’s intention to launch a campaign. Our results show that it is through the liquidity channel that institutional selling raises a firm’s probability of being targeted.⁴

We develop three novel hypotheses that capture the economic mechanism of the liquidity theories. First, these theories posit that institutional selling allows the activist, who already recognizes that his monitoring

will improve the firm's fundamental value, to quickly purchase additional shares at unrevealing prices, thus accelerating the *timing* of the campaign. We find evidence consistent with this hypothesis. By estimating discrete-time proportional hazard models, we show that a one standard deviation decrease in institutional net volume reduces the time in which a quarter of the firms will be targeted by about 2.38 years (from 11.79 to 9.41 years). Thus, all else being equal, the scale of activism should increase in periods in which nonactivist institutions experience negative funding shocks.

Second, the camouflage mechanism that underlies the liquidity theories predicts that the activist's purchases must closely track institutional sales so that the market maker is unable to differentiate, with certainty, between informed and uninformed orders. To investigate this prediction, we focus on the *daily frequency* using two unique data sets—a hand-collected data set of activist trades in the period leading up to the activist campaigns and a representative data set of institutional buy and sell transactions. We find that institutional sales and hedge fund purchases are highly synchronous at the daily frequency, consistent with the camouflage mechanism. A 1% increase in daily institutional selling volume is associated with a 0.26% increase in hedge fund buying volume.

To ensure that the demonstrated synchronicity is driven by institutional liquidity sales, we again use fire-sale based instruments but, in the absence of daily flow data, we infer the institutions' funding needs by studying their trading behavior across a large set of stocks.⁵ Specifically, we predict the buying and selling probabilities of *each* institution in a *generic* firm's stock as a function of its trading in *other* stocks outside the generic firm's industry and use these predicted trades as instruments.⁶ Our instrumental variable results confirm that institutional sales significantly increase hedge fund purchases.

Finally, we investigate the central idea of the liquidity theories that the activist covers his monitoring costs by supplementing the monitoring benefits that accrue to his initial stake with gains from trading with uninformed investors. In firms with higher net benefits, the activist will be less reliant on trading gains. To test this *substitution* hypothesis, we study the sample of targets to determine whether the synchronicity between institutional sales and hedge fund purchases varies with the expected activism benefits. We use two alternative measures of benefits, one based on the observed characteristics of typical targets and the other based on the revealed preference of known activist hedge funds. Consistent with the liquidity theories, we find that a 1% decrease in institutional net volume increases hedge fund purchase volume by 0.18%–0.26% in the sample with below median expected benefits but by only 0.10%–0.12% in the sample with above median

benefits. This implies that institutional trading may play a more critical role in recent years when activists are moving from “low hanging fruits” to potential targets for which the costs of intervention are higher relative to the benefits.

Our findings contribute to the growing literature on hedge fund activism, which has shown that institutional investors are important in the evolution and success of an activist campaign. We provide new evidence that institutions, through their trading, also affect the activist's decision to initiate a campaign. Our results indicate that institutional selling creates market conditions that permit a fast and discreet formation of an activist block. Thus, we provide direct empirical support to Maug (1998) and other similar liquidity theories, which study the role of noise trading as a mechanism that allows a large investor to gain from trading against uninformed shareholders and become an active monitor.

More broadly, our findings also contribute to the general corporate governance literature, particularly as it relates to the role of liquidity in shareholder monitoring. In this literature, blockholders use voice or the threat of exit to bring about change. Edmans et al. (2013) demonstrate that unconditionally stock liquidity improves governance by voice, but conditional on a block being formed is more conducive to governance by exit. Norli et al. (2014) show that cross-sectional differences in liquidity are positively correlated with the likelihood of shareholder activism and the accumulation of target shares immediately preceding the activism announcement. By contrast, Back et al. (2015) show that conditional on the existence of an already large block, liquidity has a harmful effect on governance (consistent with Coffee 1991, and Bhidé 1993). These empirical studies consider stock liquidity as a persistent firm characteristic and relate its cross-sectional variation to shareholder monitoring. By contrast, we interpret liquidity (in Maug 1998 and other similar theories) as the price impact of large trades, not the average price impact of all trades, and therefore focus on large liquidity shocks, which determine market depth and its transient changes, most critical to activist investors.

Finally, we also contribute to the literature on the trading behavior of hedge funds and, more generally, informed traders.⁷ We offer an institutional explanation for the results of Collin-Dufresne and Fos (2015), who show that informed traders strategically trade stocks on days with better liquidity. Our findings are also consistent with those of Sias and Whidbee (2010), who show that institutional investors trade on the opposite side of insiders and are likely to provide the liquidity necessary for the insiders to trade.

We proceed as follows. Section 2 develops a conceptual framework and formulates specific empirical hypotheses. Section 3 describes the hedge fund

activism sample. Section 4 investigates the relationship between institutional trading and activist targeting at the annual/quarterly frequency, and studies the economic mechanism underlying the liquidity theories. Section 5 examines at the daily frequency the effects of institutional selling on the activist's acquisition of target shares. Here, we also present evidence that our results are robust to other explanations. Section 6 concludes.

2. Hypotheses Development

To investigate the role of institutional selling in hedge fund activism, we develop a series of empirical hypotheses based on the theoretical contributions of Maug (1998) and other similar theories such as Kahn and Winton (1998), Kyle and Vila (1991), Back et al. (2015), and others, to which we refer collectively as *liquidity theories*.

Maug (1998) develops a model in which the decision of a large shareholder to monitor a firm depends critically on his gains from trading with uninformed households. The households trade in response to their own liquidity needs. Their trades, particularly sales, enable the activist to camouflage his purchases, i.e., buy shares in the firm at prices that do not fully reveal his intentions. Once the activist intervenes, these shares increase in price, resulting in trading gains that help offset his monitoring costs. Therefore, the larger the liquidity shocks experienced by nonactivist shareholders (mostly institutional investors in the context of activism), the higher the activist's expected trading gains and the larger his incentives to intervene. This role of uninformed investors' funding shocks in facilitating the activist's block formation is shared by all of the above liquidity theories, despite their different assumptions and predictions.⁸

Hypothesis 1 (H1) (Main). *The probability of a firm becoming an activist target increases in institutional selling.*

The liquidity theories assume that institutions sell in response to their own funding circumstances rather than in response to private information about a target firm or the activist's accumulation of target shares to launch a campaign. Although institutional selling may be uninformed, it facilitates the activist's block formation in a firm, and hence raises the firm's probability of being targeted.

Hypothesis 2 (H2) (Timing). *Conditional on the activist's recognizing the benefits of monitoring at a given firm, institutional selling accelerates the launch of a campaign.*

The liquidity theories assume that the activist already recognizes the potential improvement in firm value as a result of his intervention. However, he needs additional trading gains to help offset his monitoring costs, and institutional selling allows him to obtain

these gains. Thus, institutional selling accelerates targeting among firms whose monitoring benefits have been recognized by the activist rather than attract attention to unlikely targets.

Hypothesis 3 (H3) (Synchronicity). *Target firms experience net institutional selling before campaign announcement, and institutional sales and activist purchases are synchronous in time.*

This hypothesis spells out a test of the camouflage mechanism. To hide his intentions, the activist strategically acquires target shares at the same time that other institutions sell so that the net order imbalance is close to zero. This way, the market maker cannot differentiate with certainty between informed and uninformed order flows, and set the market price to fully reflect the intervention probability. At the daily frequency with continuous trading, we interpret this anonymous order batching as synchronicity between institutional sales and activist purchases.

Hypothesis 4 (H4) (Substitution). *The synchronicity between institutional sales and activist purchases is lower among target firms with higher net benefits from activism.*

The activist relies on the sum of activism benefits (that accrue to his toehold) and trading gains (from buying additional target shares at prices that are not fully revealing) to cover his monitoring costs. In firms with larger activism benefits, the activist relies less on trading gains and is more likely to launch the campaign quickly without waiting for large institutional liquidity shocks (assuming that there is a cost of waiting). Hence, among activist targets, we should observe a negative relationship between activism benefits and trading gains, i.e., the two sources of return are substitutes.⁹ We interpret the synchronicity between institutional sales and activist purchases as reflecting the activist's reliance on trading gains.

The above four hypotheses reflect our interpretation of the liquidity theories and their shared economic mechanism. In Section 5.5, we consider two alternative explanations and discuss our hypotheses through their lens: (i) *signaling*—institutions are privately informed and trade to signal to activists that a particular firm needs an intervention (see Attari et al. 2006); or (ii) *mechanical*—the activist demands target shares and institutions simply supply them; that is, "someone buys so someone else must sell."

3. Hedge Fund Activism Sample

The primary data set used in this paper is a comprehensive list of hedge fund activist campaigns from 2000 to 2007. The data are hand-collected from regulatory filings and supplemented with information from SharkRepellent.net, as described in Gantchev (2013). The main source is Schedule 13D, which must be

Table 1. Characteristics of Target and Nontarget Firms

	Target firms			Nontarget firms			Difference	
	N	Mean	Median	N	Mean	Median	Mean	Median
<i>log(MV)</i>	755	5.203	5.057	33,164	5.611	5.556	-0.407***	-0.499***
<i>Tobin's Q</i>	755	1.914	1.324	33,164	2.793	1.530	-0.879***	-0.206***
<i>Leverage</i>	755	0.276	0.231	33,164	0.300	0.258	-0.024**	-0.027
<i>Dividend yield</i>	755	0.008	0.000	33,164	0.010	0.000	-0.002	0.000
<i>Sales growth</i>	755	0.168	0.062	33,164	0.262	0.098	-0.093***	-0.036***
<i>ROA</i>	755	0.049	0.095	33,164	0.044	0.095	0.005	0.000
<i>R&D/Assets</i>	755	0.056	0.000	33,164	0.082	0.000	-0.025*	0.000
<i>Inst. ownership</i>	755	0.513	0.507	33,164	0.438	0.424	0.075***	0.083***
<i>log(Analysts)</i>	755	1.355	1.386	33,164	1.300	1.386	0.056	0.000
<i>-log(Amihud)</i>	755	-1.259	-1.074	33,164	-1.245	-0.973	-0.014	-0.101
<i>Herfindahl index</i>	755	0.037	0.028	33,164	0.036	0.027	0.000	0.001***
<i>Return</i>	755	0.057	-0.028	33,162	0.214	0.044	-0.157***	-0.072***
<i>Inst. buy volume/SHROUT</i>	731	0.024	0.015	30,643	0.028	0.017	-0.004***	-0.002**
<i>Inst. sell volume/SHROUT</i>	731	0.030	0.019	30,643	0.027	0.017	0.003***	0.002**
<i>Inst. net volume/SHROUT</i>	731	-0.006	-0.002	30,643	0.001	0.000	-0.007***	-0.002***
<i>No. HFs with toehold</i>	461	3.291	3.000	16,032	2.694	2.000	0.596***	1.000***
<i>HF toehold/SHROUT</i>	461	0.053	0.034	16,032	0.021	0.006	0.032***	0.029***
<i>ΔMF holdings/SHROUT</i>	636	-0.002	0.000	25,346	0.001	0.000	-0.003***	-0.001***

Notes. This table reports summary statistics of firm characteristics for the sample of CRSP-Compustat firms that were targeted/not targeted by hedge fund activists in 2000–2007. All variables are defined in the appendix. Institutional trading data are from Ancerno. Institutional ownership and holdings data are from Thomson Reuters-13F. Mutual fund holdings data are from Thomson Reuters-Mutual Funds. Additional statistics including standard deviation and various percentiles are reported in the Internet appendix.

*, **, and *** denote statistical significance (of the difference in means or medians) at the 10%, 5%, and 1% levels, respectively.

filed with the U.S. Securities and Exchange Commission (SEC) by any investor who acquires more than 5% of the voting stock of a public company with the intention of influencing its operations or management. The activist sample consists of 1,191 distinct campaigns involving 981 unique targets and 130 hedge fund families.

We merge the activism data set with the universe of the Center for Research in Security Prices (CRSP)-Compustat firms to create an annual firm-year panel. We count multiple campaigns in the same firm-year as one target observation. The full panel consists of 33,919 firm-years, including 755 target-years. Table 1 compares the typical target to nontarget firms. All variables are defined in the appendix and their measurement closely follows Brav et al. (2010) and Edmans et al. (2013).

Hedge fund targets in our sample have fundamentals similar to those reported in the activism literature. For example, compared to other CRSP-Compustat firms, the targets are smaller, have lower *Tobin's Q*, and slightly lower book *Leverage*. Typical targets operate in industries that are not more or less competitive than those of other firms (as measured by the *Herfindahl index* of segment sales) and are not poorly performing in terms of return on assets (*ROA*), even though they seem to suffer from lower *Sales growth*. They also have a higher analyst following (not statistically significant), as measured with data from the Institutional Brokers' Estimate System (I/B/E/S). Finally, hedge funds tend

to approach firms with large institutional holdings, based on data from Thomson Reuters 13F.

To investigate the role of institutional trading in the emergence of hedge fund activism, we merge the above firm-year panel with institutional trading data. We measure institutional trading in two different ways. Our first measure aggregates all buy and sell transactions in each firm by all institutions reporting to Ancerno (formerly known as the Abel/Noser Corporation).¹⁰ Ancerno provides transaction cost analysis to mutual funds, pension plan sponsors, and brokers representing (on average) 13.47% of total CRSP volume during 2000–2007. As seen in Table 1, this data requirement reduces our universe to 31,374 firm-years and our activism sample to 731 target-years. Our second measure calculates changes in mutual fund holdings using data from Thomson Reuters Mutual Funds (formerly CDA Spectrum). We focus on mutual funds since we can use mutual fund flows from CRSP to identify funding shocks. This data requirement further reduces our universe to 25,982 firm-years and our activism sample to 636 firm-years.

Table 1 shows that activist targets see substantially more negative (average quarterly) net institutional trading volume (*Inst. net volume/SHROUT*) in the year before the start of a campaign, driven by lower buying volume (*Inst. buy volume/SHROUT*) and higher selling volume (*Inst. sell volume/SHROUT*). We find a similar result using the average change in quarterly mutual fund holdings (*ΔMF holding/SHROUT*). These summary statistics suggest that institutional trading may

have an impact on an activist's decision to target a specific firm.

Finally, we also merge the firm-year panel data with activist hedge fund holdings from the 13F data set: 61% of targets and 48% of nontargets have at least one activist hedge fund owner (not necessarily the activist initiating the campaign) at the beginning of the year. Moreover, in the sample of firms with hedge fund toeholds, we see that more hedge funds have toeholds (*No. HFs with toehold*) in targets than in other firms, with the median toehold (*HF toehold/SHROUT*) being almost six times as large.

4. Effect of Institutional Trading on Hedge Fund Activism

The first part of our analysis examines the relationship between institutional trading and activist targeting at the *annual/quarterly* frequency using the full firm-year panel of CRSP-Compustat firms with available trading data. To aid in the interpretation of our results, we start with a brief sketch of the activism process, highlighting the role of institutional trading in target selection.

We view activist targeting as a *three-step screening process*. The three steps below are consistent with the evidence presented here and in the previous literature but should not be taken literally.

Step 1. The activist identifies $N1$ firms that may benefit from activism, given their fundamental characteristics and corporate policies, such as leverage, payout, etc. $N1$ is likely to be large. For example, we find that hundreds of firms in any given year look like viable targets as they have predicted target probabilities¹¹ at least as high as the 25th percentile of the target sample.

Step 2. The activist identifies $N2 < N1$ candidates that have sufficient liquidity, considering liquidity as a persistent characteristic as in Edmans et al. (2013) and Norli et al. (2014). The number of candidates $N2$ is likely to still be large, as the univariate statistics in Table 1 suggest that target firms are not much more liquid than other firms.

Step 3. The activist follows $N2$ target candidates, and ultimately targets $N3 \ll N2$ firms whose shares experience large institutional sales.

The literature has shown that the first two steps are important (e.g., Brav et al. 2008 and Edmans et al. 2013). We argue that the third step is also necessary because fundamentals and stock liquidity are persistent¹² and therefore the first two steps alone cannot explain why so few firms (less than 3% of public firms) are targeted and why they are targeted at a particular time. Our empirical tests aim to justify this argument by referring to the liquidity theories.

4.1. Does Institutional Trading Affect a Firm's Likelihood of Becoming a Target?

We first test H1 that the probability of becoming an activist target increases in institutional selling.

We do so by estimating linear probability models of activist targeting, with institutional trading volumes as the main explanatory variables. At the end of this subsection, we identify the liquidity channel using flow-induced fire sales and purchases as measures of funding shocks.

The first four columns of Table 2 report ordinary least squares (OLS) estimates. All models include industry and year fixed effects and cluster standard errors by firm. In column (1), we include as explanatory variables only firm characteristics that the extant literature has shown may affect activist targeting (all variables are described in the appendix). The coefficient estimates of these characteristics are largely similar to those previously reported in the literature. For example, targeting is positively correlated with liquidity ($-\log(\text{Amihud})$) and institutional ownership but negatively correlated with size ($\log(MV)$) and market-to-book (*Tobin's Q*).

Columns (2) and (3) add institutional trading volumes from Ancerno, calculated as the quarterly averages for each firm-year as a percent of shares outstanding (*SHROUT*). Column (2) shows that net (buy minus sell) institutional volume has a negative effect (significant at 1%) on the probability of being targeted. Column (3) separates institutional selling and buying volumes. We find that a one standard deviation increase in institutional selling volume is associated with a 0.45% (0.034×0.135) increase in the probability of becoming an activist target whereas a one standard deviation increase in institutional buying volume is related to a 0.70% (0.038×-0.185) decrease in that probability. Both effects are statistically significant at 1% and economically significant, given that the unconditional probability of becoming an activist target is 2.33%. The effects of institutional trading on activist targeting are distinct from those of firm characteristics, including corporate policies, valuation as proxied by *Tobin's Q* and previous year's stock return, as well as general stock liquidity as measured by average *Amihud* ratio.

In column (4), we use an alternative measure of institutional trading calculated as the change in mutual fund holdings as a percent of shares outstanding. This variable is the quarterly average in a given firm-year of the change in the holdings of all mutual funds in the Thomson Reuters Mutual Funds data. We find that a one standard deviation increase in mutual fund holdings decreases the probability of being targeted by 0.78% (0.009×-0.868).

To establish that institutional selling affects the activist's targeting decision through the liquidity channel, we use fire-sale based instrumental variables in the spirit of Coval and Stafford (2007). Our instruments extract the institutions' trades that are driven by institution-specific funding constraints and therefore

Table 2. Effect of Institutional Trading on Activist Targeting

	OLS				IV-LIML	
	Target dummy				ΔMF holdings/ SHROUT (First stage)	Target dummy (Second stage)
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Inst. net volume</i> /SHROUT		-0.168*** (0.045)				
<i>Inst. sell volume</i> /SHROUT			0.135*** (0.045)			
<i>Inst. buy volume</i> /SHROUT			-0.185*** (0.055)			
ΔMF holdings/SHROUT				-0.868*** (0.126)		-2.425** (1.152)
<i>Exp</i> (MF fire sales)/SHROUT					-0.133*** (0.048)	
<i>Exp</i> (MF fire purchases)/SHROUT					0.195*** (0.017)	
$-\log$ (Amihud)	0.006*** (0.002)	0.004* (0.002)	0.004** (0.002)	0.005* (0.003)	0.001*** (0.000)	0.006** (0.003)
\log (MV)	-0.008*** (0.001)	-0.008*** (0.001)	-0.008*** (0.001)	-0.008*** (0.001)	0.000*** (0.000)	-0.008*** (0.001)
Tobin's Q	-0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000** (0.000)	-0.000 (0.000)
<i>Inst. ownership</i>	0.039*** (0.004)	0.039*** (0.005)	0.041*** (0.005)	0.034*** (0.005)	-0.004*** (0.000)	0.029*** (0.007)
<i>Sales growth</i>	-0.002* (0.001)	-0.002* (0.001)	-0.002 (0.001)	-0.003*** (0.001)	0.000 (0.000)	-0.003*** (0.001)
ROA	-0.002 (0.003)	-0.003 (0.003)	-0.003 (0.003)	-0.008** (0.004)	0.001*** (0.000)	-0.006 (0.005)
<i>Leverage</i>	-0.000 (0.004)	0.000 (0.004)	0.000 (0.004)	-0.001 (0.004)	-0.000 (0.000)	-0.001 (0.004)
<i>Dividend yield</i>	-0.001 (0.005)	0.002 (0.010)	0.002 (0.010)	-0.001 (0.010)	-0.000 (0.000)	-0.001 (0.010)
<i>R&D/Assets</i>	-0.000** (0.000)	-0.000** (0.000)	-0.000** (0.000)	-0.002 (0.002)	0.001** (0.000)	-0.001 (0.002)
<i>Herfindahl index</i>	0.131 (0.233)	0.090 (0.245)	0.091 (0.245)	0.062 (0.271)	0.041*** (0.015)	0.126 (0.276)
\log (Analysts)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.002 (0.002)	-0.000*** (0.000)	-0.003* (0.002)
<i>Return</i>	-0.001 (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)	0.001*** (0.000)	0.001 (0.001)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen–Paap rank Wald statistic	N/A	N/A	N/A	N/A	F(2, 6159) = 65.057 (S-Y crit. val. at 10% maximal size = 8.68)	
Hansen J statistic	N/A	N/A	N/A	N/A	$\chi^2(1) = 1.628$	
Observations	33,919	31,374	31,374	25,982	25,982	25,982
R-squared (within)	0.012	0.014	0.014	0.017	0.026	0.010

Notes. This table reports OLS and instrumental variables-limited information maximum likelihood (IV-LIML) estimates for linear probability models of hedge fund activist targeting. Observations are firm-years and the sample period is 2000–2007. All variables are defined in the appendix. Columns (1)–(4) report OLS estimates. The dependent variable is a dummy equal to one if a firm is targeted in an activist campaign. Column (1) provides a benchmark model without nonactivist institutional trading variables. In columns (2)–(4), institutional trading is captured by *Inst. net volume*/SHROUT, *Inst. sell and buy volumes*/SHROUT, and ΔMF holdings/SHROUT, all of which are winsorized at 1%. Robust standard errors, clustered by firm, are in parentheses. Columns (5) and (6) report the first- and second-stage IV-LIML estimates, respectively, for the model in column (4) whereby the endogenous regressor, ΔMF holdings/SHROUT, is expressed as a function of the excluded instruments, *Exp*(MF fire sales/purchases)/SHROUT. Robust standard errors, clustered by firm and corrected by Monte Carlo simulation for errors in estimating the expected trading volumes, are in parentheses. All columns include year and industry fixed effects. All control variables are as of the end of the prior year.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

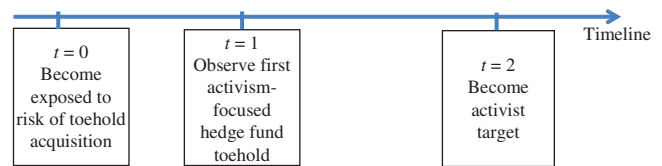
likely exogenous to the activism events.¹³ In particular, we follow the approach in Edmans et al. (2012) and instrument the change in mutual fund holdings by expected fire sales and purchases. The expected fire sales (purchases) for *each* mutual fund in each reporting quarter are the product of the percentage outflows (inflows) and the beginning-of-quarter shareholdings if the fund experiences flows that are larger than 5% in magnitude; otherwise, the expected fire sales (purchases) are zero. We then sum the expected fire sales and purchases across all mutual funds holding each stock, divide the sum by the number of shares outstanding at the beginning of the quarter, and average across all quarters to obtain the expected fire sales and purchases for each firm-year.

We estimate our model using LIML because, as demonstrated by Stock and Yogo (2005), LIML has essentially zero maximal relative bias (worst-case asymptotic bias greater than some threshold) and its maximal size distortion (worst-case false rejection of the null in small samples) is generally less than that of 2SLS. We report the first- and second-stage results in columns (5) and (6) of Table 2, respectively.¹⁴ These results confirm that a plausibly exogenous increase in mutual fund holdings reduces the probability of a firm being targeted in an activist campaign. Thus, a firm experiencing fire sales (purchases) is more (less) likely to be targeted, which establishes support for the liquidity channel. As a robustness check, in the Internet appendix, we confirm this result with an alternative version of the instruments constructed using daily institutional transaction data from Ancerno. As described in detail in the Internet appendix, we identify *each* institution's liquidity trades in a generic firm's stock by its trading in other stocks outside the firm's industry.

4.2. Does Trading Accelerate Activist Targeting?

In this subsection, we test the timing hypothesis (H2) that institutional selling accelerates the start of a campaign at firms whose potential benefits from activism have already been recognized by activists. We take the first acquisition of a toehold by any known activism-focused hedge fund (not necessarily the one that initiates a campaign) as a proxy for the recognition that a particular firm may benefit from monitoring. We define activism-focused hedge funds as those that launch more than the median number of campaigns (5) during our sample period. Because these hedge funds primarily engage in activism, their toeholds are unlikely to reflect other unrelated investment objectives. In Figure 1, we use an illustrative timeline of activist targeting to map the first arrival of an activist at time $t = 1$, before which the firm's potential activism benefits have not been recognized. At $t = 2$, an activist targets the firm. In this framework, the timing hypothesis would

Figure 1. Timeline of Activist Targeting



predict that institutional selling shortens the time between $t = 1$ and $t = 2$, i.e., increases the arrival rate of a campaign, conditional on some activists already having a toehold.

We estimate discrete-time proportional hazard models for activist targeting (starting at $t = 1$ and ending at $t = 2$), and report the coefficients in panel A of Table 3. Each observation is a firm-quarter. All specifications include firm controls and four types of fixed effects: (i) survival duration (in quarters) fixed effects to control for the length of time a firm has survived and absorb the baseline hazard rates, (ii) vintage fixed effects to absorb any regularities associated with the quarter in which a firm enters the sample, (iii) calendar year-quarter fixed effects to control for cyclicalities in activism (Burkart and Dasgupta 2015), and (iv) industry fixed effects.

The dependent variable is a “target” dummy, which equals one in the quarter in which a firm is targeted, and zero otherwise. For a given firm, the spell begins when an activism-focused hedge fund acquires a toehold for the first time (i.e., when the firm is first viewed as a target candidate), and completes when it is targeted. Thus, the sample includes only firms in which at least one activism-focused hedge fund has a toehold and tracks these firms until they are targeted or until they are right-censored at the end of our sample. Firms with existing activist toeholds at the beginning of the sample period in 2000 suffer from left censorship, which we correct using two approaches: Correction 1 sets the beginning of a left-censored spell to the later of the dates on which we observe an activist toehold or 1994Q1,¹⁵ whereas Correction 2 simply drops all left-censored spells.¹⁶

The results in column (1) show that institutional net volume negatively affects the arrival rate of an activist campaign. Column (2) includes separately institutional selling and buying volumes and confirms our findings: Institutional sell (buy) volume is positively (negatively) associated with the arrival rate of a campaign. These results are all statistically significant at 1%, and robust to changes in the correction for left-censorship, as illustrated in columns (3) and (4). The average unconditional hazard rate of 0.006 implies that in about 11.79 years, a quarter of the firms with activist toeholds will be targeted.¹⁷ From this baseline, the estimates in column (2) suggest that a one standard deviation increase in institutional selling (buying) volume decreases (increases) the average hazard rate by

Table 3. Effect of Institutional Trading on Activist Toehold Acquisition and Targeting

	Correction 1 for left censorship		Correction 2 for left censorship	
	(1)	(2)	(3)	(4)
Panel A: Failure = First activist targeting firm				
<i>Inst. net volume/SHROUT</i>	-4.176*** (0.512)		-4.012*** (0.498)	
<i>Inst. sell volume/SHROUT</i>		4.595*** (0.582)		4.421*** (0.586)
<i>Inst. buy volume/SHROUT</i>		-5.559*** (1.893)		-5.778** (2.840)
$-\log(\text{Amihud})$	-0.054 (0.139)	-0.045 (0.142)	-0.206 (0.203)	-0.193 (0.210)
$\log(\text{MV})$	-0.420*** (0.082)	-0.421*** (0.082)	-0.396*** (0.086)	-0.397*** (0.086)
<i>Tobin's Q</i>	-0.044 (0.033)	-0.041 (0.032)	-0.057 (0.045)	-0.054 (0.043)
<i>Inst. ownership</i>	1.403*** (0.254)	1.421*** (0.253)	1.416*** (0.296)	1.447*** (0.277)
<i>Sales growth</i>	-0.141 (0.086)	-0.136 (0.085)	-0.106 (0.086)	-0.100 (0.082)
<i>ROA</i>	-0.427 (0.262)	-0.406 (0.271)	-0.492** (0.194)	-0.466** (0.193)
<i>Leverage</i>	-0.238 (0.233)	-0.238 (0.233)	-0.270 (0.255)	-0.270 (0.254)
<i>Dividend yield</i>	0.401 (0.298)	0.394 (0.302)	0.438*** (0.163)	0.430** (0.170)
<i>R&D/Assets</i>	-0.754 (0.507)	-0.744 (0.509)	-0.872 (0.582)	-0.864 (0.588)
<i>Herfindahl index</i>	-4.053 (11.343)	-4.089 (11.347)	-12.434 (14.573)	-12.461 (14.543)
$\log(\text{Analysts})$	0.010 (0.071)	0.015 (0.073)	0.057 (0.089)	0.064 (0.093)
<i>Return</i>	-0.226 (0.179)	-0.216 (0.175)	-0.232 (0.149)	-0.220 (0.155)
Survival duration (in quarters) fixed effects	Yes	Yes	Yes	Yes
Vintage fixed effects	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	65,370	65,370	47,878	47,878
Pseudo-likelihood ratio statistic	438	440	324	326
Panel B: Failure = First activism-focused hedge fund acquiring toehold in firm				
<i>Inst. net volume/SHROUT</i>	0.607* (0.331)		1.106 (0.848)	
<i>Inst. sell volume/SHROUT</i>		0.162 (0.338)		0.048 (0.795)
<i>Inst. buy volume/SHROUT</i>		1.297*** (0.320)		1.556 (0.956)
$-\log(\text{Amihud})$	0.454*** (0.072)	0.439*** (0.073)	0.859*** (0.185)	0.832*** (0.181)
$\log(\text{MV})$	0.150*** (0.039)	0.152*** (0.040)	-0.092* (0.056)	-0.085 (0.054)
<i>Tobin's Q</i>	-0.004 (0.003)	-0.004 (0.004)	-0.006 (0.006)	-0.006 (0.006)
<i>Inst. ownership</i>	0.562*** (0.093)	0.491*** (0.101)	0.417 (0.304)	0.342 (0.350)
<i>Sales growth</i>	-0.001 (0.021)	-0.005 (0.021)	0.021 (0.043)	0.022 (0.044)
<i>ROA</i>	0.307*** (0.065)	0.299*** (0.063)	0.198* (0.112)	0.185* (0.108)

Table 3. (Continued)

	Correction 1 for left censorship		Correction 2 for left censorship	
	(1)	(2)	(3)	(4)
Panel B: Failure = First activism-focused hedge fund acquiring toehold in firm (Continued)				
<i>Leverage</i>	-0.041 (0.068)	-0.032 (0.069)	-0.098 (0.144)	-0.082 (0.136)
<i>Dividend yield</i>	0.010 (0.452)	0.029 (0.429)	-0.208 (0.749)	-0.225 (0.753)
<i>R&D/Assets</i>	-0.001 (0.004)	-0.002 (0.005)	-0.001 (0.002)	-0.001 (0.002)
<i>Herfindahl index</i>	7.279 (4.683)	7.197 (4.694)	6.826 (12.701)	6.501 (12.609)
<i>log(Analysts)</i>	-0.107*** (0.027)	-0.115*** (0.027)	0.184*** (0.061)	0.176*** (0.061)
<i>Return</i>	0.051*** (0.014)	0.048*** (0.014)	0.103 (0.078)	0.092 (0.077)
Survival duration (in quarters) fixed effects	Yes	Yes	Yes	Yes
Vintage fixed effects	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	53,448	53,448	6,009	6,009
Pseudo-likelihood ratio statistic	5,838	5,854	989	991

Notes. This table reports pseudo maximum likelihood estimates (MLEs) of discrete-time proportional hazard (complementary log-log) models for activist targeting (panel A) and for first acquisition of a toehold by a known activism-focused hedge fund (panel B). Activism-focused hedge funds are defined as hedge funds that launch more than the median number of campaigns during the sample period. Observations are firm-quarters. All variables are defined in the appendix. In panel A, the dependent variable is a “target” dummy, which equals one in the quarter in which a firm is targeted, and 0 in all prior quarters. For each firm, the spell starts when at least one activism-focused hedge fund acquires a toehold in the firm, and ends when the firm is targeted in an activist campaign (i.e., the spell is complete) or when the sample ends (i.e., the spell is right-censored), whichever comes first. Firms with existing activism-focused hedge fund toeholds at the beginning of the sample period in 2000 suffer from left censorship, which is corrected by two approaches to ensure robustness. Correction 1 recovers the first acquisition of a toehold through 13F reports dating back to the first quarter of 1994. Correction 2 drops all left-censored spells. In panel B, the dependent variable is a “recognition” dummy, which equals one in the quarter in which at least one activism-focused hedge fund acquires a toehold in a firm for the first time, and 0 in all prior quarters. For each firm, the spell starts when the firm is exposed to the risk of a toehold acquisition (defined as the time when the firm’s shares become publicly tradable and can be purchased by a hedge fund), and ends when at least one activist has a toehold in the firm (i.e., the spell is complete) or when the sample ends (i.e., the spell is right-censored), whichever comes first. Firms that already exist but are without any activism-focused hedge fund toeholds at the beginning of the sample period in 2000 suffer from left censorship, which is corrected by two alternative approaches. Correction 1 sets the start of a left-censored spell to the first quarter in which the firm appears in CRSP or the first quarter of 1994, whichever comes later. Correction 2 drops all left-censored spells. *Inst. net (sell/buy) volume/SHROUT* is winsorized at 1%. All models specify baseline hazards as piecewise-constant by including survival duration fixed effects. Survival duration is discrete and measured as the number of quarters from the beginning of the spell. In addition, all models include vintage, calendar year-quarter, and industry fixed effects. All control variables are as of the end of the prior quarter. Robust standard errors, clustered by survival duration, are in parentheses. For brevity, IV counterparts of the results are reported in the Internet appendix.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

about 25%, effectively reducing (extending) the time in which a quarter of the firms will be targeted by about 2.35 years.¹⁸

Our timing results have broad implications for the “scale” of activism. Given that activists have toeholds in many firms but end up launching campaigns in few of them (<1% in each quarter), the evidence suggests that one should interpret institutional selling as determining in which of the candidate firms the activist can build a block without revealing his intentions. Thus, institutional selling affects the number of viable targets and the scale of activism.

Alternatively, institutional trading may also inform the activist that a particular firm needs an intervention. For example, in the model of Attari et al. (2006),

institutions receive a signal and will sell the firm’s shares only if the signal is low (i.e., activism is beneficial), or at least uninformative. Observing the order flow and the market-clearing price, the activist then decides whether to buy shares and become active, which is more likely following the noisy signal provided by institutional sales. To the extent that a toehold reflects the activist’s recognition of monitoring benefits, we then should observe that institutional sales accelerate the first acquisition of an activist toehold, i.e., shortens the time between $t = 0$ and $t = 1$. Panel B of Table 3 tests this prediction.

The dependent variable is a “recognition” dummy, which equals one in the quarter in which at least one known activism-focused hedge fund acquires a

toehold in a firm, and zero otherwise. For a given firm, the spell starts at $t = 0$, when the firm is exposed to the risk of a toehold acquisition (defined as the time when the firm's shares become publicly tradable and can be purchased by a hedge fund), and ends at $t = 1$, when at least one activist has a toehold in the firm (i.e., the spell is complete) or when the sample ends (i.e., the spell is right-censored), whichever comes first. Firms that already exist but are without any activism-focused hedge fund toeholds at the beginning of the sample period suffer from left censorship, which is corrected by the two approaches described earlier.

Column (1) shows that institutional net trading has a marginal effect on the arrival rate of the first activist. This effect becomes statistically insignificant in column (3) and is economically weak, driven by institutional buy volume, as seen in column (2). The unconditional average hazard rate of 0.060 implies that 50% of firms will see an acquisition by at least one known activist hedge fund within about 2.89 years. The estimates in column (2) suggest that a one standard deviation increase in institutional buy volume increases the average hazard rate by just 6.83%, reducing the time in which 50% of firms will see an activist toehold by about 0.19 years. This result implies that an activist is more likely to acquire a position in a given firm when other institutions also purchase (rather than sell) shares of that firm, inconsistent with the overall relationship in Table 2. The first activist acquisition is likely driven by an informational event rather than the mechanism we describe in this paper whereby institutional selling creates favorable market conditions for the accumulation of an activist stake.

To address endogeneity concerns, we perform an IV-2SLS analysis in Table IA.III in the Internet appendix, using our instrumental variables based on institutional funding shocks.¹⁹ Our IV results confirm the timing hypothesis.

5. Effect of Institutional Trading on Hedge Fund Purchases of Target Shares

In this section, we focus at the *daily* frequency on the hedge fund's accumulation of target shares and investigate whether the mechanism by which institutional sales facilitate the activist's block formation is as described by the liquidity theories. Specifically, we test two central but untested premises of the liquidity theories, i.e., *synchronicity* between institutional sales and hedge fund purchases, and *substitution* between activism benefits and trading gains in the activist's targeting decision.

5.1. How Do Hedge Funds and Other Institutions Trade Target Stocks?

As part of Schedule 13D, the activist is required to report all transactions in the target's stock in the 60 days

before the campaign announcement (file date).²⁰ For about two-thirds of our sample of activism events, we hand-collect the hedge fund transaction history, including the date of each transaction, the number of shares purchased or sold, the price per share, and the type of each transaction (open market, private or other).²¹ After matching to institutional trading data from Ancerno, our activism sample contains 643 campaigns.

Panel A of Table 4 summarizes the trading in targets by activist hedge funds. Activists trade mostly in the open market (97.51% of all transactions) and account for an average of 15.78% of the total CRSP volume in the target's shares. Most strikingly, the average activist purchases 4.25% of the target's outstanding shares in the 60 days before filing, representing 61.89% of his total ownership on the file date.²² On the event date, the activist acquires, on average, over 1% of the target's outstanding shares, representing 41.24% of the target's total market volume. In addition, hedge funds continue to purchase shares after crossing the 5% threshold and accumulate another 1.28% of outstanding shares until the file date.

Panel B of Table 4 reports the trading of Ancerno institutions, which sell a net of 2.52% of the average target's outstanding shares in the 240 days before the activist's filing. Most of this selling (1.50% of shares outstanding, or 14.36% of the target's market volume), occurs in the 60 days immediately before the campaign. On the event date, institutions sell a net of 0.34% of the target's outstanding shares.²³ On that single day, activists and Ancerno institutions account for 61.59% of the target's market volume, suggesting that these two market players likely trade (indirectly) with each other. Figure 2 plots the mean cumulative ownership of activist hedge funds and Ancerno institutions in the year before the announcement of activism.

The mean number of selling institutions exceeds the mean number of buying institutions in all event periods.²⁴ For most campaigns, only one or two institutions are responsible for most event-date trading, and only a handful account for most trading in the prior months (see Table IA.IV in the Internet appendix). We interpret this as evidence that institutional trading is largely driven by institution-specific rather than target-specific circumstances.

5.2. Institutional Trading and Activist Purchases of Target Shares

In this subsection, we investigate the daily synchronicity between institutional trading and hedge fund purchases in the period before the hedge fund's ownership crosses the 5% threshold. We start with Figure 3, which shows that the trading of hedge funds and other institutions is highly synchronized at the daily frequency (the correlation coefficient is -0.94). This pattern is

Table 4. Activist and Nonactivist Institutional Trading in Target Firms

Panel A: Hedge fund trading									
Period	N	Trade as % of market volume	Shares purchased as % of		Average price as % of price on file date	Number of trades		% of shares purchased in open market	
			Shares outstanding	Total shares on file date		Total	Open market		
[$t - 60$, Event date)	589	12.53	2.65	41.08	94.12	185	185	98.79	
Event date	581	41.24	1.02	13.68	97.58	14	14	97.28	
(Event date, File date]	452	17.63	1.28	16.93	98.61	72	71	98.70	
[$t - 60$, File date]	643	15.78	4.25	61.89	98.17	232	232	97.51	

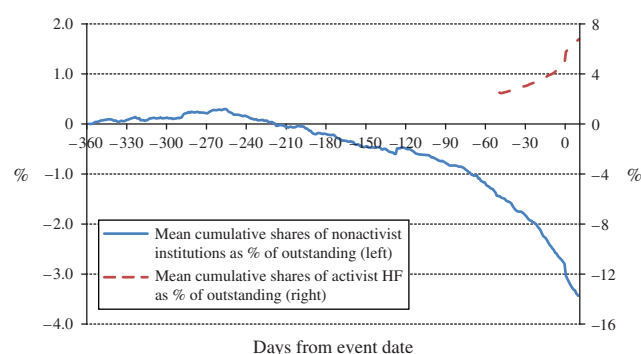
Panel B: Institutional trading									
Period	N	Trade as % of market volume	Volume/Shares outstanding (%)			Number of institutions		Number of trades per institution	
			Buy	Sell	Net	Net buy	Net sell	Buy	Sell
[$t - 240$, $t - 60$)	682	13.46	6.41	-7.43	-1.02	56	70	13	11
[$t - 60$, Event date)	625	15.14	1.93	-2.93	-1.00	25	33	9	10
Event date	447	20.35	0.12	-0.46	-0.34	3	5	3	3
(Event date, File date]	518	14.53	0.92	-1.28	-0.36	14	15	5	5
[$t - 60$, File date]	643	14.36	2.71	-4.21	-1.50	30	40	10	10

Notes. This table presents cross-sectional mean statistics of activist hedge fund and nonactivist institutional trading in firms targeted by hedge fund activists in 2000–2007. Only campaigns with available trading data are included. Panel A reports hedge fund trades for the entire 60-day period for which the hedge funds report their trades in SEC Schedule 13D. Panel B reports institutional trades for the 60-day period in which the hedge funds report their trades and for the prior 180 days. For each campaign, day $t - 60$ ($t - 240$) refers to day -60 (-240) from the file date, and event date refers to the date on which the hedge fund's ownership crosses the 5% reporting threshold. Institutional trading data are from Ancerno; an institution is a unique combination of client code and client manager code.

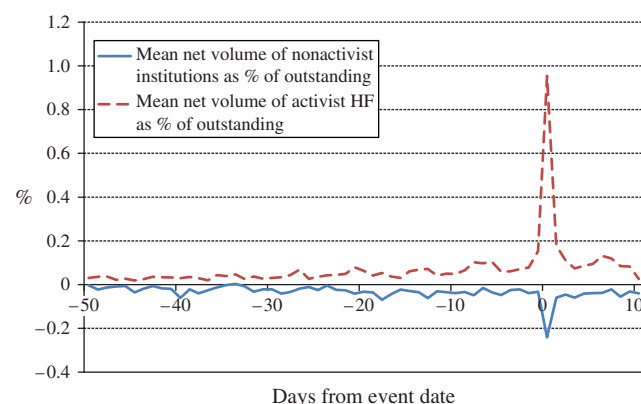
widespread among the campaigns in our sample (see Figure IA.3 in the Internet appendix), suggesting that it may not be coincidental.

Table 5 reports OLS regressions of daily net hedge fund volume on institutional net (sell and buy) volume(s). Each observation is a campaign-day (i.e., each trading day in one campaign counts as one observation). As general market controls, we include the

daily CRSP value-weighted return, Volatility Index (VIX),²⁵ and target share turnover.²⁶ We also control for the effects of general liquidity by including in some specifications five lags of the target's abnormal Amihud ratio, calculated by the mean-adjustment approach (the estimation period is from $t - 600$ to $t - 240$).

Figure 2. (Color online) Cumulative Ownership of Activist Hedge Funds and Other Institutions

Notes. This figure plots the target firms' mean cumulative ownership (as a percentage of shares outstanding) of activist hedge funds and other institutions in the one-year period (starting from 0% on day $t - 360$) before the public announcement of activism. The sample period is 2000–2007. Event date (day 0) refers to the date on which the hedge fund's ownership crosses the 5% reporting threshold. The mean is calculated across 643 campaigns for which trading data are available. Hedge fund trading data are collected from SEC filings and non-hedge-fund institutional trades are from Ancerno.

Figure 3. (Color online) Net Trading Volume of Activist Hedge Funds and Other Institutions

Notes. This figure plots the target firms' mean daily net trading volume (as a percentage of shares outstanding) of activist hedge funds and other institutions during the 60 days before the public announcement of activism. The sample period is 2000–2007. Event date (day 0) refers to the date on which the hedge fund's ownership crosses the 5% reporting threshold. The mean is calculated across 643 campaigns for which trading data are available. Hedge fund trading data are collected from SEC filings; non-hedge-fund institutional trades are from Ancerno.

Table 5. Effect of Institutional Trading on Activist Purchases of Target Shares (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Inst. net volume</i> /SHROUT	-0.166*** (0.024)		-0.167*** (0.026)		-0.154*** (0.024)	
<i>Inst. sell volume</i> /SHROUT		0.263*** (0.030)		0.268*** (0.033)		0.229*** (0.029)
<i>Inst. buy volume</i> /SHROUT		0.012 (0.023)		0.014 (0.025)		-0.005 (0.024)
<i>Net HF volume</i> /SHROUT 11			0.127*** (0.019)	0.125*** (0.019)	0.155*** (0.019)	0.152*** (0.019)
<i>Net HF volume</i> /SHROUT 12			0.045*** (0.011)	0.044*** (0.011)	0.067*** (0.011)	0.065*** (0.011)
<i>Net HF volume</i> /SHROUT 13			0.004 (0.012)	0.002 (0.012)	0.023** (0.012)	0.021* (0.012)
<i>Net HF volume</i> /SHROUT 14			0.023** (0.010)	0.023** (0.010)	0.044*** (0.010)	0.042*** (0.010)
<i>Net HF volume</i> /SHROUT 15			0.006 (0.011)	0.006 (0.011)	0.029** (0.011)	0.027** (0.011)
CRSP value-weighted return	-0.004** (0.002)	-0.004** (0.002)	-0.003* (0.002)	-0.004* (0.002)	-0.005** (0.002)	-0.005** (0.002)
VIX	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Adjusted turnover	0.025*** (0.007)	0.022*** (0.007)	0.025*** (0.008)	0.022*** (0.008)	0.021*** (0.006)	0.018*** (0.006)
Market condition controls		None	Lags 1 to 5 of abnormal return and abnormal Amihud		Lags 1 to 5 of abnormal return and abnormal Amihud	
Campaign-level controls		Campaign dummies	Campaign dummies		CAR ($t - 240$ to $t - 60$), CAT ($t - 240$ to $t - 60$), CAA ($t - 240$ to $t - 60$)	
<i>N</i>	22,809	22,809	18,117	18,117	18,091	18,091
<i>R</i> -squared (within)	0.039	0.048	0.063	0.072	0.082	0.088

Notes. This table reports OLS estimates for regressions of activist purchases of target shares on institutional trades. The sample consists of firms targeted by hedge fund activists in 2000–2007, for which hedge fund transaction data from SEC Schedule 13D and institutional transaction data from Ancerno are available. Observations are campaign-days. All variables are defined in the appendix. The dependent variable is net hedge fund volume as a percentage of shares outstanding. Columns (1)–(4) include campaign fixed effects, whereas columns (5) and (6) include CAR, cumulative abnormal turnover (CAT), and cumulative abnormal Amihud ratio (CAA) in the period from $t - 240$ to $t - 60$ as campaign-level controls. *Net HF volume*/SHROUT and *Inst. net (sell/buy) volume*/SHROUT are winsorized at 1%. All explanatory variables are contemporaneous, unless noted as lagged. Robust standard errors, clustered by campaign, are in parentheses.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

To absorb potential confounding effects of the target's valuation, we also include five lags of the target's abnormal returns, calculated by the market-model adjustment approach using the CRSP value-weighted index as the market portfolio. We cluster standard errors by campaign.

Column (1) shows that hedge funds acquire more target shares on days with more negative institutional net volume. A 1% decrease in institutional net volume (as a percentage of shares outstanding) increases net hedge fund volume by 0.17% (statistically significant at 1%). Column (2) separately reports the effects of institutional selling and buying volumes, showing that the negative correlation between net institutional and hedge fund trading is largely driven by institutional selling, whose coefficient is statistically significant at 1% and highly economically significant. A 1% increase

in institutional selling volume raises net hedge fund volume by 0.26%. The coefficient on institutional buying volume is close to zero and statistically insignificant.²⁷ Turnover is positive and significant, implying that activist hedge funds tend to buy more on days with high volume (and potentially high liquidity, as shown by Collin-Dufresne and Fos 2015). Columns (3) and (4) confirm these results after the inclusion of five lags of net hedge fund volume, abnormal return, and abnormal Amihud ratio.

Columns (1)–(4) include campaign dummies to absorb time-invariant characteristics specific to each target. To ensure that our results are not biased due to possible correlation between the lags of net hedge fund volume and the error terms (Arellano and Bond 1991),²⁸ in columns (5) and (6), we repeat the analysis using cumulative abnormal returns (CARs), cumulative

abnormal turnover (CAT), and cumulative abnormal Amihud ratio (CAA) in the period from $t - 240$ to $t - 60$ as campaign-level controls. The results suggest that the bias, if any, is minimal; institutional net (sell) volume remains significant at 1%, with largely unchanged coefficient magnitude. The coefficient on institutional buy volume remains close to zero. Overall, our results show that hedge fund purchases and institutional sales are synchronous at the daily frequency; this is consistent with the camouflage mechanism posited by the liquidity theories. In the next subsection, we formally test the synchronicity hypothesis (H3) by identifying institutional trades that are plausibly induced by liquidity shocks.

5.3. Identifying the Liquidity Channel Using Daily Institutional Funding Shocks

We identify the liquidity channel by extracting the institutions' trading in a target that is driven by institution-specific funding needs. Below we justify our measures of liquidity trades and outline a broad set of steps to calculate them. Additional details are provided in the Internet appendix.

We identify the liquidity trades of *each* institution in a generic firm's stock using its trading in other stocks outside the firm's industry. The intuition is similar to the use of extreme mutual fund flows to isolate valuation changes that may drive some endogenous events, such as mergers, but are unrelated to firm fundamentals and hence plausibly exogenous to the events. As shown by Coval and Stafford (2007) and others, an institution experiencing large inflows (outflows) often scales its existing stock positions proportionally up (down). Thus, if an institution trades in response to changes in its funding, we should see that it trades most stocks in the same direction and its trading in one stock should be positively related to its trading in others. Because we do not have daily flow data, we infer an institution's funding changes by studying its trading behavior across a large set of stocks.

We start by confirming the fire-sale trading patterns in our daily data. Figure IA.4 in the Internet appendix shows that an institution is more (less) likely to sell (buy) a stock when its fraction of other stocks sold is higher. Motivated by this pattern, we calculate firm-day expected institutional buy and sell volumes in the following steps. First, in Table IA.VI, we estimate the probabilities that *each* institution will buy or sell a generic firm's stock as a function of its trading in other stocks *outside the generic firm's industry*. We use *all* stocks, not just targets, in our estimation to ensure that we capture the general patterns of trading due to each institution's funding circumstances; hence, our estimates are not biased by the ex post classification of stocks into targets and nontargets.

Then, we use the estimated probabilities that institution i will buy or sell target stock j on day t ($\Pr_i[\text{buy}_{j,t}]$

or $\Pr_i[\text{sell}_{j,t}]$) and multiply them by the institution's conditional average trade size per day to obtain its expected buying and selling volumes:

$$E_i[\text{trade volume}_{j,t}] = \Pr_i[\text{trade}_{j,t}] \times E_i[\text{trade volume}_j \mid \text{trade}_j], \quad \text{trade} \in \{\text{buy}, \text{sell}\}.$$

Finally, we sum the above expected buying and selling volumes across all N institutions to get the expected *total* buying and selling volumes in stock j on day t :

$$E[\text{trade volume}_{j,t}] = \sum_{i=1}^N E_i[\text{trade volume}_{j,t}], \quad \text{trade} \in \{\text{buy}, \text{sell}\}.$$

We argue that our instruments are likely exogenous to a model of hedge fund purchases. First, the expected volumes reflect institution-specific funding circumstances and trading characteristics, unrelated to any particular stock and by extension not driven by the impending activist campaign. Second, we address concerns about omitted variable bias by controlling for common drivers of the institutions' funding shocks and the hedge funds' trades at the economy, industry, and firm levels. We also absorb low-frequency variation in economic conditions using campaign fixed effects in the models of hedge fund purchases (each campaign spans about 60 days). Finally, by construction, our instruments operate independently from any industry-specific conditions that may drive away institutions but attract hedge funds.

More generally, in the Internet appendix, we present additional order-level evidence that characterizes the institutions' trading behavior and transaction costs in different periods around the activism events. In Table IA.VIII, we show that institutions trade target and nontarget stocks in virtually the same manner. In Table IA.IX, we demonstrate that institutions demand liquidity when selling target and nontarget stocks whereas hedge funds appear to provide liquidity in the targets during the 60 days leading up to the campaign and on the event date. Thus, institutional trading in the target firms does not seem to be driven by target-specific information or by hedge fund trading, and hence is likely exogenous to activism.

Next we formally test the synchronicity hypothesis (H3) using expected institutional buying and selling volumes as instruments to identify the institutions' liquidity trades. Table 6 reports IV-LIML estimates of the models in columns (3) and (4) of Table 5. Columns (1), (3), and (4) present the first-stage results relating the endogenous regressors, i.e., institutional net, sell, and buy volumes, to the instruments. Columns (2) and (5) report the second-stage results predicting net hedge fund volume as a function of

Table 6. Effect of Institutional Trading on Activist Purchases of Target Shares (IV Analysis)

	<i>Inst. net volume</i> / <i>SHROUT</i> (First stage)	<i>Net HF volume</i> / <i>SHROUT</i> (Second stage)	<i>Inst. sell volume</i> / <i>SHROUT</i> (First stage)	<i>Inst. buy volume</i> / <i>SHROUT</i> (First stage)	<i>Net HF volume</i> / <i>SHROUT</i> (Second stage)
	(1)	(2)	(3)	(4)	(5)
<i>Inst. net volume/SHROUT</i>		-0.147** (0.070)			
<i>Inst. sell volume/SHROUT</i>					0.205** (0.093)
<i>Inst. buy volume/SHROUT</i>					-0.051 (0.131)
<i>Exp(Inst. sell volume)/SHROUT</i>	-0.563*** (0.060)		0.632*** (0.056)	0.063** (0.026)	
<i>Exp(Inst. buy volume)/SHROUT</i>	0.326** (0.068)		0.157*** (0.039)	0.489*** (0.059)	
<i>Net HF volume/SHROUT 11</i>	-0.015** (0.006)	0.128*** (0.020)	0.013** (0.006)	-0.002 (0.003)	0.127*** (0.020)
<i>Net HF volume/SHROUT 12</i>	-0.003 (0.005)	0.046*** (0.011)	0.005 (0.005)	0.001 (0.003)	0.046*** (0.011)
<i>Net HF volume/SHROUT 13</i>	-0.001 (0.005)	0.000 (0.012)	0.005 (0.005)	0.003 (0.003)	-0.000 (0.012)
<i>Net HF volume/SHROUT 14</i>	-0.007 (0.006)	0.024** (0.010)	0.005 (0.006)	-0.000 (0.003)	0.024** (0.010)
<i>Net HF volume/SHROUT 15</i>	0.007 (0.006)	0.007 (0.011)	-0.004 (0.004)	0.005 (0.004)	0.006 (0.011)
Market condition controls	CRSP value-weighted return, VIX, adjusted turnover, and lags 1 to 5 of abnormal return and abnormal Amihud				
Campaign-level controls	Campaign dummies				
Kleibergen-Paap rank Wald statistic	F(2, 618) = 67.247 (S-Y crit. val. at 10% maximal size = 8.68)		F(1, 618) = 51.778 (S-Y crit. val. at 10% maximal size = 7.03)		
Hansen J statistic	$\chi^2(1) = 0.824$		N/A		
N	18,117	18,117	18,117	18,117	18,117
R-squared (within)	0.044	0.038	0.087	0.063	0.046

Notes. This table reports IV-LIML estimates of the effects of institutional trades on activist purchases of target shares. OLS counterparts are in Table 5. Observations are campaign-days. All variables are defined in the appendix. The dependent variable is net hedge fund volume as a percentage of shares outstanding, and the endogenous regressors are institutional net volume (column (2)) and institutional buy and sell volumes (column (5)). Columns (1) and (3)–(4) report estimates of the first-stage equations, in which the endogenous regressors are expressed as a function of the excluded instruments, i.e., expected institutional buy and sell volumes calculated as the sums of individual institutions' expected buy and sell volumes in target stocks, conditional on their trading activities in *nontarget* stocks outside the target's SIC-2 industry (models in columns (3) and (4) of Table IA.VI in the Internet appendix). All columns include campaign fixed effects. *Net HF volume/SHROUT* and *Inst. net (sell/buy) volume/SHROUT* are winsorized at 1%. All explanatory variables are contemporaneous, unless noted as lagged. Robust standard errors, clustered by campaign and corrected by Monte Carlo simulation for errors in estimating the expected institutional buy and sell volumes, are in parentheses.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

the endogenous regressors.²⁹ We control for the CRSP value-weighted return, VIX, adjusted turnover, and five lags of the target's abnormal return and Amihud ratio, and include campaign fixed effects. We cluster standard errors by campaign and adjust them for errors in constructing the instruments.

The first-stage estimates in column (1) show that actual institutional net volume significantly loads on expected institutional buy and sell volumes. Intuitively, *actual* net volume decreases in *expected* sell volume and increases in *expected* buy volume. Columns (3) and (4)

confirm these relationships. For example, column (3) shows that *actual* institutional selling volume is significantly positively correlated with *expected* institutional selling volume. Even though the coefficient on expected buy volume is also positive and significant, its magnitude is only a quarter of the magnitude of the coefficient on expected institutional selling. Thus, within the variation of actual institutional buys and sells explained by our model, it is largely the expected buys that drive actual buys and the expected sells that drive actual sells.

The second-stage regressions in columns (2) and (5) show that institutional trading volumes have a statistically significant effect on net hedge fund volume. Column (2) shows that hedge fund purchases significantly decrease in institutional net volume. Separating institutional buy and sell volumes in column (5), we see that it is selling rather than buying that drives the liquidity effects; institutional selling raises hedge fund purchases, consistent with the synchronicity hypothesis. Our instruments, based on each institution's funding circumstances, confirm that the associations we show in Table 5 are driven by the liquidity channel.

5.4. Substitution Between Activism Benefits and Trading Gains

In this subsection, we test the substitution hypothesis (H4), which states that the synchronicity between institutional sales and activist purchases is lower among targets with higher expected activism benefits. To do so, we propose two measures of potential activism benefits. Our first measure is a firm's predicted probability of being targeted (*baseline target probability*), which is a linear combination of observable fundamentals and policies, including leverage, payout, ROA, etc., shown by the literature to affect targeting. To the extent that targets are chosen on the basis of their expected activism benefits, the baseline target probability should capture these benefits. Our second measure is the sum of all toeholds in a target by known activist hedge funds before a campaign launch. We use this alternative proxy to capture *unobserved* determinants of activism benefits, which by construction are not reflected in the baseline target probability. The idea is to exploit "revealed preference": Activist hedge funds are attracted to firms that are likely to benefit from activism, and their toeholds reflect this attraction. Firms with higher potential benefits draw a larger number of activist hedge funds, each with a larger toehold.

Table 7 reports OLS regressions of daily net hedge fund volume on institutional net volume by level of activism benefits. All specifications control for but do not report (for brevity) the CRSP value-weighted return, VIX, adjusted turnover, five lags of abnormal return and abnormal Amihud ratio, and five lags of net hedge fund volume. We also include campaign fixed effects and cluster standard errors by campaign. In panel A, we rely on our first measure of expected activism benefits, i.e., baseline target probability, calculated using the specification in column (1) of Table 2, with size and institutional ownership set to their sample means as they may be correlated with liquidity and institutional trading.

Columns (1) and (2) split activist targets into those with below and above median baseline target probabilities, respectively. Consistent with the substitution

hypothesis, the effects of institutional net volume on hedge fund purchases are greater in column (1) than in column (2). A 1% decrease in institutional net volume increases net hedge fund volume (as a percent of shares outstanding) by 0.20% in the sample with below median baseline target probability but by only 0.10% in the sample with above median baseline target probability. The difference is statistically significant at 5%, as indicated by the coefficient of the interaction term between institutional net volume and a dummy for above median baseline target probability in column (3). As a robustness check, in column (4), we interact institutional net volume directly with baseline target probability. The coefficient of the interaction term is positive and statistically significant at 1%.

Panel B of Table 7 measures potential benefits from activism by the combined total toehold in a target of all known activist hedge funds.³⁰ We match 61% of the targets to hedge fund holdings from the 13F database and use the hedge funds' toeholds in the most recent quarter before a campaign. To avoid potential mechanical relationships, we sum the toeholds across all hedge funds, *excluding* the hedge fund that launches the campaign. Columns (1)–(3) split the activist targets into three subsamples, i.e., those with zero total hedge fund toehold (column (1)) and those with below/above median (nonzero) total hedge fund toehold (columns (2) and (3), respectively).

Consistent with the substitution hypothesis, we find that the effects of institutional net volume on hedge fund purchases decrease in the total hedge fund toehold. Column (1) shows that for targets in which no hedge funds (other than the activist) hold a stake, institutional net volume has the largest negative effects on net hedge fund volume. These effects decline monotonically in columns (2) and (3) for the targets with below and above median (nonzero) total hedge fund toeholds. In column (4), we test the difference between the effects of institutional net volume in targets with below (columns (1) and (2)) and above median (column (3)) activism benefits by interacting institutional net volume with a dummy for above median total hedge fund toehold. The coefficients of the main and interaction terms show that a 1% decrease in institutional net volume increases net hedge fund volume by 0.22% in the sample with low activism benefits but by only 0.11% in the sample with high benefits. In column (5), we confirm our earlier findings by interacting institutional net volume with total hedge fund toehold.

In Table IA.VII in the Internet appendix, we test the substitution hypothesis again using our instrumental variables based on institutional funding shocks. The IV-LIML results confirm that the liquidity theories are at work.

Table 7. Effect of Institutional Trading on Activist Purchases by Level of Activism Benefits

Panel A: Benefits defined as target propensity score					
	(1)	(2)	(3)	(4)	
	Propensity < Median	Propensity ≥ Median	All	All	
<i>Inst. net volume</i> / <i>SHROUT</i>	-0.199*** (0.036)	-0.102*** (0.024)	-0.201*** (0.035)	-0.155*** (0.022)	
<i>Inst. net volume</i> / <i>SHROUT</i> × <i>High benefits dummy</i>			0.090** (0.042)		
<i>Inst. net volume</i> / <i>SHROUT</i> × <i>Benefits</i>				11.959*** (4.161)	
Market condition controls	Lags 1 to 5 of net HF volume/ <i>SHROUT</i> , CRSP value-weighted return, VIX, adjusted turnover, and lags 1 to 5 of abnormal return and abnormal Amihud				
Campaign-level controls	Campaign dummies				
<i>N</i>	7,930	8,344	16,274	16,274	
<i>R</i> -squared (within)	0.079	0.070	0.071	0.072	
Panel B: Benefits defined as total hedge fund toehold					
	(1)	(2)	(3)	(4)	(5)
	TOE(HF) = 0	TOE(HF) < Median	TOE(HF) ≥ Median	All	All
<i>Inst. net volume</i> / <i>SHROUT</i>	-0.258*** (0.092)	-0.182*** (0.039)	-0.120*** (0.036)	-0.223*** (0.043)	-0.226*** (0.039)
<i>Inst. net volume</i> / <i>SHROUT</i> × <i>High benefits dummy</i>				0.110** (0.048)	
<i>Inst. net volume</i> / <i>SHROUT</i> × <i>Benefits</i>					1.481** (0.646)
Market condition controls	Lags 1 to 5 of net HF volume/ <i>SHROUT</i> , CRSP value-weighted return, VIX, adjusted turnover, and lags 1 to 5 of abnormal return and abnormal Amihud				
Campaign-level controls	Campaign dummies				
<i>N</i>	5,116	6,484	6,517	18,117	18,117
<i>R</i> -squared (within)	0.063	0.128	0.068	0.063	0.064

Notes. This table reports OLS estimates for regressions of activist purchases of target shares on institutional trades for targets with varying levels of activism benefits. Observations are campaign-days. The dependent variable is net hedge fund volume as a percentage of shares outstanding. Panel A measures potential benefits from activism by a firm's propensity to be targeted estimated in column (1) of Table 2 (without institutional trading variables). Columns (1) and (2) split the targets into those with below/above median target propensities, respectively. Columns (3) and (4) interact institutional trading with a dummy for above median target propensity (*High benefits dummy*) and with a firm's target propensity (*Benefits*), respectively. Panel B measures activism benefits by the total toehold of known activist hedge funds in a target at the end of the most recent quarter before the campaign starts. Columns (1)–(3) split the targets into those with no toehold and those with below/above median (nonzero) total toehold, respectively. Columns (4) and (5) interact institutional trading with a dummy for above median total toehold (*High benefits dummy*) and with total toehold (*Benefits*), respectively. *Net HF volume*/*SHROUT* and *Inst. net volume*/*SHROUT* are winsorized at 1%. All variables are defined in the appendix. All models include campaign fixed effects. Robust standard errors, clustered by campaign, are in parentheses. For brevity, IV counterparts of the results are reported in the Internet appendix.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

5.5. Discussion of Alternative Explanations

In this subsection, we consider two alternative explanations for the positive relationship between institutional selling and hedge fund activism. First, the *signaling* theories argue that institutions may be informed and trade to signal to activists that a particular firm needs an intervention (see Attari et al. 2006 for a dynamic model of this mechanism). Second, the *mechanical* explanation posits that the activist demands target shares and institutions simply supply them; that is, “someone buys so someone else must sell.” Before proceeding, note that our analysis of these explanations is not geared towards accepting or rejecting them; our goal is simply

to ensure that our main findings are robust to these alternatives.

Our main hypothesis that institutional trading raises a firm's probability of becoming an activist target is consistent with all three alternatives (including the liquidity theories). The difference among these alternatives lies in the nature of institution trading. Under the mechanical explanation, causality flows from the activist's targeting to institutional selling. As the activist assembles a block, he demands target shares and institutions respond by supplying them, thus generating a positive correlation between institutional selling and targeting. By contrast, under the

signaling and liquidity theories, causality flows from institutional selling to the activist's targeting. The two theories, however, posit a different nature of institutional trading. The signaling theories assume that informed institutions sell with the intention to induce activism whereas the liquidity theories assume that uninformed institutions sell in response to their funding shocks. Our instrumental variable analysis in columns (5) and (6) of Table 2 identifies the liquidity explanation from the mechanical and signaling alternatives.

In our second hypothesis, timing, we find that institutional sales accelerate the start of a campaign at firms whose monitoring benefits have been recognized by activists (panel A of Table 3) rather than attract attention to firms that appear to be outside the activists' radar screen (panel B) as predicted by the signaling theories. Our third hypothesis, synchronicity, is consistent with the liquidity theories and the mechanical alternative (but not signaling). However, under the mechanical explanation, the activist purchases from institutions or creates favorable conditions for institutions to sell. By contrast, the liquidity theories posit that it is the institutional sales that draw the activist's purchases. In Table 6, we identify the liquidity trades of each institution using its trading in other stocks outside the firm's industry, and show that causality flows from institutional selling to activist purchases; this is consistent with the liquidity channel.

Our last hypothesis, substitution, is not consistent with the signaling and mechanical explanations. Although the signaling mechanism may operate more strongly among firms with smaller potential activism benefits (assuming that these benefits are more difficult to recognize), it is unlikely to result in higher synchronicity between institutional sales and hedge fund purchases. Under signaling, institutional sales should lead hedge fund purchases as hedge funds learn from the market-clearing price. The mechanical explanation does not predict any variation in synchronicity in relation to expected activism benefits.

Overall, our tests confirm that the documented patterns of institutional selling and activist targeting are largely driven by the liquidity channel.

6. Conclusion

In this paper, we investigate the impact of institutional trading on an activist's decision to acquire shares in a target firm and initiate a campaign. We find that institutional selling is positively associated with a firm's probability of being targeted. Our various analyses of activist targeting and daily share accumulation all lead to the conclusion that a liquidity channel is at work: (uninformed) institutional selling provides camouflage for (informed) activist purchases, allowing the activist

to quickly accumulate target shares and gain on these shares once he makes his intentions public. These trading gains help cover the activist's monitoring costs, making a campaign financially viable.

We identify the liquidity channel by extracting institutional trades that are driven by institution-specific funding shocks and thus likely exogenous to the activism events. We also appeal to the liquidity channel's postulated economic mechanism that is distinct from those of alternative explanations. First, we demonstrate that institutional sales accelerate the launch of a campaign at firms whose potential benefits from monitoring have already been recognized by activists rather than bring attention to firms that are outside the activists' radar screen. Second, we show that institutional sales and activist purchases are highly synchronous at the daily frequency, and that this synchronicity is lower among targets with higher expected activism benefits. This evidence is consistent with the liquidity channel's central ideas that the activist camouflages his purchases among other investors' liquidity trades, and that the trading gains derived from such camouflage are less critical if the expected benefits that accrue to the activist's initial stake are already large.

Acknowledgments

This paper was previously titled "Hedge Fund Activists: Do They Take Cues from Institutional Exit?" The authors thank Vikas Agarwal, Lucian Bebchuk, Ekkehart Boehmer, Nicole Boyson, Alon Brav, Alma Cohen, Robert Connolly, Peter Cziraki, Amil Dasgupta, Alex Edmans, Andrew Ellul, Vivian Fang, Francesco Franzoni, Paolo Fulghieri, Diego Garcia, Robin Greenwood, Wei Jiang, Christian Lundblad, Maria-Teresa Marchica, Ernst Maug, Oyvind Norli, Paige Ouimet, Urs Peyer, Tarun Ramadorai, Anil Shivdasani, Laura Starks, Geoffrey Tate, and especially, for their helpful discussions, Reena Aggarwal, Yong Chen, Luis Goncalves-Pinto, Martijn Cremers, Eliezer Fich, Vyacheslav Fos, Jongha Lim, Richmond Mathews, Gideon Ozik, Giorgia Piacentino, Raghu Rau, and Zhenyang Tang. The authors also thank seminar and conference participants at North Carolina State University, Southern Methodist University, University of North Carolina at Chapel Hill, University of Texas at Dallas, 2013 Hedge Fund Conference (Paris), 2013 Adam Smith Workshops in Asset Pricing and Corporate Finance (Oxford), Institutional Investor Conference at Georgia State University, 2013 Financial Intermediation Research Society Conference (Dubrovnik), 2013 Western Finance Association Meeting (Lake Tahoe), 2013 China International Conference in Finance (Shanghai), 2013 National Bureau of Economic Research Law and Economics Summer Workshop, 2013 Singapore International Conference in Finance (National University of Singapore), 2014 Financial Management Association Meetings (Tokyo), 2014 Summer Research Conference in Finance (Indian Business School, Hyderabad), and 2014 Asset Management Conference (ESMT & Humboldt University, Berlin). In addition, the authors thank Oleg Gredil for research assistance.

Appendix. Definitions of Variables

Variable	Definition
Firm-year and firm-quarter panels	
<i>Dividend yield</i>	Common plus preferred dividends divided by market value of common plus preferred stocks. (Source: Compustat.)
$Exp[Inst. buy (sell) volume]/SHROUT$	Expected buy (sell) volume as a percentage of shares outstanding. Calculation at the quarterly/annual frequency is as follows: First, the expected weekly buy (sell) volume is calculated by multiplying each institution's predicted probability of buying (selling) a given firm by the institution's average volume and then summing the product across all institutions in each week. Second, the expected buy (sell) volume for each firm-quarter is obtained by taking the 90th percentile of the expected weekly buy (sell) volume within a quarter. Third, the expected buy (sell) volume for each firm-year is the maximum of the expected quarterly buy (sell) volume within the year. More details are provided in the Internet appendix. (Source: CRSP and Ancerno.)
$Exp[MF fire purchases (sales)]/SHROUT$	Expected mutual funds' fire purchases (sales) as a percentage of shares outstanding. Calculation is as follows: First, the expected fire purchases (sales) for each mutual fund in each reporting quarter are calculated as the product of percentage inflows (outflows) and the beginning-of-quarter shareholdings if the flows are larger than 5% in magnitude; otherwise, the expected fire purchases (sales) are zero. Second, these expected fire purchases (sales) are summed across all mutual funds holding each firm, divided by the number of shares outstanding at the beginning of the quarter, and averaged across all quarters to obtain the expected fire purchases (sales) for each firm-year. (Source: CRSP and Thomson Reuters.)
$HF toehold/SHROUT$	Total ownership in a firm of all known activist hedge funds that file Schedule 13F at the end of the preceding year. (Source: Thomson Reuters.)
<i>Herfindahl index</i>	Herfindahl index of market concentration for each Fama–French 12 industry.
$Inst buy (sell) volume/SHROUT$	Annual average of cumulative quarterly institutional buy (sell) volume as a percentage of shares outstanding. (Source: Ancerno.)
$Inst. net volume/SHROUT$	$Inst. buy volume/SHROUT$ minus $Inst. sell volume/SHROUT$.
<i>Inst. ownership</i>	Total ownership of institutions that file 13F reports as a percentage of shares outstanding. (Source: Thomson Reuters.)
<i>Leverage</i>	Book value of debt divided by book value of total assets. (Source: Compustat.)
$-\log(Amihud)$	Negative of natural logarithm of one plus Amihud ratio, calculated as yearly average of $[1000 * \text{SQRT}(\text{daily return} / (\text{daily dollar trading volume}))]$. Daily ratios are capped at 30% before averaging, as in Acharya and Pedersen (2005). (Source: CRSP.)
$\log(\text{Analysts})$	Natural logarithm of one plus number of analysts following the firm over the preceding year. (Source: I/B/E/S.)
$\log(MV)$	Natural logarithm of market capitalization. (Source: Compustat.)
$\Delta MF holdings/SHROUT$	Annual average of quarterly change in ownership of all mutual funds. (Source: Thomson Reuters.)
<i>No. HFs with toehold</i>	Number of known activist hedge funds reporting an ownership stake in a firm through Schedule 13F. (Source: Thomson Reuters.)
$R\&D/Assets$	Research and development expense divided by lagged book value of assets. Missing = 0. (Source: Compustat.)
<i>Return</i>	Stock return, including dividends, over the preceding year. (Source: CRSP.)
<i>ROA</i>	Operating income before depreciation divided by lagged book value of assets. (Source: Compustat.)
<i>Sales growth</i>	Sales less lagged sales divided by lagged sales. (Source: Compustat.)
<i>Tobin's Q</i>	Market value of equity plus book value of debt divided by book value of total assets. (Source: Compustat.)
Firm-day, campaign-day, and institution-firm-day panels	
<i>Abnormal Amihud ratio and Cumulative abnormal Amihud ratio (CAA)</i>	Mean-adjusted Amihud ratio, calculated as $ \text{daily return} / (\text{daily dollar trading volume})$. The estimation period is from $t - 600$ to $t - 240$. CAA is calculated as the sum of abnormal Amihud ratios during the period from $t - 240$ to $t - 60$. (Source: CRSP.)
<i>Abnormal return and Cumulative abnormal return (CAR)</i>	Market-model-adjusted return. CRSP value-weighted index is used as the market portfolio and the estimation period is $t - 600$ to $t - 240$. CAR is calculated as the sum of abnormal return during the period from $t - 240$ to $t - 60$. (Source: CRSP.)
<i>Abnormal turnover and Cumulative abnormal turnover (CAT)</i>	Mean-adjusted turnover, calculated as trading volume divided by shares outstanding. The estimation period is from $t - 600$ to $t - 240$. CAT is calculated as the sum of abnormal turnover during the period from $t - 240$ to $t - 60$. (Source: CRSP.)
<i>Adjusted turnover</i>	Total trading volume minus the sum of hedge fund activist's and institutional trading volumes, divided by shares outstanding. (Source: CRSP, Schedule 13D, and Ancerno.)
<i>Campaign dummies</i>	Set of dummy variables, each equal to one for each campaign.
<i>CRSP value-weighted return</i>	Daily return, including all distributions, of CRSP value-weighted market portfolio.

Appendix. (Continued)

Variable	Definition
Firm-day, campaign-day, and institution-firm-day panels (continued)	
<i>Dummy</i> [buy (sell)]	Dummy variable equal to one if the institution buys (sells) the firm's stock on the day. (Source: Ancerno.)
<i>Dummy</i> [trade only one other stock]	Dummy variable equal to one if the institution buys or sells only one other stock outside the firm's SIC-2 industry on the day. (Source: Ancerno.)
<i>Dummy</i> [trade other stocks]	Dummy variable equal to one if the institution buys or sells other stocks outside the firm's SIC-2 industry on the day. (Source: Ancerno.)
<i>Exp</i> [<i>Inst. buy (sell) volume</i>]/ <i>SHROUT</i>	Expected buy (sell) volume as a percentage of shares outstanding, calculated by multiplying each institution's predicted probability of buying (selling) the firm's stock by the institution's average volume and then summing the product across all institutions. More details are provided in the Internet appendix. (Source: CRSP and Ancerno.)
<i>Fraction of trading days during sample</i>	Number of days on which the institution trades at least one stock divided by total number of days during the sample period. (Source: Ancerno.)
<i>Fraction of sell principal</i>	Dollar principal of all other stocks sold divided by total dollar principal of all stocks bought and sold. Only other stocks outside the firm's SIC-2 industry are included in the calculation. (Source: Ancerno.)
<i>Fraction of stocks sold</i>	Number of individual stocks (not shares) sold divided by total number of individual stocks bought or sold. Only other stocks outside the firm's SIC-2 industry are included in the calculation. (Source: Ancerno.)
<i>Inst. buy (sell) volume</i> / <i>SHROUT</i>	Total daily institutional buy (sell) volume as a percentage of shares outstanding. (Source: Ancerno.)
<i>Inst. net volume</i> / <i>SHROUT</i>	<i>Inst. buy volume</i> / <i>SHROUT</i> minus <i>Inst. sell volume</i> / <i>SHROUT</i> .
<i>Net HF volume</i> / <i>SHROUT</i>	Net hedge fund activist's trading volume (buy minus sell) as a percentage of shares outstanding. (Source: Schedule 13D.)
<i>Return</i>	Stock return, including all distributions. (Source: CRSP.)
<i>VIX</i>	CBOE volatility index, constructed using the implied volatilities of near- and next-term put and call options with 23–37 days to expiration and various strike prices. (Source: CBOE.)

Endnotes

¹Prior work has shown that among activist investors, hedge funds achieve better success as monitors than mutual funds, pension funds, and labor unions (see Karpoff 2001, Kahan and Rock 2007, Gillan and Starks 2007).

²In any given year, hundreds of firms look like viable activist targets as their predicted probabilities of being targeted, based on fundamentals and market characteristics, are at least as high as the 25th percentile of the sample of targets.

³We focus on trading by institutions rather than retail investors for a few reasons. First, institutions hold the majority of shares in public firms, particularly firms targeted by activists. Second, retail investors are small but many; consequently, unless there is an aggregate macro shock (affecting all firms), retail investors' liquidity trades in a particular stock are likely to have little impact on order imbalances. Finally, institutional transaction data are more readily available and representative, while retail transaction data often come from a small group of investors over a short time period. We do not in any way suggest that institutions are uninformed.

⁴Our use of institutional funding circumstances for identification should not be interpreted as suggesting that activists need to forecast these funding circumstances to pick a target firm. In reality, the activists may use a variety of trading approaches, such as limit orders, etc., to take advantage of market conditions generated by institutional liquidity sales that may affect some firms but not others.

⁵Coval and Stafford (2007) show that mutual funds, experiencing large inflows (outflows), tend to proportionally scale up (down) their stock holdings. Thus, if an institution trades a firm in response to its own funding shocks, then its trading in that firm must be proportional to its trading in other firms.

⁶Note that we use all stocks, not just targets, in our estimation to ensure that we capture the general patterns of trading due to each institution's funding circumstances and that our estimates are

not biased by the ex post classification of stocks into targets and nontargets.

⁷Chen et al. (2008) provide evidence that hedge funds profit from front-running distressed mutual funds. Shive and Yun (2013) find that hedge funds profitably trade on predicted mutual fund flows, especially in small and illiquid stocks. Campbell et al. (2009) infer daily institutional trading from TAQ data and show that institutions demand liquidity, especially when they sell.

⁸For example, in Back et al. (2015), the activist is endowed with a block of a random size. They find that if the initial block is sufficiently large, liquidity may be harmful for governance as it helps the activist camouflage his sales and exit. Though closing their model in a similar way, Faure-Grimaud and Gromb (2004) arrive at the opposite conclusion that liquidity improves governance, even in the case where the activist's initial stake is large. They highlight the role of liquidity in improving price informativeness rather than providing camouflage for informed trading. Kahn and Winton (1998) focus on how firm characteristics affect the large shareholder's ex ante intervention costs and (indirect) benefits, and find ambiguous effects of liquidity.

⁹This hypothesis follows from Maug (1998)'s starting assumption that the firm in question is a natural target, i.e., the fundamental improvement in firm value as a result of activism is higher than the activist's monitoring costs. Therefore, our tests focus on the sample of activist targets for which the above assumption is presumably satisfied.

¹⁰See Puckett and Yan (2011) for a broad description of the data. Anand et al. (2012) show that Ancerno institutions are representative of 13F institutions in terms of the characteristics of their holdings.

¹¹This is based on the estimated model in column (1) of Table 2.

¹²For example, both liquidity measures in Edmans et al. (2013) are highly auto-correlated with Pearson and Spearman autocorrelations between 0.85–0.94. Thus, Edmans et al. (2013) and Norli et al. (2014)

effectively rely on the cross-sectional variation in liquidity to identify its effects on shareholder monitoring. Other fundamentals are also highly auto-correlated (e.g., the autocorrelations of leverage and ROA are 0.87 and 0.58, respectively).

¹³Jotikasthira et al. (2012) among others confirm that flow-induced trades by mutual funds are largely uninformed.

¹⁴Our instruments are statistically valid, comfortably passing the Kleibergen-Paap rank Wald test (see Stock and Yogo 2005) as well as the test of overidentifying restrictions (based on Hansen's J statistic) implying that they are generally orthogonal to the second-stage errors.

¹⁵The 1994Q1 cutoff is imposed because hedge fund activism in its current form only took off at that time due to a change in the regulation of proxy communications.

¹⁶Dropping left-censored spells can incur a substantial loss of power but yields asymptotically consistent estimates, and is very common in practice, as discussed by Allison (2010) and Rabe-Hesketh and Skrondal (2008).

¹⁷This is a static interpretation of the hazard probability, which assumes that a firm experiences a similar level of institutional trading in every quarter.

¹⁸These statistics should not be interpreted as the time it takes to accumulate an activist block because the first toehold acquisition and the campaign launch are often by different activists.

¹⁹We also perform a reduced-form analysis by simply replacing the potentially endogenous institutional trading variables by their corresponding instruments. The highly nonlinear nature of our proportional hazard models renders usual IV estimation methods inefficient and hard to interpret due to the unknown true functional form of the first-stage equation. We note that the IV and reduced-form results provide consistent support for the timing hypothesis.

²⁰An investor is allowed up to 10 days after crossing the 5% ownership threshold to report his activist intentions.

²¹The remaining campaigns do not provide transaction data because of previous Schedule 13G filings, missing share or price information, etc. The 13G filing is a passive version of the 13D filing and does not allow activist practices.

²²Figure IA.2 in the Internet appendix shows the average cumulative abnormal returns (CARs) of target stocks in the 240 days leading up to the start of a campaign and documents a significant price run-up before the campaign.

²³The mean (median) of the ratio of institutional sales to hedge fund purchases on the event date is 1.41 (0.44) (these statistics are 1.33 (0.39) for the 60 days before the event date).

²⁴We conservatively define an institution as the unique combination of Ancerno client and client manager codes.

²⁵Nagel (2012) uses a reversal strategy to proxy for the returns from liquidity provision and shows that the time variation in this strategy can be predicted with the VIX index.

²⁶To avoid collinearity, we adjust turnover by subtracting total hedge fund volume and institutional buy/sell volumes.

²⁷We further investigate the effects of institutional selling and buying volumes on activist purchases by estimating several piecewise linear specifications. While the effects of institutional selling volume are significantly positive in all ranges, the effects of institutional buying volumes are negative (though mostly insignificant) at volumes below the 60th percentile (0.03% of shares outstanding) and become zero in the higher ranges. Therefore, our linear specifications show largely zero coefficients on institutional buying volume.

²⁸This problem is severe in settings with a very small number of time-series observations, which is not the case here because we use a daily firm panel with about 60 observations per firm.

²⁹All specifications pass the Kleibergen-Paap rank Wald test, indicating that our instruments sufficiently explain the variation in the endogenous regressors and hence are relevant. In addition, the overidentified models in columns (1) and (2) pass the test of overidentifying restrictions (based on Hansen's J statistic) at conventional levels.

³⁰On average, activist hedge funds hold about 135 different stocks on each report date and intervene in only 0.7% within the following 6 months, 1.0% within the following year, and 1.5% within the following three years.

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