Anticipatory Trading Against Distressed Mega Hedge Funds*

Vikas Agarwal
Georgia State University

George O. Aragon
Arizona State University

Vikram Nanda
University of Texas at Dallas

Kelsey Wei
University of Texas at Dallas

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ABSTRACT

We examine the trading activity of institutional investors when mega hedge funds (MHFs) experience financial distress. Stocks that are anticipated to be sold by distressed MHFs next quarter experience greater selling by other institutions and elevated short interest in the current quarter. We also find that a one standard-deviation higher measure of anticipatory trading predicts 1.57% per year lower abnormal equity portfolio returns for distressed MHFs. Stocks that are anticipated to be sold by distressed MHFs experience negative abnormal returns and subsequent return reversals. We conclude that institutions trade ahead of the distressed trades of MHFs and destabilize stock prices.

Keywords: Hedge funds, Anticipatory trading, Front-running, Mega hedge funds, Fire sales
JEL Codes: G12, G20, G23

* Agarwal is with Finance Department, J. Mack Robinson College of Business Georgia State University Atlanta, GA. (404) 413-7326, vagarwal@gsu.edu. Aragon is with Finance Department, W.P. Carey School of Business, Arizona State University, Tempe, AZ. (480) 965-5810, george.aragon@asu.edu. Nanda and Wei are with Naveen Jindal School of Management, University of Texas at Dallas, Richardson, TX. Nanda: (404) 769-4368, vikram.nanda@utdallas.edu. Wei: (972) 883-5978, kelsey.wei@utdallas.edu. This research has benefitted from the comments of Amber Anand, Mustafa Caglayan, Jaewon Choi, Jay Kahn, Bing Liang, Christian Lundblad, Lubomir Petrasek, Oliver Rath, Christopher Schwarz, Sophie Shive, Raisa Velthuis, Blerina Zykaj, and seminar participants at Case Western University, Centre for Financial Research (CFR), Syracuse University, Tulane University, 2021 Financial Management Association Meetings, 2021 Fixed Income and Financial Institutions Conference, and the 13th Annual Hedge Fund Research Conference. Vikas Agarwal thanks the CFR in Cologne for its continued support.

1. Introduction

The hedge fund industry provides an ideal setting for the best and brightest investment managers to leverage their best investment ideas and reap handsome rewards from doing so. The largest and most successful managers are among the world's wealthiest people and achieve celebrity status. Therefore, perhaps not surprisingly, the trading strategies of such mega hedge fund managers (hereafter, MHFs) are heavily scrutinized by market participants. Public disclosures of MHFs' long stock positions (mandated by regulation) are regularly discussed by the financial media and closely followed by competitors and copycat investors.[1] However, when MHFs suffer large losses that force them to liquidate assets in response to margin calls or redemptions, their need to liquidate is often known to other traders. This is important because a forced liquidation of a stock can adversely impact its price (Coval and Stafford, 2007). In anticipation of the price impact of liquidating trades by distressed MHFs, other traders may rush to sell stocks held in common with distressed MHFs to mitigate portfolio losses.[2] Furthermore, institutions who do not already own the stocks may see an opportunity to engage in predatory trading through short selling prior to distressed sales by MHFs. Together, we argue that such "anticipatory trading" (or, "front-running") activities can exacerbate the price impacts from forced liquidations, escalate the distress of MHFs, and destabilize asset prices.

In this context, we address the following research questions: Do institutional investors trade in the same direction prior to the anticipated stock trades of distressed MHFs? Does such

[1] "More ETFs Play Hedge Fund Copycat," *Institutional Investor*, October 17, 2012. "Big Investors Shed Tech Stocks as Markets Tumbled Last Quarter," *New York Times*, February 15, 2019. "Soros Doubles His Bet Against S&P 500 Index," *Wall Street Journal*, August 15, 2016. "How Star Investors Bet Last Quarter," *Wall Street Journal*, February 15, 2011. "A Peek at Moneymakers' Cards," *Wall Street Journal*, May 19, 2006.

[2] Alleged targets of predatory trading in the past include Long Term Capital Management during its collapse in the Fall of 1998 and the predictable trading strategies of portfolio insurers during the 1987 stock market crash. More recently, Melvin Capital was apparently caught in a "short squeeze" on its short position in GameStop – as other short sellers rushed to exit their positions, the surge in demand to buy back stock pushed up the price of GameStop to Melvin's detriment ("Melvin Capital, GameStop and the road to disaster," *Financial Times*, February 6, 2021).

anticipatory trading adversely impact distressed MHFs, as reflected in worse portfolio performance? Finally, are stocks that are anticipated to be sold by distressed MHFs associated with greater price drops and reversals – i.e., are such stocks more prone to prices deviating from their fundamental values?

We address these questions using the quarterly stock holdings of MHFs and other institutions over the 1994 – 2018 period. Following Edelman, Fung, and Hsieh (2013), we identify hedge fund management companies that manage over $1 billion in assets as MHFs. We focus on financially distressed MHFs for three reasons. First, despite their stellar track records, MHFs are not immune from financial distress and portfolio losses. These losses can trigger redemptions from fund investors and/or margin calls on levered positions that force the MHF to liquidate large positions. As Figure 1 shows, MHFs experience significantly negative investor flows during periods of distress (around –5% per quarter).[3] Second, due to their sheer size, MHFs' trading activities can impact stock prices, motivating other institutions to trade ahead of distressed MHFs. Third, MHFs' portfolio holdings are closely watched by other investors as evidenced by their visibility in financial media and their quarterly 13F filings being downloaded more than twice as often as those of non-MHFs.[4] Consequently, the market impact of anticipatory trading is potentially greater for stocks held by distressed MHFs as compared to those owned by distressed non-MHFs that are not followed as closely. Together, our setting provides novel insights into the

[3] We identify distressed MHFs based on both poor absolute (i.e., negative) and relative (i.e., bottom quartile) performance. One example of MHF distress is Bill Ackman's losing investment in Valeant Pharmaceuticals, which was the biggest contributor to his hedge fund's losses of 13.5% and 20.5% in 2014 and 2015, respectively ("Ackman ditches disastrous Valeant investment," *Financial Times*, March 13, 2017).

[4] We thank Sean Cao, Kai Du, Baozhong Yang, and Liang Zhang for sharing the data on the institutions whose 13F filings are downloaded by other institutions. Over 75% of the hedge funds appearing on Institutional Investors' Alpha Magazine's "Rich List" or Institutional Investor's "Hedge Fund 100" list come from the set of MHFs.

trading activities of institutional investors when the need to liquidate by distressed mega investors is predictable.

Our empirical analysis reveals several new findings and documents the anticipatory trading by institutions ahead of distressed MHFs' trading and its implications for MHFs' performance and asset prices. Our first major finding is that institutional investors trade in the same direction as the anticipated trades of distressed MHFs. For example, in anticipation of a 1% drop in stock ownership by all distressed MHFs next quarter, non-distressed MHFs collectively reduce their stock ownership by 1.79% in the current quarter. The evidence of anticipatory trading is concentrated among institutions that arguably have greater discretion and stronger incentives to engage in anticipatory trading, such as non-distressed hedge funds and mutual funds. In contrast, other institutional types (e.g., banks, insurance companies, pensions) exhibit no such behavior. Anticipatory trading is strongest in stocks most vulnerable to fire sales (e.g., illiquid stocks) and among institutions that hold larger positions in stocks targeted for forced selling by distressed MHFs (and therefore have a greater incentive to trade ahead of distressed MHFs). Anticipatory trading is also stronger among funds with more resources and more patient capital (e.g., large funds, mutual funds with smaller flow volatility, and hedge funds with lockup provisions). Moreover, we find that institutions appear to sell ahead of anticipated selling by distressed MHFs, but do not similarly front run the expected purchases of distressed MHFs. This is consistent with distressed MHFs having fewer choices about which stocks to sell compared to which ones to buy, making it easier for other institutions to anticipate their sell trades.

Two falsification tests show that these findings are not due to common factors driving the trading behavior of distressed MHFs and other institutional investors. First, institutions do not trade in anticipation of distressed *non*-MHFs, whose investment strategies are not followed as

closely by other investors and, due to their smaller size, whose forced liquidations are less likely to have a substantial price impact. Second, there is no evidence of anticipatory trading against *well-performing* MHFs, suggesting that fire sales, not fire purchases, create greater front-running opportunities.

Our second major finding relates to whether anticipatory trading by other institutions worsens the performance of distressed MHFs. We show that a MHF with greater exposure to anticipatory trading (i.e., "front-running beta") experiences worse performance during periods of distress. The economic magnitude is significant: a one standard deviation increase in front-running beta predicts 1.57% lower DGTW characteristics-adjusted abnormal returns for long-equity portfolios held by distressed MHFs over the following year, relative to other MHFs. This evidence is consistent with distressed MHFs realizing lower liquidation values on their stock trades due to the anticipatory selling by other institutions.

Furthermore, although most of our evidence on anticipatory trading is based on changes in institutions' long-equity positions, we also examine aggregate short interest data and find evidence that short sellers open short positions in stocks that are anticipated to be sold by distressed MHFs in the following quarter, and then cover those short positions soon after the distressed selling period. Collectively, our findings show that institutions front-run the stock trades of distressed MHFs on both the long and short side.

Finally, we provide evidence that anticipatory trading contributes to stock prices deviating from their fundamental values. Stocks that are anticipated to be sold by distressed MHFs in the next quarter (q+1) are associated with 1.66% lower abnormal returns during the current quarter (q). These effects are temporary since the same stocks earn positive abnormal returns over the following year (q+1 to q+4). The reversal of negative abnormal returns over subsequent periods

helps rule out that the negative returns reflect a deterioration in stock fundamentals; instead, the price effects are more likely a reflection of temporary price pressure from anticipatory selling. Furthermore, we find no evidence of return reversals among stocks that are anticipated to be sold by distressed MHFs but are *not heavily sold* by other institutions during the current quarter, indicating that anticipatory trading is indeed responsible for the destabilization in stock prices. Second, we do not find evidence of return reversals among stocks that are expected to be sold by *non-mega*, distressed hedge funds. This makes sense given that non-MHFs tend to hold smaller positions than MHFs, attract less attention from other institutions, and, as discussed above, are not targeted for front-running by institutional investors when they are in distress. Similarly, we find no evidence of return reversals among stocks that are expected to be traded by *well-performing* MHFs.

Our paper contributes to several strands of literature. First, our findings are consistent with theoretical models predicting that strategic traders can profit by selling the stock in anticipation of selling by distressed traders (Brunnermeier and Pedersen, 2005). Consistent with this idea, Shive and Yun (2013) find that the relatively impatient capital flows of mutual funds often fall prey to the patient capital of hedge funds.[5] We find that large and high-profile hedge funds (i.e., MHFs) can suffer when other institutions anticipate their need to liquidate holdings. Barbon et al. (2019) find that brokers alert their best clients to front-running opportunities by sharing proprietary (private) order flow information about distressed clients. In contrast, we show that strategic traders can use *public* signals from Form 13F filings to front-run MHFs who are themselves likely to be favored clients of prime brokers.

[5] Aragon, Martin, and Shi (2019) show that hedge fund managers with more patient capital (e.g., longer lockups) trade opportunistically against the relatively impatient hedge fund managers during periods of crisis.

Second, our paper is related to the literature on crowded trading and fire sales by leveraged informed traders. Stein (2009) argues that levered traders can inflict negative externalities on each other when they hold the same stocks.[6] In the case of such "crowded" trading, a funding shock that forces one trader to de-lever and sell securities could cause a negative return shock to other traders holding the same stock. This could trigger further deleveraging and stock liquidation, with prices sharply falling below fundamentals.[7] We contribute by focusing on a group of mega managers whose long-equity portfolios are closely tracked and mimicked by other traders and are therefore most likely subjects of crowded trading. As we show, such crowded trading can adversely impact stock prices and worsen the performance of distressed MHFs.

Third, our findings inform the debate on the adverse effects of portfolio disclosure. While disclosure can be costly for institutional investors due to front-running exposure and the revelation of trading strategies (Wermers, 2001; Shi, 2017; Cao et al., 2021), these costs can be mitigated by deliberately delaying disclosure (Agarwal et al., 2013; Aragon, Hertzel, and Shi, 2013). We identify a new setting where large institutions (i.e., MHFs) have already disclosed their stock holdings and, therefore, are unable to conceal their trading needs. As we show, anticipatory trading magnifies the distress of MHFs and increases non-fundamental volatility in stock prices. In this regard, our study has implications for the real economy given that non-fundamental shocks to security prices affect corporate decisions, including takeovers (Edmans, Goldstein, and Jiang, 2012), investments (Chen, Goldstein, and Jiang, 2007; Hau and Lai, 2013; Dessaint et al., 2019),

[6] Negative externalities from trading can also arise in settings such as open-ended mutual funds where investors face a strategic risk due to the externalities from other investors' redemptions (Chen, Goldstein, and Jiang, 2010).

[7] There is mixed evidence of crowded trading by hedge funds. Khandani and Lo (2011) find that quant or statistical arbitrage hedge funds incurred record losses in August 2007 due to deleveraging concentrated positions; Brown, Howard, and Lundblad (2021) find that crowded hedge fund ownership generates downside risk in stock returns. In contrast, Sias, Turtle, and Zykaj (2016) show that hedge funds do not engage in crowded trades and that their equity portfolios are remarkably independent.

and equity financing (Baker, Stein, and Wurgler, 2003; Khan, Kogan and Serafeim, 2012).[8] Finally, our paper reveals another mechanism that can contribute to diseconomies of scale in active management.[9] Specifically, we show that anticipatory trading by other investors can hurt the performance of large active institutions during times of distress.

2. Data and Methodology

In this section, we first describe the main databases used in our analysis and sample construction. We then explain and summarize the constructed sample.

2.1 Form 13F filings

We use Thomson Reuters (TR) Institutional (13f) Holdings database to obtain the quarterly filings of Form 13F. These filings disclose the quarter-end long positions in equity securities held by all institutions with at least $100 million in equity and other publicly traded securities. Our classification of 13F filing institutions largely follows Agarwal, Fos, and Jiang (2013). Specifically, we classify institutions into the following seven categories including hedge funds: 1) banks (type 1 institutions by the TR classification); 2) insurance companies (type 2 institutions by the TR classification); 3) mutual fund management companies (type 3 institutions by the TR classification); 4) independent investment advisors (type 4 institutions by the TR classification); 5) pension funds (manually identified from type 5 institutions by the TR classification); 6) investment banks (manually identified from type 5 institutions by the TR classification); and (7) hedge funds (manually identified from type 5 institutions by the TR classification and those included in commercial hedge fund databases as described in Section 2.2). We infer institutional

[8] See Baker and Wurgler (2012) and Bond, Edmans, and Goldstein (2012) for surveys of the literature on the real effects of non-fundamental shocks to stock prices.
[9] See, e.g., Chen et al. (2004), Pollet and Wilson (2008), Yan (2008), Fung et al. (2008), and Teo (2009).

trades in a stock from the quarterly changes of split-adjusted institutional holdings, normalized by the stock's shares outstanding in the prior quarter, i.e., $(Q_t - Q_{t-1}) / Shrout_{t-1}$.

2.2 Hedge fund data

We follow Agarwal, Green, and Ren (2018) and construct our hedge fund sample from a union of four commercial hedge fund databases (henceforth union hedge fund database): Eurekahedge, Hedge Fund Research (HFR), Morningstar, and Lipper Trading Advisor Selection System (TASS). This database provides monthly net-of-fees returns, monthly assets under management (AUM), and other fund characteristics such as management and incentive fees, lockup period, notice period, redemption period, and age. To be included in our analyses, we require a hedge fund to file 13F and exist in the commercial hedge fund databases. Form 13F is filed at the level of the fund management company, and not the fund. Therefore, when a management company runs several funds, we aggregate individual fund characteristics at the company level using asset-weighted averages. A company's age is the age of its oldest fund.

As discussed above, we focus on mega hedge fund managers (MHFs) who have a large footprint in asset markets and who are likely to be closely watched by other institutional investors and vulnerable to front-running during distress. Following Edelman, Fung, and Hsieh (2013), we consider hedge fund management companies that manage over $1 billion in assets as MHFs.[10] In some of our analyses, we split the remaining sample of (non-mega) hedge funds into two groups:

[10] Our main findings are robust to the inclusion of MHFs from two other sources—Institutional Investors' Alpha Magazine list of the top 25 most highly compensated hedge fund managers and Institutional Investor's "Hedge Fund 100" list of the 100 largest hedge fund firms in the world. We acknowledge that we may still be missing some MHFs that report non-publicly to the Securities and Exchange Commission (SEC), e.g., Form PF filings (Barth et al., 2021). This should result in the underreporting of the extent and consequences of anticipatory trading against distressed MHFs in our study.

those with assets under management below sample median each quarter ("Non-mega hedge funds, small") and the rest ("Non-mega hedge funds, large").

Our analysis focuses on trading activity around periods in which MHFs experience financial distress. Each quarter, to identify distressed managers, we rank their reported returns. We consider hedge funds that meet the following two conditions as distressed hedge funds: 1) returns ranked in the lowest quartile during the quarter; 2) returns below zero. The above two conditions account for both relative and absolute performance and help ensure that we do not misclassify hedge funds as being distressed during boom periods when most funds deliver stellar performance.

An important consideration is how institutional investors learn about which MHFs are in distress and, therefore, which stock positions to target for anticipatory trading. We propose several potential channels. First, institutions may subscribe to commercial hedge fund databases and track (as we do) their reported monthly returns. Indeed, even a delay in the disclosure of reported returns to commercial databases can convey a significant negative signal about fund performance (Aragon and Nanda, 2017). Second, stock market participants may use timely data on stock market returns to track the performance of long equity positions disclosed by MHFs in prior quarters. Such positions may still be held by MHFs in which case stock tracking portfolios are informative. Third, information about a hedge fund's distress may be leaked to the public by industry insiders including a fund's existing investors, prime brokers, security lenders, counterparties, or competitors. In sum, institutional investors may receive information from several sources to help identify which MHFs are distressed and choose their targets for anticipatory trading.

To verify that our distressed fund classification effectively captures MHFs that face significant liquidation pressure, in Figure 1 we illustrate the quarterly flows of distressed MHFs during the period of q-1 to q+4 with quarter q being the quarter in which distressed funds are

identified. For comparison, we also examine the flow patterns of non-distressed MHFs during the same period. Indeed, relative to their non-distressed peers, flows of distressed MHFs are almost the same during q-1. However, starting from quarter q, distressed MHFs begin to suffer significant net outflows that last for several quarters before slightly retreating in q+4. Particularly, the average quarterly outflows of distressed MHFs in q+2 and q+4 exceed 5%. Interestingly, t-tests also show that the net flows of distressed MHFs are significantly (at 1% level) more negative than those of their distressed *non-MHF* counterparts in each of the five quarters during q to q+4. Therefore, distressed MHFs appear to suffer a much bigger blow in money flows following their poor performance, relative to both non-distressed MHFs and distressed non-MHFs. This suggests that distressed MHFs are particularly hard hit following poor performance and are vulnerable to front-running as a result.

2.3 Mutual fund data

Thomson Reuters Institutional (13f) Holdings database (S34) provides scant information at the *institutional* level and only includes large equity positions (exceeding 10,000 shares or $200,000). Therefore, we also use Thomson Reuters' mutual fund holding database (S12) to obtain quarterly portfolio holdings and fund characteristics for *individual* U.S. equity mutual funds, to examine the effect of fund characteristics and constraints on mutual funds' front-running activities. Compared to the S34 data, S12 provides more detailed data that includes all positions, small or large. We also use the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database to extract monthly net-of-fees returns and AUM for each fund, in addition to annual and quarterly data on fund characteristics. Fund characteristics include the year of inception, asset allocation, portfolio turnover, and management company names. We merge these two mutual fund databases using MFLINKS provided by the Wharton Research Data Services

(WRDS). We focus on actively managed domestic equity mutual funds. To account for funds with multiple share classes, we aggregate flows across share classes and calculate other fund variables (e.g., fund returns and expenses) using asset-weighted averages across share classes.

2.4. Other databases

The remaining databases we use are the CRSP monthly stock files for data on stock characteristics and stock returns, the stock-level abnormal short interest measure used in Karpoff and Lou (2010) and Agarwal et al. (2022), and the monthly returns on the four benchmark factors of Fama and French (1993) and Carhart (1997) from Kenneth French's website.[11]

2.5 Summary statistics

Our final sample spans the period of 1994 to 2018 across all 13F filers that can be classified into one of the institutional types discussed above. Panel A of Table 1 summarizes the frequency of observations and stock portfolio size by institutional type. Mutual funds and independent investment advisors account for the majority of 13F filers, while MHFs, banks and pension funds have larger average long-equity portfolios. Note that, MHFs, while having higher assets under management (AUM) by design, also tend to have much larger long-equity holdings.

Panel B of Table 1 reports summary statistics for hedge funds. "Mega" is a dummy variable indicating MHFs. MHFs account for about 25% of the universe of hedge funds that file 13F and exist in the commercial hedge fund databases. Hedge fund managers' long-equity portfolio values exceed their AUM, on average, consistent with their use of significant leverage. About 56% of hedge funds have lockup provisions. The total restriction period on investor redemptions (i.e., the sum of redemption and notice periods) averages about 140 days. The median incentive and

[11] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

management fees are 20% and 1.5%, respectively. Panel C of Table 1 presents summary statistics for mutual funds. In contrast to hedge funds, average equity portfolio value is lower than average AUM for mutual funds, consistent with mutual funds using less leverage and retaining cash.

3. The trading behavior of MHFs and other institutional investors

In this section, we examine whether institutional investors trade in the same direction as the anticipated trades of MHFs experiencing financial distress.

3.1. Predicting the stock trading of MHFs

We focus on predicting the stock market trading activity of MHFs from the perspective of a real-time outside observer. Since Form 13F filings are usually disclosed 45 days after each quarter end, stocks that were held by MHFs at the end of quarter q-1 are likely to be publicly observable around the middle of quarter q.[12] Consequently, other institutions may not be able to use information in MHFs' quarter q-1 holdings to predict (and trade ahead of) the quarter q trades of MHFs because those trades may occur during the first half of quarter q and, therefore, before the q-1 holdings are publicly disclosed. To be conservative, therefore, we focus on predicting MHFs' quarter q+1 trading activity of their quarter q-1 stock holdings (i.e., holdings that are publicly revealed in the middle of quarter q), according to the timeline shown in Figure 2. That is, our model predicts the quarter q+1 trading activity of MHFs based only on information that is observable to other institutions in quarter q.

[12] Some institutions could access more timely information than quarterly 13F filings, such as proprietary information leakage by connected brokers (Barbon et al., 2019). However, 13F filings are an important source of publicly available information about the stock holdings of MHFs and are often cited by the popular press and tracked by third parties such as Insider Monkey and Whale Wisdom.

We predict the stock trading of hedge funds using stock characteristics that include the logarithm of stock market capitalization, quarterly returns, cumulative returns in the four-quarter period ending as of the current quarter, book-to-market ratio, and Amihud's (2002) illiquidity measure. We also include prior quarter trade and existing ownership of a stock by all hedge funds in the fund group (MHFs or non-MHFs), both of which can influence a fund's trading decisions. All characteristics are measured at the end of quarter q-1.

Table 2 shows the results from estimating our predictive model of hedge fund trading, separately for MHFs and non-MHFs whose status is observable in quarter q. The dependent variable is either an indicator variable that equals one if the net change in aggregate hedge fund holdings of the stock is negative (*sell* (q+1); Model 1) or a continuous variable measuring the net change in aggregate hedge fund holdings of the stock (*trade* (q+1); Model 2). We see that existing holdings of a stock strongly predicts hedge fund trading, i.e., larger holdings of a stock in quarter q-1 predicts greater selling of the stock in quarter q+1. This is true for both MHFs and non-MHFs. Past stock returns also strongly predict MHFs' trading. Overall, the significant predictability in selling by MHFs could enable other institutions to reliably anticipate and trade ahead of their selling when they are in distress.[13]

3.2. Do institutions front-run the anticipated trades of distressed MHFs?

We examine whether institutional investors trade in the same direction as the anticipated trades of distressed MHFs using the following regression specification:

[13] We also estimate a simple AR(1) model of regressing quarter q+1's net trade in a stock by MHFs on their quarter q's net trade in the same stock. The AR(1) model delivers a poorer fit to the data compared to our model, as indicated by a lower R-squared (less than 0.1% versus roughly 3%), indicating that our predictive model based on stock characteristics provides a better fit than a naïve AR(1) model of stock trading.

$$Trade_{f,i,q} = \alpha + \beta Ptrade_{i,q-1} + Controls_{f,i,q-1} + \varepsilon_{f,i,q} \quad (1)$$

where $Trade_{f,i,q}$ is institution *f*'s quarter *q* trading in stock *i*. In this regression, we only include stocks that were held by at least one distressed MHF in quarter *q*-1. In addition, as discussed in Section 2.2 and Figure 2, we classify a MHF as either distressed or non-distressed based on their performance during quarter *q*. $Ptrade_{i,q-1}$ is the predicted quarter *q+1* aggregate trades in stock *i* by distressed MHFs. It is defined as $Ptrade_{i,q-1} = \sum_m Ptrade_{m,i,q-1}$, where $Ptrade_{m,i,q-1}$ is the predicted quarter *q*+1 trades in stock *i* by distressed MHF *m* based on a rolling-window estimation of the predictive model reported in Table 2. Our rolling window uses data only from the prior four quarters so that the estimated coefficients used to predict the expected trades of MHFs in the next quarter (i.e., quarter *q*+1) are based only on real-time information of investors in the current period (i.e., quarter *q*). $Controls_{f,i,q-1}$ are measured as of prior quarter *q*-1 and include institution *f*'s trading in stock *i*, the logarithm of the size of institution *f* as measured by its equity portfolio value, and stock *i*'s quarterly returns, cumulative returns in the prior four-quarter period, logarithm of market capitalization, book-to-market ratio, and Amihud illiquidity measure. We include fund fixed effects and quarter fixed effects to control for unobservable institutional characteristics and macroeconomic conditions, respectively. Standard errors are clustered by institution and quarter. The estimated slope coefficient, β, in regression (1) provides the relation between institutional trading and the predicted trades of distressed MHFs; $\beta > 0$ would indicate that institutions trade in the same direction as anticipated trades by distressed MHFs.

Table 3 presents the estimated regression coefficients of Eq. (1). For ease of presentation, we express the raw *Trade* measure, its one-quarter lagged value, and *Ptrade* in basis points (i.e., multiplied by 1,000). Panel A reports the results for all institutions (excluding distressed MHFs).

We find that β is significantly positive, suggesting institutions trade in the same direction as the anticipated trades of distressed MHFs. In Column 2, we split *Ptrade* into *Pbuy* versus *Psell*, where *Pbuy* is equal to max(*Ptrade*, 0) and *Psell* is equal to min(*Ptrade*, 0). We find that institutions appear to sell ahead of anticipated selling by distressed MHFs, but do not similarly front run the expected purchases of distressed MHFs. This is consistent with distressed MHFs having fewer choices about which stocks to sell versus buy, making it easier for other institutions to anticipate their sell trades.

Panel B of Table 3 examines whether anticipatory trading is concentrated among certain institution types. We find that β is larger and significantly positive for non-distressed MHFs and non-mega hedge funds.[14] Therefore, larger hedge funds, likely more skillful as well, that are themselves not distressed are more likely to engage in front-running activities when their prominent peers in the spotlight become vulnerable. In terms of magnitudes, we estimate that an individual non-distressed MHF would reduce its stock ownership (as a percentage of total market capitalization) by 0.046% in the current quarter, or all non-distressed MHFs would reduce their total ownership of the stock by 1.79% in a typical quarter, in anticipation of a 1% drop in stock ownership by all distressed MHFs next quarter.[15] We also observe that mutual funds, insurance companies, and independent investment advisors engage in anticipatory trading though the economic magnitudes are smaller. In contrast, pension funds, banks, and investment banks do not show propensity to engage in anticipatory trading, suggesting that these institutions follow more conservative investment policies.

[14] In untabulated analyses, we also find that among non-mega hedge funds, anticipatory trading is more pronounced among those that are not distressed.

[15] The average number of non-distressed MHFs is about 39 each quarter. Therefore, the total average reduction across all non-distressed MHFs is equal to 0.046% x 39, i.e., 1.79% per quarter.

3.3. Falsification test #1: Do institutions front-run distressed non-MHFs?

Table 3 provides evidence that institutional investors front-run distressed MHFs by trading in the same direction and ahead of the anticipated trades of their vulnerable peers. A potential concern is that unobserved variables drive the trading behavior of both groups of institutional investors, and some institutions move faster than others. Alternatively, distressed MHFs may simply follow aggregate institutional trading when liquidating their portfolios. To address this concern, we analyze institutions' trading in stocks held by distressed *non*-MHFs. Our basic idea is that, in contrast to MHFs, non-MHFs, particularly those that are smaller, should be less vulnerable to front-running because their holdings are not closely monitored and thus followed by other investors, even during times of distress. For example, as mentioned in the introduction, MHFs' most recent quarter's 13F filings are downloaded twice as much as those of non-MHFs. Moreover, non-MHFs typically have a smaller ownership stake in stocks compared to MHFs, resulting in a lower price impact from fire sales in the event of distress. In our sample, MHFs' stock ownership is about three times that of non-MHFs. Therefore, due to the presumably smaller negative shocks, we expect to find weaker evidence of anticipatory trading among stocks that are held by distressed non-MHFs.

Table 4 reports the results from re-estimating Eq. (1) where $Ptrade_{i,q-1}$ now represents the predicted trades of distressed *non*-MHFs. As mentioned above, we focus on "small" non-mega hedge funds with below-median AUM to further isolate a group of hedge funds that are relatively low profile and plausibly less susceptible to front running. To control for the overlap between the portfolios of MHFs and non-MHFs, we also exclude any stocks that are held by both groups in quarter q-1. When estimating $Ptrade_{i,q-1}$ for small distressed non-MHFs, we re-estimate the predictive model employed in Table 2 within the sub-sample of non-MHFs with below-median

AUM using prior four-quarter rolling window regressions. In stark contrast to the findings in Table 3, the results in Table 4 show that none of the hedge fund groups' trades in quarter q are significantly influenced by the expected trades of distressed non-MHFs in quarter q+1. Similarly, there is no evidence that mutual funds front run distressed non-MHFs. Therefore, it is unlikely that the observed trading pattern of potential front runners identified in Table 3 is merely due to unobservable characteristics that drive common trading among institutional investors and MHFs. Rather, institutions either try to profit from the potential price impacts resulting from the needs of distressed MHFs to liquidate their positions, or aim to mitigate the adverse effect of such price swings on their portfolios, and therefore trade ahead of them.

3.4. Falsification test #2: Do institutions front-run well-performing MHFs?

We also analyze institutions' trading in stocks held by *non-distressed* MHFs. This falsification test is in similar spirit as the one discussed in Section 3.3 but addresses the concern that other institutions may only act on the same trading signals that affect the trading of MHFs, as opposed to non-MHFs. If other institutions' trading responses as documented in Table 3 are driven by common investment signals rather than imminent selling activities by distressed MHFs, we should observe similar trading responses to $Ptrade_{i,q-1}$ of well-performing MHFs.

Table 5 reports the results where $Ptrade_{i,q-1}$ represents the predicted trades of *well-performing* MHFs (i.e., MHFs with performance ranked in the top quartile during the quarter). In addition, to control for potential portfolio overlap between distressed and well-performing MHFs, we exclude any stocks that are simultaneously held by both well-performing MHFs and distressed MHFs in quarter q-1. Again, Table 5 indicates no evidence that institutional trading in quarter q is significantly related to anticipated trading in quarter $q+1$ by well-performing MHFs.

Together, the two falsification tests suggest that institutional investors front run the trades only of MHFs, and only when they are perceived to be in a vulnerable position due to financial distress.

4. Role of fund and stock characteristics in predatory trading

In this section, we conduct further analyses on the trading activities of mutual funds and hedge funds. The availability of detailed fund-level information for these two groups of institutions allows for a richer set of variables to test whether fund and stock characteristics influence anticipatory trading against distressed MHFs. Our baseline regression model is as follows:

$$Trade_{f,i,q} = \alpha + \beta_1 Ptrade_{i,q} + \beta_2 Ptrade_{i,q-1} \times Rank_{f,i,q-1} + \beta_3 Rank_{f,i,q-1} + Controls + \varepsilon_{f,i,q} \quad (2)$$

where $Rank_{f,i,q-1}$ is a dummy variable indicating a fund (*f*) or stock (*i*) characteristic above/below median at the end of quarter *q*-1. In addition to the same set of stock-level control variables employed in Table 3, we also include as additional control variables the logarithm of a fund's AUM, prior-period performance, prior-quarter flows, lagged trade ($Trade_{f,i,q-1}$), and quarter fixed effects. For mutual funds, we measure risk-adjusted performance using the Carhart (1997) four-factor alpha estimated using monthly fund returns in the past 36-month period.[16] For hedge funds, given their diverse investment strategies, we measure abnormal performance of individual funds by their style-adjusted performance and compute the family-level abnormal performance as the AUM-weighted average style-adjusted performance across all funds in a hedge fund family.[17] We

[16] Each quarter, we estimate the four-factor model of Carhart (1997) using the fund's lagged monthly returns in the past 36-month period. We then take the difference between current quarter's raw fund returns and the projected returns, i.e., sum product of estimated factor loadings and current quarter's factor returns.

[17] Due to the different style classification by different data vendors, we follow the mapping of strategies in Agarwal, Daniel, and Naik (2009) and classify funds into four broad strategies: directional, relative value, security selection, and multiprocess.

cluster standard errors by fund and quarter. From the regression, we can infer the relation between institutional trading and the predicted trades of distressed MHFs from parameter β_1. We can infer the impact that $Rank_{f,i,q-1}$ has on this relation from parameter β_2. A finding of $\beta_2 > 0$ would indicate that a higher characteristic rank is associated with greater front-running activity.

Panel A of Table 6 presents the results of Eq. (2), but without the *Rank* variables. We see that, relative to mutual funds, other hedge funds (excluding distressed MHFs) are more aggressive in predatory trading against distressed MHFs as indicated by their significantly higher loading on $Ptrade_{i,q-1}$ (0.0262 versus 0.0025). This difference is both economically and statistically significant. This is consistent with the idea that, compared to mutual funds, hedge funds are more likely to aggressively engage in anticipatory trading due to their high-powered compensation contracts, greater investor sophistication and patience, or greater discretion to trade opportunistically. This evidence also aligns with the estimated coefficients reported in Table 3; we now observe that the difference in β_1 between mutual funds and hedge funds remains highly significant even after incorporating fund-level information beyond the 13F data.

Panels B and C of Table 6 show the results from estimating Eq. (2) where $Rank_{f,i,q-1}$is based on stock characteristics. We find that anticipatory trading is stronger in smaller (*Size*) and less liquid (*Amihud*) markets, and in markets with greater ownership by "vulnerable'' distressed MHFs as measured by having above-median leverage (*Leverage*). Hedge fund leverage is defined as a fund's total equity portfolio value from 13F divided by AUM reported from hedge fund databases. In addition, anticipatory trading is weaker in markets with greater ownership by

distressed MHFs who are less vulnerable to investor flows (*Lockup*, *Restriction*). [18] Together, this evidence indicates that the benefits from anticipatory trading are greater when there is a greater potential for price impact due to distressed selling by vulnerable MHFs in illiquid markets.

Table 6 also shows that a fund's anticipatory trading activity is stronger in stocks that represent a larger (i.e., top quartile) weight in the fund's portfolio. This makes sense as a fund would be more motivated to exit larger positions in stocks that are targeted for liquidation by distressed MHFs, to avoid negative price impacts from spilling over into the fund's portfolio performance. Finally, in comparing Panels B and C, the effects of stock characteristics on anticipatory trading are qualitatively similar for mutual funds and hedge funds; however, the magnitude of the effects are larger for hedge funds that appear more aggressive in targeting front-running opportunities.

We also examine whether anticipatory trading is related to fund characteristics of potential front-runners. On one hand, anticipatory trading may be more prevalent among larger funds and funds with more active portfolio managers. Such funds would be better able to absorb the risk of front-running strategies and have more discretion to seize front-running opportunities. Similarly, funds that are less exposed to funding liquidity shocks themselves, for example, mutual funds with less volatile flows or hedge funds with more redemption restrictions, would have a stronger incentive to pursue predatory trading. On the other hand, among funds that engage in front running mainly to reduce their exposure to the price impact from forced liquidations of distressed MHFs, those with better liquidity protection might feel less need to rush to sell early. So how a fund's liquidity position affects its incentive to conduct front-running trades is an empirical question. To

[18] We apply a 75th percentile cutoff (rather than the median) to lockup and restriction periods because these variables are often right skewed. For example, during our sample period, the 25th percentile of the lockup period is 0, the median is 45 days, and the 75th percentile is 360 days.

shed light on these issues, we estimate Eq. (2) where $Rank_{f,i,q-1}$is an indicator variable based on fund characteristics.

Panel A of Table 7 presents the results for mutual funds. The coefficient on the interaction term between $Ptrade_{i,q-1}$ and an indicator variable for above-median fund AUM is significantly positive, suggesting that larger funds participate more in front-running. Column 2 shows that the interaction term between $Ptrade_{i,q-1}$ and the indicator variable denoting above-median flow volatility is significantly negative, indicating that greater funding liquidity risk makes funds shy away from front-running. There is a positive and significant coefficient on the interaction term between $Ptrade_{i,q-1}$ and the indicator variable denoting above-median number of funds within the family. This suggests that potential liquidity provision from affiliated funds and, therefore, lower funding liquidity risk (e.g., Bhattacharya, Lee, and Pool, 2013; Agarwal and Zhao, 2019) is associated with more front-running behavior. Lastly, higher return volatility and portfolio turnover are associated with more front-running, indicating that mutual funds that are more active in portfolio management are more likely to engage in anticipatory trading against distressed MHFs.

Panel B of Table 7 reports the results for hedge funds. As with mutual funds, hedge funds (besides distressed MHFs) with larger AUM are more likely to front run their distressed peers. Hedge funds with above-median lockup period also exhibit a significantly higher proclivity to front-run distressed MHFs. This indicates that greater redemption restrictions provide managers with greater discretion to engage in front-running. Finally, the coefficient is negative (though not significant) on the interaction variable between $Ptrade_{i,q-1}$ and the indicator variable for above-

median fund leverage, providing some evidence that anticipatory trading is lower among highly leveraged hedge funds that presumably have more exposure to funding liquidity risk.[19]

Overall, the extent of front-running against distressed MHFs varies with fund characteristics: larger funds and funds that are less exposed to funding liquidity risk from their own investors engage in more front-running behavior.

5. The impact of anticipatory trading on performance of MHFs

We now examine whether a MHF's exposure to front-running activity by other institutions adversely impacts its performance during periods of distress. Financial distress could trigger redemption requests from fund investors and/or margin calls from prime brokers, thereby forcing a MHF to liquidate its stock holdings. Trading by other institutions in anticipation of MHFs' stock sales could negatively impact underlying stock prices, reducing liquidation values for distressed MHFs and resulting in worse performance. In contrast, non-distressed MHFs are less vulnerable to the adverse effects of front-running as they do not face liquidation pressure and have more flexibility in terms of the type of stocks to trade and the direction and timing of the trades.

We measure a MHF's exposure to anticipatory trading using the predictive model in Table 2, estimated at the fund-quarter level. That is, we estimate the model on a rolling basis using data only from the prior four quarters to generate predicted trades of *each individual* MHF *f* on each stock *i* held as of quarter *q-1* ($Ptrade_{f,i,q-1}$). We then regress aggregate mutual fund and hedge fund trades (excluding trades by hedge fund *f* itself) on $Ptrade_{f,i,q-1}$. The estimated coefficient on *Ptrade*, denoted by $\beta_{f,q}$, is the front-running beta of MHF *f* and measures its exposure to front-

[19] Our leverage measure only captures long-only leverage, not short sales and off-balance-sheet transactions in derivatives. Therefore, our leverage measure may underestimate a fund's actual exposure to funding liquidity risk.

running during quarter q. We impose several filters when estimating front-running betas to ensure that they meaningfully reflect individual funds' front-running risk. First, we only include stocks held by distressed MHFs. The reason is that non-distressed MHFs are more likely to hold well-performing stocks and have more anticipated purchases than sales. Therefore, given our earlier findings that anticipatory trading is stronger on the sale side versus the purchase side (Table 3), restricting the set of stock holdings to those held by distressed MHFs makes our estimates of front-running betas more comparable across groups. Second, we require a minimum of 30 observations of holdings in the estimation of a fund's front-running beta. Finally, we address the concern that some MHFs may hold diversified portfolios with many equity positions with small portfolio weights (and thus small $Ptrade_{f,i,q-1}$), leading to artificially high front-running betas even though such funds face little front-running risk. Therefore, we i) exclude fund-quarters with more than 1,000 holdings, ii) only focus on those holdings with portfolio weight greater than 0.1% in quarter q-1, iii) exclude fund quarters where the maximum $Ptrade_{f,i,q-1}$ in absolute value is less than 0.1%; and iv) estimate $\beta_{f,q}$ using weighted least square regressions with individual stocks' portfolio weight in quarter q-1 as the weight.

In the second stage, we use the estimated front-running betas ($\beta_{f,q}$) to predict the performance of MHFs:

$$Perf_{f,q+k}=\alpha+\gamma_1\beta_{f,q}+\gamma_2 Distress_{f,q}+\gamma_3 Distress_{f,q}\times\beta_{f,q}+Controls+\varepsilon_{f,q+1} \qquad (3)$$

where $Perf_{f,q+k}$ is the performance of MHF f's long-equity portfolio during quarter q+1 or quarters q+1 through q+4 and $Distress_{f,q}$ is an indicator variable denoting financial distress. We measure performance using both the raw return and Daniel et al. (1997) characteristics-adjusted abnormal returns (DGTW). From the regression, we can infer the marginal impact that $\beta_{f,q}$ has on

the performance of distressed versus other MHFs from parameter γ_3. A finding of $\gamma_3 < 0$ would indicate that a higher front-running beta is associated with worse performance following periods of distress. Such a difference-in-differences specification allows us to isolate the effect of anticipatory trading on the performance of distressed MHFs while controlling for unobserved common factors that affect the performance of all MHFs. We also control for various observable factors that could affect hedge fund performance, including the logarithm of a fund's long-equity portfolio value, the logarithm of its assets under management, current quarter long-equity portfolio performance, a dummy variable indicating funds with lockup provisions, the logarithm of the restriction period (i.e., sum of redemption and notice periods), incentive fees (in percent), management fees (in percent), and the logarithm of fund age. We compute *t*-statistics after clustering standard errors by fund.

Table 8 reports the results. While the coefficient on $\beta_{f,q}$ is insignificant, the coefficient of its interaction term with the distress dummy is significantly negative. This implies that the anticipatory trading of other institutions does not adversely affect MHFs in the absence of distress, but the performance of *distressed* MHFs is significantly hurt by such trading. We obtain similar results using raw returns or DGTW-adjusted returns that control for a stock's size and book-to-market ratio along with momentum. The adverse impact of anticipatory trading on the equity portfolio performance of distressed MHFs is economically large. A one standard deviation increase in front-running beta is associated with 1.57% lower DGTW characteristics-adjusted abnormal returns for equity portfolios of distressed MHFs over the following year, relative to other MHFs.[20]

[20] We looked at which characteristics of MHFs are associated with greater front-running betas and, hence, a greater exposure to anticipatory trading by institutions. We find (not tabulated) greater exposure among MHFs that employ greater leverage and allow more frequent investor redemptions and, hence, are more exposed to funding liquidity risk.

Overall, while prior literature finds that hedge funds profit from anticipatory trading against flow-induced mutual fund trades and such trading significantly hurts mutual fund performance (Shive and Yun, 2013), we find that distressed MHFs themselves suffer from anticipatory trading by other institutions because of their size and attention they receive from market participants.

6. Additional evidence of front-running based on short interest

Our analysis heretofore focuses on the long-equity positions to examine the extent of anticipatory trading among institutional investors that benefit from mitigating the negative return shocks to their portfolios on account of distressed selling by MHFs. However, institutions that do not hold stocks that distressed MHFs are expected to sell can also benefit from selling these stocks short, while closing out the shorts promptly after the distressed selling period. While data limitations do not allow us to analyze short selling activity at the individual fund level, we use aggregate short interest data to provide some evidence along these lines. Specifically, we compute a stock's abnormal short interest (*ABSI*) following Karpoff and Lou (2010). *ABSI* equals raw short interest minus expected short interest based on stock characteristics.[21] If anticipated selling of stocks by distressed MHFs motivates institutions to engage in front-running, we would expect a significantly negative relation between abnormal short interest of the stocks in quarter q and anticipated trading of the stocks in quarter q+1 (i.e., $Ptrade_{i,q-1}$) by distressed MHFs. Given the strong persistence in *ABSI*, we regress changes in ABSI in quarter q on $Ptrade_{i,q-1}$ along with lagged market returns that account for the effect of overall market conditions on short interest.

[21] Specifically, we adopt ABSI (1) of Karpoff and Lou (201) to measure abnormal short interest. Prior work shows that short interest is related to stock characteristics that may be correlated with hedge fund trading activity (see, e.g., Dechow et al., 2001; Asquith, Pathak, and Ritter, 2005; and Duarte, Lou, and Sadka, 2006).

The results are reported in Table 9. The first column shows that lower $Ptrade_{i,q-1}$ (i.e., greater anticipated selling by distressed MHFs) is associated with significantly larger increases in abnormal short interest in quarter q. This corroborates our earlier evidence based on changes in institutions' long-equity positions. Institutional investors not only divest their long positions in stocks that are targeted for selling by distressed MHFs, but also short sell these stocks.

The remaining four columns in Table 9 examine changes in abnormal short interest at longer horizons. We find that lower $Ptrade_{i,q-1}$ is associated with significantly larger *decreases* in abnormal short interest in quarters $q+1$ through $q+4$, with the exception of quarter q+2, where the coefficient of $Ptrade_{i,q-1}$ is insignificant. Therefore, there exists a subsequent *reversal* in the higher abnormal short interest of stocks that are anticipated to be sold more by distressed MHFs. Taken together, the evidence in Table 9 is consistent with short sellers profiting by opening short positions in stocks that are anticipated to be sold by distressed MHFs in the following quarter, and then covering those short positions soon after the distressed selling period.

7. Anticipatory trading and the pattern of stock returns

Sections 4 through 6 show that institutions trade in anticipation of stocks subject to liquidations by distressed MHFs, and that such behavior hurts the performance of distressed MHFs. To assess the broader impact of anticipatory trading on underlying stock markets, we now analyze the return pattern of stocks held by distressed MHFs.

7.1 Baseline analysis

Our baseline analysis examines the return dynamics of stocks held by distressed MHFs. Specifically, we focus on stocks held by distressed MHFs in quarter q-1 but are expected to be

sold in quarter q+1 (i.e., with $Ptrade_{i,q-1}$<0). We expect anticipatory trading by other institutions in quarter q to lead to significantly negative returns for these stocks in the quarter. If these negative returns reflect temporary price pressure as we suspect, the price impact from anticipatory trading should reverse in the following periods. In contrast, if the negative returns on stocks expected to be sold by distressed MHFs reflect poor fundamentals, we should observe a permanent price impact without a subsequent reversal.

In Table 10, we report the results from Carhart (1997) four-factor regressions of quarterly value-weighted returns of stocks held by distressed MHFs in quarter q-1 but are expected to be sold in quarter q+1, with the weight being the percentage of shares outstanding held by these funds. We estimate this regression for each quarter during quarter q and quarters q+1 through q+5. Results in Panel A indicate that stocks that are expected to be liquidated by distressed MHFs experience a negative and significant alpha of –1.7% in quarter q that reverses to a positive and significant alpha of 1.4% in quarter q+4. This evidence is consistent with our hypothesis that anticipatory trading causes a temporary decline in stock prices. Panels B and C further show that the price impacts are primarily driven by stocks with high ownership by distressed MHFs in q-1 and, therefore, instances where there may be greater benefits from anticipatory trading.

To further assess whether trading by front-runners is responsible for the observed return patterns, we examine whether the negative alpha in quarter q is related to the trading activities of mutual funds and other hedge funds (again, excluding trading by distressed MHFs themselves). Specifically, we compute the ratio of aggregate trading of a stock by mutual funds and other hedge funds in quarter q to anticipated trading of the same stock by distressed MHFs (i.e., $Ptrade_{i,q-1}$) and classify stocks with above-median anticipatory-trading ratio as the strong anticipatory trading group. We then repeat the analysis separately for the strong versus weak anticipatory trading

groups. Consistent with anticipatory trading causing stock price overreaction, the return patterns observed in Panel A of Table 10 are mainly driven by the group of stocks that are subject to stronger anticipatory institutional trading (see Panel D). In contrast, Panel E shows that stocks held by distressed MHFs but not subject to strong anticipatory trading do not experience any negative abnormal returns in quarter *q*. Overall, the evidence supports our interpretation that institutions engaging in anticipatory trading are responsible for the negative returns in stocks targeted for selling by distressed MHFs.

One concern is that the poor performance of stocks held by distressed MHFs explains why MHFs become distressed, and the return patterns observed in Table 10 have little to do with anticipatory trading by front-runners. To address this concern, we conduct a falsification test on stocks held by distressed *non*-MHFs as of quarter *q*-1 but are expected to be sold in quarter *q*+1. We follow our approach in Table 4 and focus on distressed non-MHFs that are relatively small, i.e., with below-median AUM. We then repeat the same analysis as in Table 10 but using stocks held exclusively by distressed non-MHFs, excluding those stocks that are simultaneously held by distressed MHFs. Our idea is that stocks held exclusively by non-MHFs are unlikely to fall on the radar screen of front-running institutions and therefore not subject to anticipatory trading. Consistent with this idea, Panel A of Table 11 shows that stocks that are anticipated to be sold by distressed non-MHFs in quarter *q*+1 do not experience negative abnormal returns in quarter *q*, and do not show patterns of return reversals.

In another falsification test, we repeat the analyses in Table 10 using stocks held by well-performing MHFs as of quarter *q*-1. As shown in Table 5, there is no evidence of anticipatory trading on stocks held by these funds. Therefore, if the return reversal pattern illustrated in Table 10 for stocks held by distressed MHFs indeed results from other institutions' front-running

activities, it should not show up for stocks held by well-performing MHFs as these stocks are not expected to be liquidated. Indeed, Panel B of Table 11 shows that stocks held by well-performing MHFs have significantly positive, not negative, 4-factor alpha in quarter *q*, and there is no evidence of subsequent return reversal.

Overall, the stark contrast between the results in Table 10 and Table 11 suggest that front-running against distressed MHFs causes large, destabilizing price impacts and is the main driver behind the return reversals experienced by stocks held by these funds.

8. Conclusion

We provide novel evidence on the vulnerability of mega hedge funds (MHFs) to anticipatory trading ("front-running") by other active institutional investors, and its consequences for the performance of target funds as well as for asset prices. Active institutions such as mutual funds and other hedge funds, especially those that are well incentivized and have greater investment flexibility, are more likely to front-run the distressed trading by MHFs, particularly in illiquid stocks that are subject to greater price impact. Unobserved factors that drive common trading behavior among institutional investors are unlikely to explain this finding as distressed non-MHFs do not suffer the same fate, nor do well-performing MHFs.

We also find that front-running behavior is asymmetric in that institutions sell ahead of anticipated selling of distressed MHFs, but do not buy ahead of anticipated buying. In addition, while our main analysis focuses on institutional trading of long equity positions, we provide evidence from aggregate short interest data as well. We show that short sellers open short positions in stocks that are anticipated to be sold by distressed MHFs in the following quarter and then cover

those short positions soon after the distressed selling period. This evidence suggests that other institutions benefit from the distress of MHFs on the long side by mitigating the negative return shocks from distressed selling as well as on the short side by aggressively trading in stocks that they do not hold in common with distressed MHFs.

Regarding consequences of front-running, we find that MHFs that are most vulnerable to front-running exhibit worse performance during financial distress on account of being targeted by other institutions. Moreover, stocks that are anticipated to be sold by distressed MHFs in the following quarter experience a sharp price decline in the present quarter, and these negative returns are subsequently reversed. These price patterns are directly attributed to the anticipatory trading by other institutional investors, not the liquidation activities of distressed MHFs.

Collectively, our study is the first to provide evidence on astute hunters getting hunted when in trouble and contributes to the debate on the mandated portfolio disclosure of active and informed traders. For example, the SEC has recently proposed to raise the reporting threshold from $100 million to $3.5 billion for institutional managers to file 13F, for the purpose of mitigating the front-running costs of 13F filers.[22] Our evidence suggests that significant costs of disclosure remain even for the largest asset managers (MHFs) who would still be required to disclose their 13F positions despite an elevated reporting threshold.

[22] See https://www.sec.gov/news/press-release/2020-152 for details.

References

Agarwal, Vikas, Naveen D. Daniel, and Narayan Y. Naik, 2009, Role of managerial incentives and discretion in hedge fund performance, Journal of Finance 64, 2221−2256.

Agarwal, Vikas, Vyacheslav Fos, and Wei Jiang, 2013, Inferring reporting-related biases in hedge fund databases from hedge fund equity holdings, Management Science 59, 1271−1289.

Agarwal, Vikas, Clifton T. Green, and Honglin Ren, 2018, Alpha or beta in the eye of the beholder: What drives hedge fund flows?, Journal of Financial Economics 127, 417−434.

Agarwal, Vikas, Wei Jiang, Yuehua Tang, and Baozhong Yang, 2013, Uncovering hedge fund skill from the portfolios they hide, Journal of Finance 68, 739–783.

Agarwal, Vikas, Honglin Ren, Ke Shen, and Haibei Zhao, 2022, 1. Redemption in kind and mutual fund liquidity management, Working Paper.

Agarwal, Vikas, and Haibei Zhao, 2019, Interfund lending in mutual fund families: Role in liquidity management, Review of Financial Studies 32, 4079–4115.

Amihud, Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effects, Journal of Financial Markets 5, 31–56.

Aragon, George O., Michael Hertzel, and Zhen Shi, 2013, Why do hedge funds avoid disclosure? Evidence from confidential 13F filings, Journal of Financial and Quantitative Analysis 48, 1499−1518.

Aragon, George O., Spencer Martin, and Zhen Shi, 2019, Who benefits in a crisis? Evidence from hedge fund stock and option holdings, Journal of Financial Economics 131, 345−361.

Aragon, George O. and Vikram Nanda, 2017, Strategic delays and clustering in hedge fund reported returns, Journal of Financial and Quantitative Analysis 52, 1–35.

Asquith, Paul, Parag A. Pathak, and Jay R. Ritter, 2005, Short interest, institutional ownership, and stock returns, Journal of Financial Economics 78, 243–276.

Baker, Malcolm, Jeremy C. Stein, and Jeffrey Wurgler, 2003, When does the market matter? Stock prices and the investment of equity dependent firms, Quarterly Journal of Economics 118, 969–1006.

Baker, Malcolm, and Jeffrey Wurgler, 2012, Behavioral corporate finance: An updated survey, In Handbook of the economics of finance Volume 2, eds. G. M. Constantinides, M. Harris, and R. M. Stulz.

Barbon, Andrea, Margo Di Maggio, Francesco Franzoni, and Augustin Landier, 2019, Brokers and order flow leakage: Evidence from fire sales, Journal of Finance 74, 2707−2749.

Barth, Daniel, Juha Joenvaara, Mikko Kauppila, and Russ Wermers, 2021, The hedge fund industry is bigger (and has performed better) than you think, Working Paper.

Bhattacharya, Utpal, Jung Hoon Lee, and Veronika K. Pool, 2013, Conflicting family values in mutual fund families, Journal of Finance 68, 173–200.

Bond, Philip, Alex Edmans, and Itay Goldstein, 2012, The real effects of financial markets, Annual Review of Financial Economics 4, 339–360.

Brown, Gregory, Philip Howard, and Christian Lundblad, 2021, Crowded trades and tail risk, Review of Financial Studies, forthcoming.

Brunnermeier, Markus K., and Lasse Heje Pedersen, 2005, Predatory trading, Journal of Finance 60, 1825−1863.

Cao, Sean Shun, Kai Du, Baozhong Yang, and Alan L. Zhang, 2021, Copycat skills and disclosure costs: Evidence from peer companies' digital footprints, Journal of Accounting Research 59, 1261−1302.

Carhart, Mark, 1997, On the persistence in mutual fund performance, Journal of Finance 52, 57−82.

Chen, Joseph, Harrison Hong, Ming Huang, and Jeffrey Kubik, 2004, Does fund size erode mutual fund performance? The role of liquidity and organization, American Economic Review 94, 1276−1302.

Chen, Qi, Itay Goldstein, Wei Jiang, 2007, Price informativeness and investment sensitivity to stock price, Review of Financial Studies 20, 619–650.

Chen, Qi, Itay Goldstein, Wei Jiang, 2010, Payoff complementarities and financial fragility: evidence from mutual fund outflows, Journal of Financial Economics 97, 239–262.

Coval, Joshua and Erik Stafford, 2007, Asset fire sales (and purchases) in equity markets, Journal of Financial Economics 86, 479–512.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, Journal of Finance 52, 1035–1058.

Dechow, Patricia M., Amy P. Hutton, Lisa Meulbroek, and Richard G. Sloan, 2001, Short-sellers, fundamental analysis and stock returns, Journal of Financial Economics 61, 77–106.

Dessaint, Olivier, Thierry Foucault, Laurent Frésard, and Adrian Matray, 2019, Noisy stock prices and corporate investment, Review of Financial Studies 32, 2625–2672.

Duarte, Jefferson, Xiaoxia Lou, and Ronnie Sadka, 2006, Can liquidity events explain the low short-interest puzzle? Implications from the options market, Working paper.

Edelman, Daniel, William Fung, and David A. Hsieh, 2013, Exploring uncharted territories of the hedge fund industry: Empirical characteristics of mega hedge fund firms, Journal of Financial Economics 109, 734−758.

Edmans Alex, Itay Goldstein, and Wei Jiang, 2012, The real effects of financial markets: the impact of prices on takeovers, Journal of Finance 67, 933–971.

Fama, Eugene F. and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, Journal of Financial Economics 33, 3–56.

Fung, William, David A. Hsieh, Narayan Y. Naik, and Tarun Ramadorai, 2008, Hedge funds: Performance, risk, and capital formation, Journal of Finance 63, 1777–1803.

Hau, Harald, and Sandy Lai, 2013, Real effects of stock underpricing, Journal of Financial Economics 108, 392−408.

Karpoff, Jonathan M., and Xiaoxia Lou, 2010, Short sellers and financial misconduct, Journal of Finance 65, 1879–1913.

Khan, Mozaffar, Leonid Kogan, and George Serafeim, 2012, Mutual fund trading pressure: firm-level stock price impact and timing of SEOs, Journal of Finance 67, 1371–1395.

Khandani, Amir E., and Andrew W. Lo, 2011, What happened to the quants in August 2007? Evidence from factors and transactions data, Journal of Financial Markets 14, 1−46.

Pollet, Joshua M., and Mungo Wilson, 2008, How does size affect mutual fund behavior? Journal of Finance 63, 2941–2969.

Shi, Zhen, 2017, The impact of portfolio disclosure on fund performance, Journal of Financial Economics 126, 36−53.

Shive, Sophie, and Hayong Yun, 2013, Are mutual funds sitting ducks? Journal of Financial Economics 107, 220−237.

Sias, Richard, Harry J. Turtle, and Blerina Zykaj, 2016, Hedge fund crowds and mispricing, Management Science 62, 764−784.

Stein, Jeremy C., 2009, Sophisticated investors and market efficiency, Journal of Finance 64, 1517−1548.

Teo, Melvyn, 2009, Does size matter in the hedge fund industry? Working Paper.

Wermers, Russ, 2001, The potential effects of more frequent portfolio disclosure on mutual fund performance. Investment Company Institute Perspective 7.

Yan, Xuemin (Sterling), 2008, Liquidity, investment style, and the relation between fund size and fund performance, Journal of Financial and Quantitative Analysis 43, 741−767.

Figure 1: Flow Patterns of Distressed and Other Hedge Funds

This figure compares quarterly flows across distressed MHFs (*MHFs_distressed*), non-distressed MHFs (*MHFs_others*), non-MHFs that are financially distressed (*OHFs_distressed*), and non-MHFs that are not financially distressed (*OHFs_others*) during the period of Qtr *q*-1 to Qtr *q*+4 (−1 to 4 in the figure below), where Qtr *q* denotes the quarter financial distress is identified.

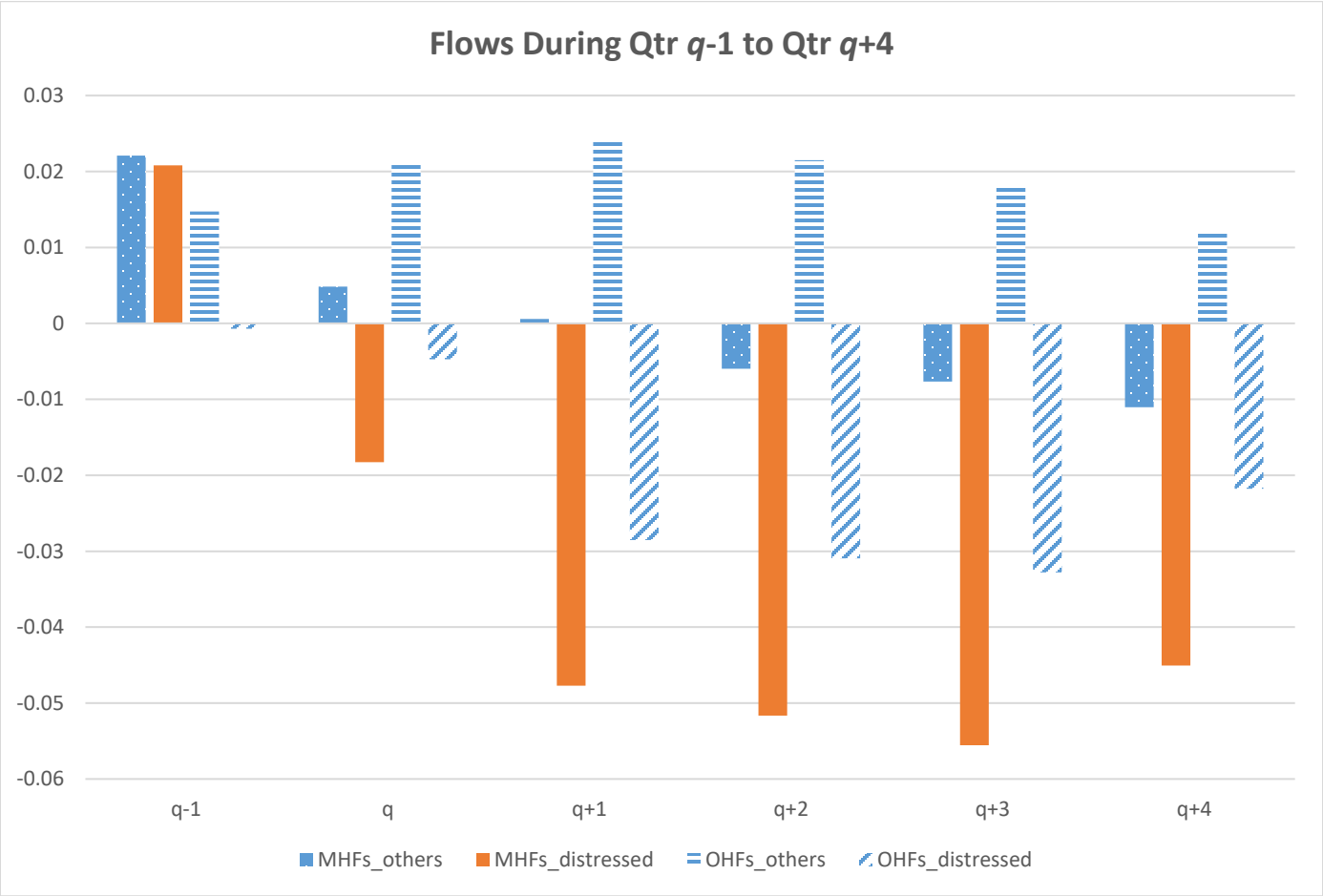

Figure 2: Timeline of Anticipatory Trading Activities

This figure shows the timeline of trading by institutional investors after portfolio disclosure of mega hedge funds (MHFs) and before their distressed trading.

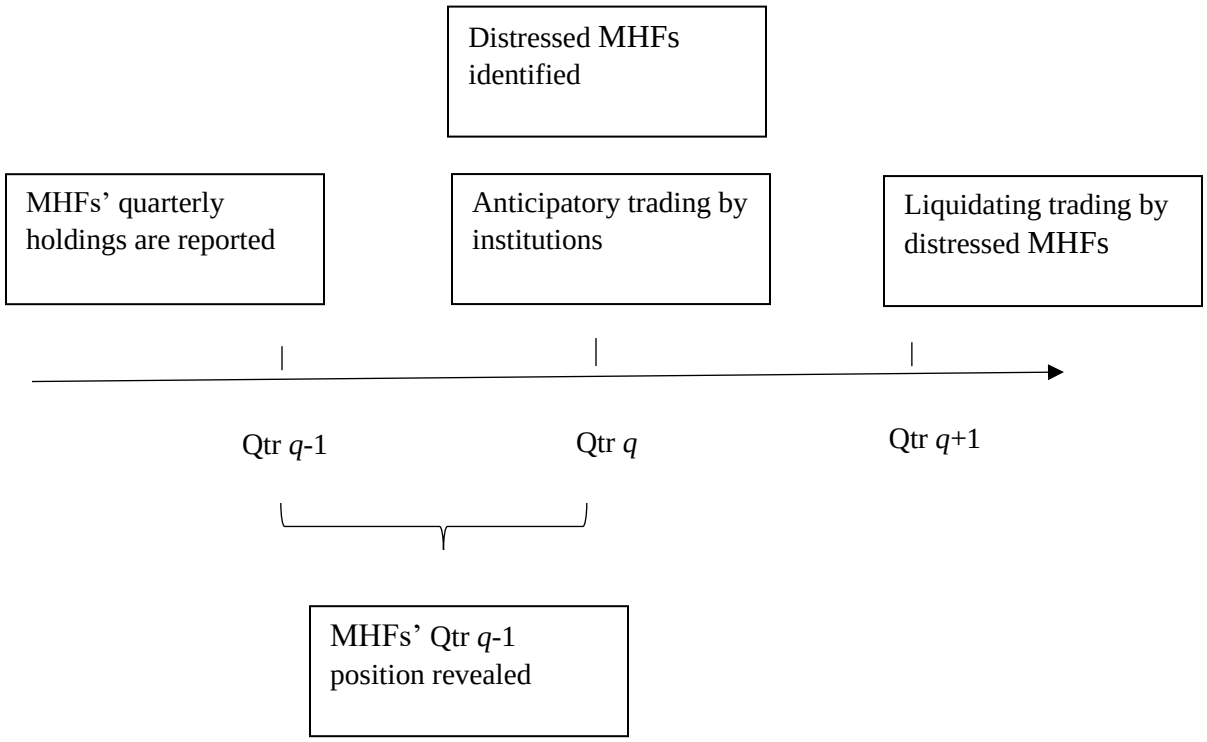

Table 1: Summary Statistics

This table provides summary statistics for our sample of 13F institutions and subsamples of mutual funds and hedge funds. Panel A provides the number of institutions in each subcategory along with summary statistics on their equity portfolio value. Mega hedge funds (MHFs) are those funds with assets under management (AUM) over $1 billion. The rest of the hedge funds are classified as non-mega hedge funds. Distressed hedge funds have returns ranked in the lowest quartile during the quarter and returns below 0. Mutual funds are those extracted from Thomson Reuters mutual fund holding data. Panel B provides descriptive statistics on our sample hedge funds that report to commercial databases. *Mega* is a dummy variable indicating MHFs. *Distress* is a dummy variable indicating distressed hedge funds. *Equity Value* is the sum of dollar equity holdings of a fund. *AUM* and *Fund Return* are quarter-end assets under management in $ millions and quarterly fund returns. *Abnormal returns* are measured as style-adjusted fund returns. *Quarterly flow* is the quarterly change of AUM adjusted for fund returns. *Fund Age* is the number of years since inception. *Return Volatility* is the standard deviation of monthly fund returns in the past 12-month period. *Lockup Fund* is a binary variable indicating whether a fund has a lockup provision. *Restriction Period* is the sum of redemption and notice periods. *Incentive Fees* and *Management Fees* are annual incentive and management fees in percent. Panel C reports descriptive statistics on our sample mutual funds. *Equity Value*, *AUM*, *Fund Return*, *Quarterly Flows*, *Fund Age*, and *Return Volatility* are defined similarly as in Panel B for hedge funds. *Abnormal Return* is computed as the Carhart (1997) 4-factor alpha. *Flow Volatility* is standard deviation of monthly flows during the past 36-month period.

Panel A: Summary statistics of long equity holdings for 13F institutions

Institutions	No. of Obs	No. of Institutions	Mean	Median	P25	P75	Std Dev
Distressed MHFs	733	178	6,592	1,019	293	3,451	27,394
Non-distressed MHFs	3,768	210	10,443	998	326	2,851	54,254
Non-mega hedge funds	13,570	629	1,394	287	129	761	6,187
Mutual funds	250,567	7,503	807	102	21	447	3,452
Independent Inv. Advisors	121,379	3,268	2,411	323	142	1,080	11,759
Banks	19,573	528	12,804	438	167	1,719	64,866
Insurance Companies	7,191	175	6,433	1,097	268	3,849	22,385
Pension funds	3,336	74	11,363	4,879	733	16,349	15,140
Investment Banks	5,452	189	7,255	369	137	1,699	26,266

Panel B: Summary statistics for hedge funds

Variable	**Mean**	**Median**	**P25**	**P75**	**Std Dev**
Mega	0.2491	0	0	0	0.4325
Distress	0.1987	0	0	0	0.3990
Equity Value	3492	368	146	1190	26202
AUM	1349	300	102	1002	4761
Fund Return	0.0188	0.0187	−0.0104	0.0491	0.0777
Abnormal Return	0.0014	−0.0001	−0.0264	0.0264	0.0658
Quarterly Flow	0.0704	0.0001	−0.0477	0.0519	1.7989
Fund Age	10	9	5	14	7
Return Volatility	0.0526	0.0465	0.0339	0.0638	0.0273
Lockup Fund	0.5555	1	0	1	0.4969
Restriction Period	143	120	83	155	107
Incentive Fees (%)	18.37	20.00	20.00	20.00	4.71
Management Fees (%)	1.46	1.49	1.00	1.56	2.72

Panel C: Summary statistics for mutual funds

Variable	**Mean**	**Median**	**P25**	**P75**	**Std Dev**
Equity Value	807	102	21	447	3452
AUM	1328	201	52	792	5440
Fund Return	0.0207	0.0298	−0.0234	0.0761	0.0998
Abnormal Return	−0.0008	−0.0008	−0.0026	0.0010	0.0039
Quarterly Flow	0.0585	−0.0110	−0.0418	0.0337	3.7343
Fund Age	13	10	5	17	13
Return Volatility	0.0137	0.0116	0.0085	0.0164	0.0087
Flow Volatility	0.0458	0.0295	0.0153	0.0549	0.0468

Table 2: Predicting Trades by Hedge Funds

This table presents the results from regressions of aggregate hedge fund trading (columns 2 and 4) of a stock on stock characteristics. The model is estimated separately for mega hedge funds (MHFs) and non-MHFs. The dependent variable is a dummy variable indicating aggregate selling (columns 1 and 3) or the aggregate hedge fund dollar trades (columns 2 and 4) of a stock (standardized by the stock's market capitalization) in quarter q+1. The independent variables include one-quarter lagged hedge fund ownership of the stock measured by the total dollar holdings of the stock by all hedge funds in the group (MHFs or non-MHFs) standardized by the stock's market capitalization (*Ownership*), quarterly returns, cumulative returns in the four-quarter period ending as of the current quarter, the logarithm of the stock's market capitalization, book-to-market (BM) ratio, Amihud's (2002) illiquidity measure (*Amihud*), and aggregate trades on the stock by hedge funds in the group in quarter q-1 (*Lagged Trade*). All independent variables are measured as of quarter q-1. t-statistics computed with standard errors clustered by stock and quarter are reported in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Mega Hedge Funds		**Non-Mega Hedge Funds**	
VARIABLES	Sell (q+1)	Trade (q+1)	Sell (q+1)	Trade (q+1)
Ownership	0.7025***	−0.0369***	0.5504***	−0.0446***
	(6.42)	(−12.45)	(7.41)	(−14.36)
Return (q-1)	−0.0734***	0.0030*	−0.0096	0.0002
	(−4.18)	(1.87)	(−0.86)	(0.96)
Return (q-4, q-1)	0.0250***	−0.0007*	0.0091***	−0.0003***
	(4.81)	(−1.68)	(2.87)	(−5.59)
Log (Size)	0.0218***	−0.0000	0.0204***	0.0001***
	(8.31)	(−1.10)	(10.91)	(8.68)
BM Ratio	−0.0007	0.0001	−0.0089**	0.0002***
	(−0.16)	(0.59)	(−2.17)	(3.05)
Amihud	−0.0073***	−0.0000	−0.0286***	0.0002***
	(−6.10)	(−0.69)	(−19.54)	(8.57)
Lagged Trade	−0.0038	−0.0199***	0.0079	−0.0372***
	(−0.03)	(−4.48)	(0.06)	(−7.98)
Constant	0.3574***	0.0008***	0.4598***	−0.0020***
	(17.43)	(2.99)	(31.47)	(−13.19)
Observations	267,532	267,532	287,211	287,211
Adj. R-square	0.0164	0.0228	0.0144	0.0336

Table 3: Institutional Anticipatory Trading of Stocks Held by Distressed MHFs

This table presents the results of regressing individual institutions' trading (in basis points, bps) of stocks in quarter *q* on the predicted quarter *q*+1 distressed mega hedge fund (MHF) trading (*Ptrade*) of the stocks held by them in quarter *q*-1. *Ptrade* is the projected quarter *q*+1 trading of stocks that were held by distressed MHFs in quarter *q*-1 (in bps). MHFs are classified as distressed based on their performance in quarter *q*. *Pbuy* is max(*Ptrade*, 0) and *Psell* is min(*Ptrade*, 0). Control variables include one-quarter lagged Log (Equity) defined as the logarithm of the sum of dollar equity holdings of an institution, quarterly returns, cumulative returns in the four-quarter period ending as of the current quarter, the logarithm of the stock's market capitalization, book-to-market (BM) ratio, Amihud's (2002) illiquidity measure (*Amihud*) and one-quarter lagged trading of the stock by the institution (*Lagged Trade*). The analyses are conducted for all 13f institutions (Panel A) and separately for each institution type (Panel B). Panel A also presents the difference in *Pbuy* and *Psell* along with its statistical significance based on *F*-test. All regressions include fund and quarter fixed effects. *t*-statistics computed with standard errors clustered by fund and quarter are reported in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A: All Institutions

Dep. Variable	Trade	Trade
Ptrade	0.0021**	
	(2.58)	
Pbuy		−0.0010
		(−1.21)
Psell		0.0033***
		(4.31)
Log (Equity)	−0.3538***	−0.3538***
	(−5.11)	(−5.11)
Return (*q*-1)	0.4075***	0.4399***
	(3.49)	(3.86)
Return (*q*-4, *q*-1)	0.0534	0.0495
	(1.44)	(1.35)
Log (Size)	0.2887***	0.2890***
	(16.99)	(16.94)
BM Ratio	0.0407	0.0418*
	(1.64)	(1.71)
Amihud	−0.0240	−0.0261
	(−0.45)	(−0.49)
Lagged Trade	0.0068	0.0068
	(0.47)	(0.48)
Observations	26,968,867	26,968,867
Adj. R-square	0.0176	0.0176
F-Test (Psell - Pbuy)	0.0043***	

Panel B: By Institution Types

	Non-Distressed MHFs	Non-MHFs	Mutual Funds	Independent Inv. Advisors	Banks	Insurance Co.	Pension Funds	Investment Banks
Dep. Variable	Trade	Trade	Trade	Trade	Trade	Trade	Trade	Trade
Ptrade	0.0457***	0.0045*	0.0008**	0.0017***	−0.0017	0.0013*	0.0005	0.0017
	(2.81)	(1.77)	(2.08)	(2.90)	(−1.59)	(1.85)	(0.77)	(1.06)
Log (Equity)	−0.0207	−1.1346***	−0.4269***	−0.3172***	−0.2048	−0.0179	−0.2759**	−0.7427*
	(−0.04)	(−7.11)	(−17.16)	(−7.91)	(−0.32)	(−0.33)	(−2.19)	(−1.94)
Return (*q*-1)	1.3938	0.8567	0.0613	0.1793	1.0796***	0.8886**	0.3900***	0.9041*
	(0.69)	(1.40)	(1.11)	(0.96)	(3.22)	(2.31)	(3.24)	(1.88)
Return (*q*-4, *q*-1)	0.6499**	−0.1479	0.0252	−0.1083	0.4303***	0.0165	0.0912	0.2112**
	(2.06)	(−0.99)	(1.37)	(−1.56)	(3.07)	(0.25)	(1.66)	(2.27)
Log (Size)	0.3683	1.0881***	0.2973***	0.3464***	0.0932***	0.1326***	0.0811**	0.1766***
	(1.40)	(12.13)	(20.22)	(16.09)	(3.59)	(4.47)	(2.33)	(3.93)
BM Ratio	−0.4404	−0.0043	0.0214	0.0994**	−0.0248	0.0622	0.0359	0.0156
	(−1.51)	(−0.05)	(1.24)	(2.57)	(−0.58)	(1.16)	(1.06)	(0.20)
Amihud	−0.2541	0.4071**	0.1205***	−0.0589	−0.2342***	−0.2634	0.1022***	0.0415
	(−0.95)	(2.15)	(6.91)	(−0.54)	(−2.73)	(−1.07)	(3.41)	(0.27)
Lagged Trade	0.0101	−0.0456**	0.0460***	0.0548***	−0.0148	−0.0015	−0.0106	−0.1164***
	(0.17)	(−2.46)	(6.12)	(3.59)	(−0.47)	(−0.06)	(−1.13)	(−3.22)
Observations	523,130	736,584	9,129,836	9,733,881	3,378,918	1,208,229	1,182,909	1,075,378
Adj. R-square	0.0147	0.0347	0.0483	0.0244	0.0080	0.0082	0.0099	0.0272

Table 4: Falsification Test #1: Institutions' Anticipatory Trading of Stocks Held by Distressed Non-MHFs (Small)

This table presents the results from a falsification test involving regressions of institutions' trading (in bps) in quarter *q* on the predicted quarter *q*+1 trading (*Ptrade*) of the stocks held in quarter *q*-1 by distressed non-MHFs with below-median AUM, excluding stocks that are also held by distressed MHFs in quarter *q*-1. *Ptrade* is the projected quarter *q*+1 trading of stocks that were held by distressed non-MHFs with below-median AUM in quarter *q*-1 (in bps). Non-MHFs are classified as distressed based on their performance in quarter *q*. Control variables include one-quarter lagged Log (Equity) defined as the logarithm of the sum of dollar equity holdings of an institutions, quarterly returns, cumulative returns in the four-quarter period ending as of the current quarter, the logarithm of the stock's market capitalization, book-to-market (BM) ratio, Amihud's (2002) illiquidity measure (*Amihud*) and one-quarter lagged trading of the stock by the institution (*Lagged Trade*). The analyses are conducted separately for each institution type. All regressions include fund and quarter fixed effects. *t*-statistics computed with standard errors clustered by fund and quarter are reported in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Non-Distressed Non-Mega Hedge Funds (Small)	**Non-Mega Hedge Funds (Large)**	**Mutual Funds**	**Independent Inv. Advisors**	**Banks**	**Insurance Cos.**	**Pension Funds**	**Inv. Banks**
Dep. Variable	Trade	Trade	Trade	Trade	Trade	Trade	Trade	Trade
Ptrade	−0.0093	0.0962	0.0017	−0.0326	0.0006	−0.0187	−0.0128	−0.0356
	(−0.09)	(1.45)	(0.12)	(−1.34)	(0.04)	(−0.59)	(−1.13)	(−1.22)
Log (Equity)	−4.4031*	−13.9407***	−2.3029***	−0.5750	−1.3063*	−0.5144	0.5041	−2.4452**
	(−1.80)	(−3.88)	(−2.88)	(−1.46)	(−1.88)	(−0.85)	(0.39)	(−1.99)
Return (*q*-1)	−1.3548	−3.4492	−0.8448	1.7423	1.7772**	1.2538	1.6019**	1.0022
	(−0.33)	(−1.18)	(−1.19)	(1.61)	(2.32)	(0.80)	(2.37)	(0.93)
Return (*q*-4, *q*-1)	−0.9692	0.0423	−0.1683	−0.0385	0.5997**	0.0276	0.0068	0.3309
	(−1.02)	(0.03)	(−0.69)	(−0.11)	(2.25)	(0.08)	(0.03)	(1.36)
Log (Size)	0.3931	2.2399***	1.2776***	0.6221***	0.2641	0.5380***	−0.1911	0.3259***
	(0.90)	(2.90)	(3.38)	(4.79)	(1.66)	(2.66)	(−0.50)	(2.65)
BM Ratio	−1.8252	−2.9702	−0.8624*	0.6217	0.2575	−0.4414	−1.0587*	−0.0605
	(−1.09)	(−1.16)	(−1.82)	(1.13)	(0.59)	(−0.81)	(−1.89)	(−0.10)
Amihud	−6.3016	−3.0194	0.2259	−0.3067	−3.0015***	−3.8295	2.0834	−2.0470**
	(−0.84)	(−0.68)	(0.25)	(−0.16)	(−3.43)	(−1.54)	(0.59)	(−2.11)
Lagged Trade	−0.0403	0.1533***	0.2991**	0.1661***	0.1944**	0.0437	0.0724***	0.2340***
	(−0.97)	(3.77)	(2.02)	(5.18)	(2.18)	(1.17)	(3.07)	(3.50)
Observations	7,112	7,676	74,347	206,926	158,598	51,661	26,333	32,892
Adj. R-square	0.0326	0.0559	0.146	0.0597	0.0426	0.0171	0.0238	0.113

Table 5: Falsification Test #2: Institutions' Anticipatory Trading of Stocks Held by Well-Performing MHFs

This table presents the results from a falsification test involving regressions of institutions' trading (in bps) in quarter *q* on the predicted quarter *q*+1 trading *(Ptrade*) of the stocks held in quarter *q*-1 by well-performing mega hedge funds (MHFs), excluding stocks that are also held by distressed MHFs in quarter *q*-1. Well-performing MHFs are MHFs with performance ranked in the top quartile during quarter *q*. *Ptrade* is the projected quarter *q*+1 trading of stocks that were held by well-performing MHFs in quarter *q*-1 (in bps). Control variables include one-quarter lagged Log (Equity) defined as the logarithm of the sum of dollar equity holdings of an institution, quarterly returns, cumulative returns in the four-quarter period ending as of the current quarter, the logarithm of the stock's market capitalization, book-to-market (BM) ratio, Amihud's (2002) illiquidity measure (*Amihud*) and one-quarter lagged trading of the stock by the institution (*Lagged Trade*). The analyses are conducted separately for each institution type. All regressions include fund and quarter fixed effects. *t*-statistics computed with standard errors clustered by fund and quarter are reported in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Non-Mega Hedge Funds	**Mutual Funds**	**Independent Inv. Advisors**	**Banks**	**Insurance Cos.**	**Pension Funds**	**Inv. Banks**
Dep. Variable	Trade	Trade	Trade	Trade	Trade	Trade	Trade
Ptrade	0.0380	−0.0015	−0.0195*	−0.0077	0.0058	−0.0108	−0.0074
	(1.09)	(−0.38)	(−1.73)	(−0.95)	(0.71)	(−0.76)	(−1.13)
Log (Equity)	−1.5552	−0.6577**	−0.1005	−0.0693	0.1006	−0.1557	−0.4557
	(−0.82)	(−2.49)	(−0.40)	(−0.22)	(0.26)	(−0.11)	(−1.12)
Return (*q*-1)	4.5739*	0.2232	0.6574	2.8351***	2.0006***	0.4235	2.0872*
	(1.82)	(0.69)	(1.17)	(2.64)	(3.32)	(0.78)	(1.82)
Return (*q*-4, *q*-1)	−1.2055*	0.0250	−0.2312	0.4820**	0.0553	−0.0030	0.2718*
	(−1.92)	(0.25)	(−1.00)	(2.07)	(0.18)	(−0.01)	(1.67)
Log (Size)	1.8420***	0.3965***	0.4323***	0.3527**	0.3753**	0.1861	0.6675***
	(3.15)	(4.21)	(3.92)	(2.28)	(2.27)	(0.64)	(3.66)
BM Ratio	−0.1781	−0.3385**	−0.0365	−0.2772	−0.4245	0.0760	−0.0920
	(−0.19)	(−2.25)	(−0.12)	(−0.74)	(−0.67)	(0.38)	(−0.29)
Amihud	1.4530	0.1364	0.0641	−0.3469***	0.9467	−0.0561	−0.0773
	(1.12)	(1.52)	(0.30)	(−3.04)	(0.77)	(−0.44)	(−0.55)
Lagged Trade	0.1282**	0.1408***	0.1483***	0.1422***	0.1047***	0.2135**	0.1034**
	(2.18)	(9.56)	(5.71)	(5.53)	(4.01)	(2.54)	(2.19)
Observations	29,703	240,983	345,856	203,565	66,035	56,299	61,629
Adj. R-square	0.0406	0.0726	0.0492	0.0374	0.0248	0.0568	0.0157

Table 6: Anticipatory Trading and Stock Characteristics

This table presents the results of analyzing mutual funds' and hedge funds' trading (in bps) of stocks in quarter *q* on the predicted quarter *q*+1 distressed mega hedge fund (MHF) trading (*Ptrade*) of the stocks held by them in quarter *q*-1. *Ptrade* is the projected quarter *q*+1 trading of stocks that were held by distressed MHFs in quarter *q*-1 (in bps). MHFs are classified as distressed based on their performance in quarter *q*. Panel A compares anticipatory trading by hedge funds versus mutual funds and provides the difference in the coefficients of *Ptrade* along with its statistical significance based on χ^2 test at the bottom of the panel. Panel B analyzes the effect of stock characteristics on anticipatory trading of mutual funds by augmenting the baseline specification with an interaction term between *Ptrade* and *Rank*. *Rank* is an indicator variable denoting above-median market capitalization, an indicator variable denoting above-median Amihud's (2002) illiquidity measure, indicator variables denoting top quartile ownership by distressed MHFs with top quartile lockup and restriction periods, respectively, an indicator variable denoting above-median ownership by distressed MHFs with high leverage, or an indicator variable denoting top quartile portfolio weight of a stock in the fund (*Position*). Hedge fund leverage is defined as a fund's total equity portfolio value from 13F divided by AUM reported from hedge fund databases. Panel C conducts similar analyses using the sample of hedge funds. Control variables (not tabulated in Panels B and C) include a fund's one-quarter lagged abnormal returns (four-factor alpha for mutual funds and style adjusted returns for hedge funds), the logarithm of a fund's AUM, quarterly flows, quarterly returns, cumulative returns in the four-quarter period ending as of the current quarter, the logarithm of the stock's market capitalization, book-to-market (BM) ratio, Amihud's (2002) illiquidity measure (*Amihud*), and one-quarter lagged trading of the stock by the institution (*Lagged Trade*). All regressions include quarter fixed effects. *t*-statistics computed with standard errors clustered by fund and quarter are reported in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A: Mutual funds versus hedge funds

	Mutual Funds	**Hedge Funds**
Dep. Variable	Trade	Trade
Ptrade	0.0025***	0.0262***
	(3.78)	(3.68)
Fund Abret	50.7368***	3.6208*
	(6.54)	(1.97)
Log (AUM)	−0.3211***	0.3150**
	(−16.47)	(2.34)
Flow	4.3568***	1.2544***
	(16.66)	(2.91)
Return (*q*-1)	0.0364	0.9547
	(0.40)	(1.04)
Return (*q*-4, *q*-1)	−0.0741**	-0.1367
	(−2.42)	(-0.75)
Log (Size)	0.3124***	0.6718***
	(14.28)	(5.01)
BM Ratio	0.1887***	-0.0576
	(6.08)	(-0.42)
Amihud	0.2581***	0.4549**
	(7.62)	(2.23)
Lagged Trade	0.0287***	-0.0247
	(3.19)	(-0.76)
Observations	6,041,837	1,274,965
Adj. R-square	0.0181	0.0057
χ^2 test (HF-MF)	0.0237***	

Panel B: Anticipatory trading by mutual funds and stock characteristics

Rank	Size	Amihud	Lockup	Restriction	Leverage	Position
VARIABLES	Trade	Trade	Trade	Trade	Trade	Trade
Ptrade	0.0064***	0.0014**	0.0026***	0.0027***	0.0014**	0.0023***
	(5.66)	(2.31)	(3.71)	(3.73)	(2.29)	(3.27)
Ptrade×Rank	−0.0049***	0.0041***	−0.0016**	−0.0019**	0.0017**	0.0016**
	(−4.43)	(4.02)	(−2.15)	(−2.47)	(2.29)	(2.53)
Rank	−0.0731	0.2889***	−0.0835***	−0.0664***	0.0520*	−1.1448***
	(−1.17)	(5.34)	(−3.84)	(−2.76)	(1.80)	(−26.86)
Other controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,041,837	6,041,837	6,041,837	6,041,837	6,041,837	6,034,235
Adj. R-square	0.0182	0.0183	0.0182	0.0181	0.0182	0.0243

Panel C: Anticipatory trading by hedge funds and stock characteristics

Rank	Size	Amihud	Lockup	Restriction	Leverage	Position
Dep. Variable	Trade	Trade	Trade	Trade	Trade	Trade
Ptrade	0.0428***	0.0205***	0.0271***	0.0274***	0.0190***	0.0184**
	(4.18)	(3.27)	(3.58)	(3.63)	(3.41)	(2.63)
Ptrade×Rank	−0.0242***	0.0171**	−0.0125**	−0.0130**	0.0103*	0.0157**
	(−3.01)	(2.00)	(−2.45)	(−2.19)	(1.85)	(2.02)
Rank	0.0045	0.6935**	−0.3469**	−0.1444	0.1976	−5.7680***
	(0.01)	(2.06)	(−2.30)	(−0.82)	(0.94)	(−16.12)
Other controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,274,965	1,274,965	1,274,965	1,274,965	1,274,965	1,274,699
Adj. R-square	0.00584	0.00579	0.00570	0.00570	0.00571	0.0147

Table 7: Anticipatory Trading and Fund Characteristics

This table presents the results from examining the effect of fund characteristics on mutual fund and hedge fund anticipatory trading (in bps) of the stocks held by distressed mega hedge funds (MHFs) in quarter *q*-1. Panel A examines mutual fund trading while Panel B examines hedge fund trading. *Ptrade* is the projected quarter *q*+1 trading of stocks that were held by distressed MHFs in quarter *q*-1 (in bps). MHFs are classified as distressed based on their performance in quarter *q*. In Panel A, *Rank* represents indicator variables denoting above-median fund AUM, flow volatility computed using monthly flows during the past 36-month period, number of funds in the family, return volatility during the past 12-month period, and fund turnover. In Panel B, *Rank* represents indicator variables denoting above-median AUM, the length of the lockup period, the total length of redemption and notification periods, return volatility during the past 12-month period, turnover (computed as the sum of total dollar purchase and sale divided by the mean of prior- and current-quarter dollar holdings), and leverage. Control variables (not tabulated) include a fund's one-quarter lagged abnormal returns (four-factor alpha for mutual funds and style-adjusted returns for hedge funds), the logarithm of a fund's AUM, quarterly flows, quarterly returns, cumulative returns in the four-quarter period ending as of the current quarter, the logarithm of the stock's market capitalization, book-to-market (BM) ratio, Amihud's (2002) illiquidity measure (*Amihud*), and one-quarter lagged trading of the stock by the institution (*Lagged Trade*). All regressions include quarter fixed effects. *t*-statistics computed with standard errors clustered by fund and quarter are reported in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A: Mutual funds

Rank	**AUM**	**Flow Vol**	**Family Funds**	**Return Vol**	**Turnover**
Dep Variable	Trade	Trade	Trade	Trade	Trade
Ptrade	−0.0000	0.0033***	0.0012*	0.0015*	0.0004
	(−0.03)	(3.69)	(1.92)	(1.70)	(0.73)
Ptrade×Rank	0.0040**	−0.0010*	0.0021**	0.0024**	0.0028**
	(2.27)	(−1.75)	(2.57)	(2.02)	(2.54)
Rank	0.1486*	−0.0075	0.1431**	−0.4730***	−0.5002***
	(1.75)	(−0.14)	(2.25)	(−5.66)	(−8.18)
Other controls?	Yes	Yes	Yes	Yes	Yes
Observations	6,041,837	4,575,393	4,603,935	5,905,547	5,715,759
Adj. R-square	0.0182	0.0209	0.0208	0.0186	0.0205

Panel B: Hedge funds

	AUM	**Lockup**	**Restriction**	**Return Vol**	**Turnover**	**Leverage**
Dep Variable	Trade	Trade	Trade	Trade	Trade	Trade
Ptrade	0.0106**	0.0206***	0.0255***	0.0279***	0.0301***	0.0293***
	(2.40)	(3.44)	(4.02)	(3.83)	(3.36)	(4.47)
Ptrade×Rank	0.0229***	0.0109*	−0.0025	−0.0050	−0.0096	−0.0054
	(3.09)	(1.98)	(−0.35)	(−0.65)	(−1.26)	(−0.81)
Rank	−1.2560**	−1.3469***	−1.5144***	−1.7701***	−1.5566***	0.9887***
	(−2.03)	(−4.20)	(−2.88)	(−5.09)	(−3.44)	(3.16)
Other controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,274,965	1,257,254	1,253,720	1,175,269	1,274,015	1,274,699
Adj. R-square	0.0061	0.0069	0.0069	0.0061	0.0065	0.0060

Table 8: Anticipatory Trading and Hedge Fund Performance

This table reports the results from regressions of mega hedge funds' (MHFs') long-equity portfolio performance during quarter q+1 or quarters q+1 through q+4 on their front-running β measured as of quarter q. The dependent variables are hedge fund performance measured as raw returns and Daniel et al. (1997) characteristics-adjusted returns (DGTW) of the fund's long-equity portfolio. The independent variables include front-running β and its interaction term with an indicator variable denoting distressed MHFs. We regress aggregate mutual fund and hedge fund trading on the anticipated trades of stocks held by each MHF to estimate individual MHFs' front-running βs in each quarter. One quarter lagged control variables include the logarithm of a fund's long-equity portfolio value, the logarithm of a fund's AUM, raw fund returns (*Portfolio Ret*) or DGTW abnormal returns (*Portfolio Abret*), a dummy variable indicating funds with lockup provision, the logarithm of one plus the restriction period, incentive fees, management fees and the logarithm of one plus fund age. *t*-statistics computed with standard errors clustered by fund are reported in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Qtr q+1		**Qtr (q+1, q+4)**	
Dep Variable	**Raw**	**DGTW**	**Raw**	**DGTW**
HF β	0.0002	0.0000	0.0001	0.0000
	(0.88)	(0.22)	(0.39)	(0.27)
HF β × Distress	−0.0010**	−0.0004**	−0.0025**	−0.0011***
	(−2.06)	(−2.06)	(−2.52)	(−2.73)
Distress	0.0011	0.0012	0.0029	0.0128*
	(0.13)	(0.39)	(0.16)	(1.66)
Log (Portfolio)	0.0012	0.0006	−0.0035	0.0005
	(0.63)	(0.55)	(−0.42)	(0.13)
Log (AUM)	−0.0145***	−0.0023	−0.0614***	−0.0137**
	(−4.09)	(−1.50)	(−3.57)	(−2.50)
Portfolio Ret	0.2361***		0.0204	
	(6.98)		(0.33)	
Portfolio Abret		0.0482		0.1134
		(1.16)		(1.03)
With Lockup	0.0061	0.0001	0.0053	−0.0025
	(0.92)	(0.04)	(0.23)	(−0.25)
Restriction	−0.0016	−0.0001	−0.0070	0.0008
	(−0.54)	(−0.08)	(−0.68)	(0.20)
Incentive Fee	−0.0000	0.0002	0.0008	0.0004
	(−0.00)	(0.68)	(0.35)	(0.45)
Management Fee	0.0111*	0.0009	0.0466**	0.0089
	(1.87)	(0.35)	(2.29)	(1.27)
Log (Age)	0.0027	−0.0013	0.0049	−0.0070
	(0.39)	(−0.43)	(0.23)	(−0.64)
Constant	0.1012***	0.0135	0.5339***	0.1056*
	(3.36)	(0.89)	(3.87)	(1.92)
Observations	1,276	1,276	1,194	1,194
Adj. R-square	0.0491	0.000478	0.0303	0.0170

Table 9: Short Interest in Stocks Held by Distressed Mega Hedge Funds

This table examines the relation between change in abnormal short interest relative to the prior quarter during each quarter from quarter *q* through *q+4* and the predicted quarter *q*+1 trading of the stocks held in quarter *q*-1 by distressed mega hedge funds (*Ptrade*). Abnormal short interest (*ABSI*) is estimated according to *ABSI (1)* of Karpoff and Lou (2010). *Lagged Market Ret* denotes market return in the prior quarter. *t*-statistics computed with standard errors clustered by stock are reported in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

Dep. Variable	ΔABSI(*q*)	ΔABSI(*q*+1)	ΔABSI(*q*+2)	ΔABSI(*q*+3)	ΔABSI(*q*+4)
Ptrade	−0.0725**	0.0480*	−0.0137	0.0768**	0.1011***
	(−2.73)	(1.92)	(−0.46)	(2.76)	(3.55)
Lagged Market Ret	−0.0031***	−0.0010	−0.0024***	−0.0028***	−0.0015
	(−3.86)	(−1.03)	(−2.91)	(−3.37)	(−1.62)
Constant	0.0002***	0.0001*	−0.0003***	−0.0004***	0.0000
	(3.32)	(1.85)	(−4.40)	(−5.39)	(0.42)
Observations	95,670	95,644	94,804	91,605	88,079
Adj. R-square	0.0003	0.0000	0.0001	0.0002	0.0001

Table 10: Returns of Stocks Expected to be Sold by Distressed MHFs

This table presents the results of quarterly Carhart (1997) four-factor regressions of stocks held by distressed mega hedge funds (MHFs) in quarter *q*-1 but are expected to be sold in quarter *q*+1 during each of the 6 quarters starting from quarter *q*. Quarterly value-weighted portfolios of stocks are formed with the weight being the percentage of shares outstanding held by these funds in quarter *q*-1. Panel A reports the results from analysis of all stocks. We separately report results for stocks with larger versus small ownership by distressed MHFs (Panels B and C) and stocks subject to strong versus weak anticipatory trading by mutual funds and hedge funds (Panels D and E). *t*-statistics are reported in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A: Baseline analysis

Qtr	Qtr 0	Qtr 1	Qtr 2	Qtr 3	Qtr 4	Qtr 5
Intercept$_t$	−0.0166***	−0.0042	0.0026	0.0039	0.0141***	0.0025
	(−2.90)	(−0.74)	(0.38)	(0.65)	(2.89)	(0.41)
(MKT-RF)$_t$	1.0238***	1.1490***	1.1321***	1.1604***	0.9313***	0.9195***
	(13.66)	(16.14)	(12.10)	(14.51)	(15.29)	(11.02)
SMB$_t$	0.9936***	0.6541***	0.7537***	0.6944***	0.9540***	0.7605***
	(7.61)	(5.11)	(4.93)	(4.85)	(8.57)	(5.09)
HML$_t$	−0.0702	−0.0154	0.0653	0.2280**	0.1030	0.0826
	(−0.76)	(−0.16)	(0.61)	(2.33)	(1.26)	(0.85)
MOM$_t$	−0.2944***	−0.2354***	−0.2908***	−0.2808***	−0.2850***	−0.2828***
	(−4.03)	(−3.54)	(−3.37)	(−3.85)	(−5.02)	(−3.89)

Panel B: Large holdings by distressed MHFs

Qtr	Qtr 0	Qtr 1	Qtr 2	Qtr 3	Qtr 4	Qtr 5
Intercept$_t$	−0.0173**	−0.0042	0.0030	0.0030	0.0148***	0.0023
	(−2.64)	(−0.73)	(0.40)	(0.45)	(2.81)	(0.37)
(MKT-RF)$_t$	0.9758***	1.1517***	1.1244***	1.1797***	0.9377***	0.8885***
	(11.37)	(15.66)	(11.04)	(13.55)	(14.28)	(10.17)
SMB$_t$	1.0431***	0.6603***	0.7683***	0.6546***	0.9812***	0.8271***
	(6.97)	(4.99)	(4.61)	(4.20)	(8.17)	(5.29)
HML$_t$	−0.0213	−0.0116	0.0847	0.2648**	0.1224	0.0999
	(−0.20)	(−0.12)	(0.73)	(2.49)	(1.38)	(0.98)
MOM$_t$	−0.3182***	−0.2375***	−0.2759***	−0.2551***	−0.2699***	−0.2697***
	(−3.80)	(−3.46)	(−2.94)	(−3.21)	(−4.41)	(−3.55)

Panel C: Small holdings by distressed MHFs

Qtr	Qtr 0	Qtr 1	Qtr 2	Qtr 3	Qtr 4	Qtr 5
Intercept$_t$	−0.0009	0.0027	0.0118**	0.0086**	0.0055	0.0075
	(−0.21)	(0.45)	(2.32)	(2.06)	(1.02)	(1.04)
(MKT-RF)$_t$	1.1464***	1.1884***	1.2029***	1.0777***	1.0899***	1.0143***
	(20.09)	(15.51)	(17.26)	(19.60)	(16.17)	(10.18)
SMB$_t$	0.6264***	0.5156***	0.2000*	0.4913***	0.7429***	0.6617***
	(6.30)	(3.74)	(1.76)	(4.99)	(6.03)	(3.71)
HML$_t$	−0.0878	−0.0033	−0.0194	0.0918	0.1491	0.1247
	(−1.26)	(−0.03)	(−0.24)	(1.37)	(1.64)	(1.07)
MOM$_t$	−0.1989***	−0.1992***	−0.1736***	−0.2978***	−0.1357**	−0.1762**
	(−3.58)	(−2.78)	(−2.70)	(−5.94)	(−2.16)	(−2.03)

Panel D: Strong anticipatory trading

Qtr	Qtr 0	Qtr 1	Qtr 2	Qtr 3	Qtr 4	Qtr 5
Intercept$_t$	−0.0384***	−0.0061	−0.0007	0.0027	0.0154**	0.0021
	(−5.50)	(−1.41)	(−0.10)	(0.29)	(2.35)	(0.27)
(MKT-RF)$_t$	1.2770***	1.0555***	1.2140***	1.2380***	0.9086***	0.9317***
	(13.99)	(19.19)	(12.27)	(10.10)	(11.07)	(8.55)
SMB$_t$	0.7681***	0.5073***	0.5243***	0.7530***	1.0031***	0.7393***
	(4.83)	(5.13)	(3.24)	(3.43)	(6.69)	(3.79)
HML$_t$	0.1066	0.1175	0.0954	0.2793*	0.1395	0.1245
	(0.95)	(1.59)	(0.85)	(1.87)	(1.26)	(0.98)
MOM$_t$	−0.1875**	−0.3412***	−0.3934***	−0.3931***	−0.2834***	−0.3206***
	(−2.11)	(−6.65)	(−4.31)	(−3.52)	(−3.71)	(−3.38)

Panel E: Weak anticipatory trading

Qtr	Qtr 0	Qtr 1	Qtr 2	Qtr 3	Qtr 4	Qtr 5
Intercept$_t$	−0.0000	−0.0017	0.0051	0.0069	0.0140***	0.0014
	(−0.01)	(−0.21)	(0.62)	(1.13)	(2.73)	(0.26)
(MKT-RF)$_t$	0.7747***	1.2197***	1.0883***	1.0398***	0.9575***	0.9106***
	(11.20)	(12.48)	(9.67)	(12.86)	(14.97)	(12.40)
SMB$_t$	1.1635***	0.6956***	0.8893***	0.7547***	0.9302***	0.8012***
	(9.65)	(3.96)	(4.83)	(5.22)	(7.95)	(6.09)
HML$_t$	−0.2284***	−0.0715	0.0489	0.1710*	0.0697	0.0494
	(−2.69)	(−0.54)	(0.38)	(1.73)	(0.81)	(0.58)
MOM$_t$	−0.3601***	−0.1262	−0.1719	−0.1976***	−0.3222***	−0.2873***
	(−5.34)	(−1.38)	(−1.66)	(−2.68)	(−5.41)	(−4.49)

Table 11: Returns of Stocks Expected to be Sold by Distressed Non-MHFs (Small) or Well-Performing MHFs

This table presents the results of quarterly Carhart (1997) four-factor regressions of stocks held in quarter *q*-1 by distressed non-MHFs with below-median AUM (Panel A) or by well-performing MHFs (Panel B) but are expected to be sold in quarter *q*+1 during each of the 6 quarters starting from quarter *q*. Quarterly value-weighted portfolios of stocks are formed with the weight being the percentage of shares outstanding held by these funds in quarter *q*-1. *t*-statistics are reported in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A: Stocks held by distressed non-MHFs (Small)

Qtr	Qtr 0	Qtr 1	Qtr 2	Qtr 3	Qtr 4	Qtr 5
Intercept$_t$	−0.0268	−0.0385***	−0.0095	0.0003	0.0110	0.0217
	(−1.58)	(−3.49)	(−0.60)	(0.02)	(0.63)	(1.27)
(MKT-RF)$_t$	1.1328***	0.8227***	0.7781***	0.8998***	0.8334***	0.8087***
	(5.28)	(5.92)	(3.84)	(5.25)	(3.85)	(3.67)
SMB$_t$	1.4200***	1.2053***	1.2981***	0.9385***	0.8881**	0.6238
	(3.85)	(4.97)	(3.74)	(3.14)	(2.33)	(1.66)
HML$_t$	0.2850	0.0679	0.1310	−0.0923	−0.0493	−0.0712
	(1.09)	(0.39)	(0.53)	(−0.43)	(−0.18)	(−0.27)
MOM$_t$	−0.1882	−0.3845***	−0.4500**	−0.4777***	−0.6622***	−0.9045***
	(−0.93)	(−2.91)	(−2.36)	(−2.92)	(−3.25)	(−4.49)

Panel B: Stocks held by well-performing MHFs

Qtr	Qtr 0	Qtr 1	Qtr 2	Qtr 3	Qtr 4	Qtr 5
Intercept$_t$	0.0265**	−0.0004	−0.0024	−0.0134	−0.0117	−0.0079
	(2.12)	(−0.04)	(−0.14)	(−1.11)	(−0.97)	(−0.46)
(MKT-RF)$_t$	1.0434***	0.7868***	0.7699***	0.9197***	1.0530***	0.9031***
	(6.25)	(6.56)	(3.75)	(5.57)	(6.74)	(4.00)
SMB$_t$	0.5476**	1.3677***	1.0248**	0.6448**	0.6110**	0.6121
	(2.00)	(6.77)	(2.59)	(2.34)	(2.12)	(1.57)
HML$_t$	−0.2065	0.0462	−0.3989	−0.1837	−0.0536	0.0001
	(−1.11)	(0.32)	(−1.44)	(−0.99)	(−0.28)	(0.00)
MOM$_t$	0.0253	0.0510	−0.3102	0.0351	−0.2515	−0.2204
	(0.18)	(0.44)	(−1.59)	(0.25)	(−1.63)	(−0.99)