Anticipatory Trading Against Distressed Mega Hedge Funds*

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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. Using downloads of 13F filings to proxy for exposure to anticipatory trading, we find that more exposed distressed MHFs subsequently experience 2.21% lower style-adjusted returns. 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 distressed MHFs and destabilize stock prices.

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

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1. Introduction

The hedge fund industry provides an ideal setting for the best and brightest investment managers to leverage their investment ideas and reap handsome rewards from doing so. Managers of the largest and most successful hedge funds are among the world's wealthiest people and achieve celebrity status. Therefore, perhaps not surprisingly, the trading strategies of such mega hedge funds (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] As the result, 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 the 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 that 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.

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[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] For example, Zoetis (ZTS) suffered a negative return of 15% during February to March of 2016 because it was a big holding of Bill Ackman's Pershing Square Capital Management, which at the time experienced large losses due to a significant plunge of 80% in the stock price of Valeant Pharmaceuticals (VRX), another significant holding of Pershing. It turned out later that followers of Bill Ackman sold ZTX in anticipation of his imminent selling of it. Other 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.

In this context, we address the following research questions: Do institutional investors 'front-run' the anticipated stock trades of distressed MHFs? Does such anticipatory trading adversely impact distressed MHFs, as reflected in worse performance? Finally, are stocks that are anticipated to be sold by distressed MHFs associated with greater price drops and reversals – i.e., are the prices of such stocks more prone to temporary deviation 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 (inflation adjusted to 2006Q2) in assets as MHFs. We focus on financially distressed MHFs for three reasons. First, despite their significant visibility in the industry, 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 MHFs 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, distressed 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 distressed 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 neither as large

[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 our sample of MHFs.

nor followed as closely. Together, our setting provides novel insights into the trading activities of institutional investors when the need to liquidate by distressed mega investors is predictable.

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 aggregate stock ownership by distressed MHFs next quarter, non-distressed MHFs collectively reduce their stock ownership by 1.56% in the current quarter. Notably, institutions 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 being more likely to sell and also 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. The asymmetry in anticipatory trading also suggests that it is unlikely to be attributed to common investment signals that influence trading of all institutions.

Our evidence of anticipatory trading is more pronounced in certain stocks and among certain institutional investors. Anticipatory trading is strongest in stocks that are small, illiquid, and represent a larger weight in the portfolio of front-running institutions. This makes sense because the forced selling of such stocks by distressed MHFs would adversely impact the stocks' market value and, hence, the portfolio returns of common owners. We also find stronger evidence of anticipatory trading on stocks held by distressed MHFs with higher leverage and less liquidity protection such as lockup periods and redemption restrictions. Also, other hedge funds (non-distressed and non-MHFs), particularly those with more resources and more patient capital, and more active mutual funds engage in more anticipatory trading behavior. Such funds are better able to absorb the risk of front-running strategies and have more discretion to seize front-running opportunities.

As a placebo test, we exploit the SEC's confidential treatment provisions whereby institutions may delay the public disclosure of part, or all, of their stock holdings. During the delay period, therefore, other institutions would be unable to use Form 13F filings to anticipate the selling by distressed MHFs. Indeed, during such delay periods, we find no evidence of anticipatory trading in such "confidentially-held" stocks that would otherwise be anticipated to be sold by distressed MHFs. These results are striking because confidentially held stocks tend to be smaller and more illiquid (Agarwal et al., 2013, Aragon et al., 2013) and, as we show in our analysis, such stocks are also subject to a greater intensity of anticipatory trading. Yet, we still do not find evidence of anticipatory trading in confidentially held stocks, suggesting that the public nature of mandatory portfolio disclosures, rather than common investment signals, explains our evidence of anticipatory trading.

Although most of our evidence on anticipatory trading is based on changes in long-equity positions disclosed in Form 13F filings, we also examine aggregate short interest data and find evidence that short sellers open short positions in stocks that are expected 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 sides.

Our second major finding is that MHFs with greater exposure to anticipatory trading experience worse performance during periods of distress. We measure exposure to anticipatory trading using the number of downloads of a MHF's 13F filings. We find that the portfolio holdings of such MHFs attract more attention and are more susceptible to front-running. The economic magnitude is significant: the style-adjusted returns of distressed MHFs in the highest tercile of downloads have over 2% lower abnormal returns over the following quarter, relative to MHFs with less exposure to front running. This evidence is consistent with distressed MHFs realizing lower liquidation values on their stock trades due to the anticipatory selling by other institutions.

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 1.69% 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 the possibility 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. Indeed, we find that the price impact is driven by stocks with high ownership by distressed MHFs, stocks that are subject to stronger anticipatory trading, and stocks that are not expected to exhibit poor future performance. In these instances, there may be greater benefits from anticipatory trading and the reversal patterns are more consistent with anticipatory trading causing overreaction in stock prices.

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) that are closely followed by market participants can suffer when other institutions anticipate their need to liquidate holdings. Therefore, our findings illustrate that astute hunters can also get hunted.

[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.

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. In another related study, van Kervel and Menkveld (2019) provide evidence of front running against the information-driven trades of institutional investors who are privately informed. In contrast, we provide evidence that front-running can occur against the liquidity driven trades of institutional investors – specifically, MHFs in distress who are forced to liquidate their equity portfolios. As a result, we show that front-running can move prices away from, instead of towards, fundamental value, and amplify the distress of distressed investors.

Our paper is also related to the literature on crowded trading and fire sales by leveraged informed traders. Stein (2009) argues that leveraged 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 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.

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[6] Negative externalities from trading can also arise in settings such as open-ended mutual funds where investors face 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.

Finally, 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, these costs can be mitigated by deliberately delaying disclosure.[8] We identify a new setting where large institutions (i.e., MHFs) have already disclosed their stock holdings and, therefore, are unable to conceal the stocks they will likely sell. 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, investments, and equity financing.[9] Finally, our paper reveals another mechanism that can contribute to diseconomies of scale in active management.[10] 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 analyses 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 (S34) 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

[8] See, e.g., Wermers (2001), Agarwal et al. (2013), Aragon, Hertzel, and Shi (2013), Shi (2017), and Cao et al. (2021).
[9] See, e.g., Baker, Stein, and Wurgler (2003), Chen, Goldstein, and Jiang (2007), Edmans, Goldstein, and Jiang (2012), Khan, Kogan and Serafeim (2012), Hau and Lai (2013), and Dessaint et al., (2019). Also, 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.
[10] See, e.g., Chen et al. (2004), Pollet and Wilson (2008), Yan (2008), Fung et al. (2008), and Teo (2009).

(2013). Specifically, we classify institutions into the following four categories: 1) mutual fund management companies (type 3 institutions by the TR classification); 2) independent investment advisors (type 4 institutions by the TR classification); (3) 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), and 4) other institutions (banks, insurance companies, pension funds, and investment banks). We infer institutional 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: 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 set to 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 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 AUM as MHFs. We adjust for inflation by comparing the $1 billion threshold with a fund's AUM expressed in 2006Q2 dollars, since 2006Q2 is the midpoint of our sample period.[11]

Our analysis focuses on institutional trading activities around periods in which MHFs experience financial distress, i.e., when those MHFs are likely to liquidate part of their portfolios. 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. There are several potential channels for such information. First, institutions may subscribe to commercial hedge fund databases and track (as we do) their reported monthly returns. In fact, 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, institutions 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 and plans to liquidate holdings 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

[11] Our main findings are robust to the classification of MHFs based on 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.

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. The average quarterly net flows of distressed MHFs are around –5% in *q*+1 to *q*+3 and 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 fund 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, therefore, more vulnerable to front-running. Their continued outflows may also partially result from the performance consequence of being front run, which we examine in Section 5.

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 and 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 such as 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. (2023), and the monthly returns on the four benchmark factors of Fama and French (1993) and Carhart (1997) from Kenneth French's website.[12] We also obtain data on hedge fund leverage used in Jiang (2023).[13]

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 earlier. 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 tend to have larger average long-equity portfolios.

[12] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[13] We are grateful to Wenxi Jiang for providing this data.

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 median total restriction period on investor redemptions (i.e., the sum of redemption and notice periods) is about 120 days. The median incentive and 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 long-equity portfolio value is lower than average AUM for mutual funds, consistent with mutual funds using less long-only leverage. Lastly, Panel D of Table 1 presents summary statistics on stocks held by distressed MHFs. Our key measure of anticipatory trading, *Ptrade*, has a positive sample median of 3.24 bps, indicating that MHFs are typically expected to increase their stock positions. However, many of their positions are also anticipated to be sold as indicated by a negative lower quartile of –3.59 bps.

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 distressed MHFs.

3.1. Predicting the stock trading of MHFs

We focus on predicting the aggregate stock 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.[14] 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. We also determine whether a fund is a MHF or a non-MHF based on its AUM as of quarter q-1. In short, our model predicts the quarter q+1 trading activity of MHFs based only on information that is observable to other institutions in quarter q.

We predict the aggregate trading of MHFs in a stock 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 the prior quarter trade and existing ownership of a stock by all MHFs, both of which can influence a fund's trading decisions. All characteristics are measured at the end of quarter q-1. The unit of observation is stock-quarter.

Table 2 shows the results from estimating our predictive model of MHF trading. In Columns 1 and 2, the dependent variable is an indicator variable that equals one if the net change in aggregate MHF holdings of the stock is positive (Buy_{q+1}) and negative ($Sell_{q+1}$), respectively. In Column 3, the dependent variable is a continuous variable measuring the net change in aggregate MHF holdings of the stock, $Trade_{q+1}$. *Ownership* is a negative predictor MHF trading, i.e., larger

[14] 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.

ownership of a stock in quarter q-1 predicts greater selling of the stock in quarter q+1. Amihud illiquidity negatively predicts both *Buy* and *Sell*, i.e., more illiquid stocks are less likely to be bought or sold by MHFs. Moreover, stock characteristics explain more of the variation in MHF selling than buying as indicated by a higher adjusted R-squared.

Overall, our predictive model analysis reveals that MHFs' trading decisions are closely related to their current holdings and several stock characteristics, especially their selling decisions. This suggests that institutional investors could reliably anticipate and trade ahead of MHFs' selling when they are in distress.[15]

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:

$$Trade_{f,i,q} = \alpha + \beta_1 \min(Ptrade_{i,q-1}, 0) + \beta_2 \max(Ptrade_{i,q-1}, 0) + Controls_{f,i,q-1} + \varepsilon_{f,i,q} \quad (1)$$

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. $Ptrade_{i,q-1}$ is the predicted quarter $q+1$ aggregate trades in stock i by distressed MHFs. It is based on a rolling-window estimation of the predictive model reported in Table 2 and utilizes the set of holdings in the portfolios of distressed MHFs and their ownership of the securities. Our rolling window uses data only from the prior four quarters so that the estimated coefficients used to predict the expected trades of distressed MHFs in the next quarter (i.e., quarter q+1) are based only on real-time

[15] 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.

information of investors in the current period (i.e., quarter q). To alleviate the effect of outliers, we winsorize both $Trade_{f,i,q}$ and $Ptrade_{i,q-1}$ at the 1% and 99% levels. $Controls_{f,i,q-1}$ are measured as of quarter q-1 and include institution *f*'s trading in stock *i*, the logarithm of the dollar value of institution *f*'s 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.

Our key variables of interest in Eq. (1) are the negative and positive parts of *Ptrade*, i.e., *Psell* and *Pbuy*, respectively. We would expect anticipatory trading to be stronger for stocks that distressed MHFs are predicted to sell versus buy given that distress is more likely to trigger forced selling rather than buying. Moreover, distressed MHFs have fewer choices about which stocks to sell versus buy, making it easier for other institutions to anticipate their sell trades. The estimated slope coefficient, β_1, in regression (1) provides the relation between institutional trading and the predicted sell trades of distressed MHFs; a finding $\beta_1 > 0$ would indicate that institutions trade in the same direction as anticipated sales by distressed MHFs.

Panel A of Table 3 presents the estimated regression coefficients of Eq. (1), separately for different groups of 13f institutions. For ease of presentation, we express the raw *Trade* measure, its one-quarter lagged value, and *Ptrade* in basis points (i.e., multiplied by 10,000). We find that institutions sell ahead of anticipated selling of distressed MHFs, but do not similarly front run their anticipated buying. This finding is consistent across institutional types. In addition, β_1 is larger and significantly positive for non-distressed MHFs and non-MHFs.[16] 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, an individual non-distressed MHF reduces its stock ownership (as a percentage of total market capitalization) by 0.040% in the current quarter and, collectively, all non-distressed MHFs reduce their ownership by 1.56%, in anticipation of a 1% drop in stock ownership by all distressed MHFs next quarter.[17] There exists some suggestive evidence of anticipatory trading across other types of institutions though the economic magnitudes are typically much smaller.

The results above show that institutions front-run the anticipated sell trades of distressed MHFs, but do not front-run their anticipated purchases. Therefore, in the subsequent analysis, we focus our analyses on the subsample of stocks for which $Ptrade_{i,q-1}$ is less than zero, i.e., stocks expected to be sold by distressed MHFs, using the following regression:

$$Trade_{f,i,q} = \alpha + \beta Ptrade_{i,q-1} + Controls_{f,i,q-1} + \varepsilon_{f,i,q} \qquad (2)$$

Consistent with our findings from the full sample of stocks in Panel A of Table 3, the results in Panel B show that institutions front-run the sell trades of institutions for the subsample of stocks held that are anticipated to be sold by distressed MHFs (i.e., *Ptrade*<0). The finding that front-running occurs mainly on the sell side suggests that it is unlikely to be attributed to institutions acting on commonly observed investment signals.

3.3. Robustness: Alternative predictors of distressed MHFs' sell trades

[16] In untabulated analyses, we also find that among non-mega hedge funds, anticipatory trading is more pronounced among those that are not distressed.
[17] 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 0.04% x 39, i.e., 1.56% per quarter.

In Panel C of Table 3, we examine whether our baseline results are sensitive to estimation error in the predicted sell trades of distressed MHFs using several different approaches. First, to the extent that distressed hedge funds might adopt a different liquidation strategy, we re-estimate our predictive model in Table 2 for the subsample of distressed hedge funds. Specifically, we re-run the rolling regression of quarter q+1 trades on quarter q-1 stock characteristics, separately for distressed versus non-distressed hedge funds, to generate an alternative estimate of *Ptrade*. We then repeat our main test of anticipatory trading using the alternative predictor (*Ptrade*) of selling by distressed MHFs. The results are reported in Panel C1 of Table 3 and, once again, show that the trading activity of other institutions load positively on *Ptrade*, suggesting anticipatory trading. In our baseline analysis, we nevertheless continue to use the full sample of MHFs to estimate our predictive model and construct *Ptrade* because distressed MHFs do not exist in every period and, therefore, the predictive model based solely on distressed MHFs could introduce significant noise in *Ptrade*.

Like estimates from any predictive model, *Ptrade* is estimated with noise. To alleviate the potential concern on estimation error, we replace *Ptrade* with an indicator variable that equals one if the stock has a large portfolio weight in the aggregate portfolio of distressed MHFs, otherwise zero. This approach follows Lou (2012) who focuses on stocks that carry the highest portfolio weights. The assumption is that when in financial distress, MHFs are likely to liquidate their positions on a pro rata basis and stocks that account for larger portfolio weights are therefore more likely to be heavily sold. These stocks are therefore more likely to become targets of anticipatory trading. In unreported analyses, we verify that distressed MHFs themselves are indeed more likely to liquidate their largest positions as revealed in their q-1 13f filings, i.e., stocks with portfolio weight in the top quartile or decile.

The results of the robustness analysis concerning top holdings are reported in Panels C2 and C3. Overall, there exists a negative relation between institutions' trading in *q* and the dummy variable indicating top holdings (top quartile or top decile) of distressed MHFs in *q*-1. That is, other institutions sell more of a stock in *q* if it is among the top holdings of distressed MHFs in the previous quarter. The estimated coefficients in Panel C3 are larger than those in Panel C2, providing even stronger evidence of anticipatory trading when we focus on the top decile instead of the top quartile of positions of distressed MHFs. While the advantage of this approach is that it is straightforward and avoids the use of a generated regressor like *Ptrade*, it does not incorporate characteristics other than ownership, such as past trades, that drive the selling decisions of MHFs as shown in Table 2. We therefore continue to use *Ptrade* in our baseline analysis.

3.4. Falsification test: Do institutions front-run stocks in confidential filings?

Table 3 provides evidence that institutional investors front-run the sell trades of distressed MHFs. Moreover, there is no evidence of similar anticipatory activities on the buy side, which is inconsistent with the interpretation that unobserved variables drive the trading behavior of both groups of institutional investors, and some institutions move faster than others. In another effort to address the concern on observed factors, we analyze institutions' trading in stocks reported in distressed MHFs' confidential filings. Hedge funds often seek confidential treatment for some of their 13f reportable positions to delay the disclosure on certain positions.[18] Such confidentially held stocks tend to be smaller and less liquid stocks with a greater price impact and, therefore, provide greater benefits for anticipatory trading. If the relation between predicted trades of distressed MHFs and current period trades of other institutions merely reflects the response to

[18] See, e.g., Agarwal et al. (2013), Aragon, Hertzel, and Shi (2013), and Cao et al. (2023).

common investment signals, then the relation should hold even more so for stocks that distressed MHFs report in confidential filings. In addition, testing anticipatory trading against confidential positions allows us to use disclosed holdings as a control group, essentially holding fund characteristics constant. We therefore re-do the baseline analysis in Table 3 focusing on a subset of stock positions that only appear on confidential filings of distressed MHFs for quarter q-1 or only appear in restatements of the funds' holdings at the end of quarter q. Since these stock holdings are not publicly observable in quarter q then, unless the relation is driven mainly by common shocks, we would expect to find weaker evidence of anticipatory trading.

Table 4 reports the results from re-estimating Eq. (2) using predicted selling of concealed stocks. When estimating $Ptrade_{i,q-1}$ for confidential stock positions held by distressed MHFs, we apply the coefficients estimated from the predictive model employed in Table 2 to the subset of stocks held by distressed MHFs as of quarter q-1 but not reported in the quarter's 13f filings. In stark contrast to the findings in Table 3, the results in Table 4 show that none of the hedge fund groups' sell trades in quarter q are significantly (and positively) influenced by the expected trades of distressed MHFs in quarter q+1. Similarly, there is no evidence that mutual funds front run distressed MHFs against their trades of concealed stocks.[19] Therefore, it is unlikely that the observed trading pattern of potential front runners identified in Table 3 is due to unobserved shocks that drive common trading among institutional investors and MHFs. The evidence also suggests that non-public channels such as broker information leakage (e.g., Barbon et al., 2019) are unlikely to be the main drivers of our findings on front running. If, on the other hand, non-public channels were at work, then even the confidentially-held positions can be subjected to anticipatory trading. Rather, institutions try to profit from the price impact of distressed MHFs' forced liquidations

[19] We also find similar results of insignificant loadings on *Ptrade* using bootstrapped standard errors.

and/or aim to mitigate the adverse effect of such price swings on their own portfolios, and therefore trade ahead of them.

4. A closer look at front-running by mutual funds and hedge funds

In this section, we focus 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:

$$Trade_{f,i,q}=\alpha + \beta_1 Ptrade_{i,q-1} + \beta_2 Ptrade_{i,q-1} \times Rank_{f,i,q-1} + \beta_3 Rank_{f,i,q-1} + Controls + \varepsilon_{f,i,q} \qquad (3)$$

where $Rank_{f,i,q-1}$ is a dummy variable indicating a fund (*f*) or stock (*i*) characteristic in high or low groups at the end of quarter q-1. As in our earlier analyses, the regression is estimated using only observations with $Ptrade_{i,q-1}$ less than zero, i.e., stocks anticipated to be sold by distressed MHFs.

In addition to the stock-level control variables employed in Table 3, we also include as additional controls, the logarithm of a fund's AUM, prior-period abnormal performance, prior-quarter flows, 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.[20] For hedge funds, given their diverse investment strategies, we measure abnormal performance of individual funds by their style-adjusted performance.[21] We include time fixed

[20] 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.
[21] 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.

effects and 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 various stock and fund characteristics ($Rank_{f,i,q-1}$) have on this relation from parameter β_2. A finding of β_2 >0 would indicate that a higher characteristic rank is associated with greater front-running activity.

4.1. Baseline results without interaction terms

Panel A of Table 5 presents the baseline results shown in Table 3 but adds fund-level control variables given availability of more detailed data for mutual funds and hedge funds. 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 $Psell_{i,q-1}$ (0.0379 versus 0.0109). This difference is both economically and statistically significant. Columns 2 and 3 focus on the subsample of stocks that distressed MHFs are expected to sell and show similar findings. This is consistent with the idea that, compared to mutual funds, hedge funds engage in more anticipatory trading due to their performance-based compensation contracts, greater investor sophistication and patience, and/or more discretion to trade opportunistically. This evidence also aligns with the estimated coefficients reported in Table 3; we now observe that the difference in anticipatory trading between mutual funds and hedge funds remains significant after incorporating fund-level information beyond the 13F data.

To account for potential measurement error in estimating *Ptrade*, we conduct a bootstrap exercise. In a bootstrap iteration, for each quarter with at least one MHF being distressed, we randomly match trades of stocks held by MHFs with characteristics of other stocks in their portfolios using data of MHFs' stock holdings during the past four-quarter estimation period. This resampling is done with replacement. We then estimate the predictive model using the same rolling regressions employed earlier in Section 3.2 and apply the coefficient estimates to stock characteristics of a randomly drawn stock held by distressed MHFs in q-1 to generate the stock's *Ptrade*. Lastly, we estimate Equations (1) and (2) separately for mutual funds and hedge funds, using *Ptrade* estimated based on randomly generated data and record the coefficients of *Psell* and *Ptrade (<0)*, respectively. This iteration is repeated 1,000 times. The distributions of the 1,000 estimates for each model are shown in Panels A-D of Figure 3. Panels A and C concerning Eq. (1) show that, under bootstrapped distributions, the estimated coefficients of *Psell* using our sample of mutual funds and hedge funds (depicted by the straight line) are always statistically significant at 1% level for both mutual funds and hedge funds. Panels B and D concerning Eq. (2) showing the bootstrapped distribution of *Ptrade (<0)* indicate that our estimates as reported in Panel A of Table 6 are again statistically significant at 1% level for mutual funds and 10% level for hedge funds.

4.2. Role of stock characteristics in predatory trading

Panels B and C of Table 5 show the results from estimating Eq. (3) where $Rank_{f,i,q-1}$ is based on stock characteristics. Anticipatory trading is stronger in smaller (*Size*) and less liquid (*Amihud*) markets. On the other hand, anticipatory trading is weaker in stocks with greater ownership by distressed MHFs that are less vulnerable to redemptions (*Lockup*, *Restriction*).[22] In a similar vein, the results concerning fund leverage suggest stronger evidence of anticipatory trading in stocks held by distressed MHFs with above-median extrapolated leverage ratio as

[22] We consider whether a MHF has a lockup clause and has a restriction period (i.e., the sum of redemption and notice periods) longer than 120 days. A stock is considered as vulnerable to front running if the percentage of MHFs holding it and having lockup periods or long restriction periods, respectively, is above median.

measured in Jiang (2023). In addition, anticipatory trading is weaker among stocks mostly held by MHFs with above-median total volatility. Perhaps, it is more difficult for outsiders to predict the liquidation strategies of funds with more volatile performance. Together, this evidence indicates that the benefits from anticipatory trading are greatest when there is a greater potential for price impact due to distressed selling by vulnerable MHFs in illiquid markets.

Table 5 also shows that a fund's anticipatory trading activity is stronger in stocks that represent a larger (i.e., above median) 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 in general larger (with the exception of stock illiquidity) for hedge funds that appear more aggressive in targeting front-running opportunities.

4.3. Role of fund characteristics in predatory trading

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 to avoid fire sales.

So how a fund's liquidity position affects its incentive to conduct front-running trades is an empirical question. To shed light on these issues, we estimate Eq. (3) where $Rank_{f,i,q-1}$is an indicator variable based on fund characteristics. Again, the analysis is done only using the subsample of stocks anticipated to be sold by distressed MHFs.

Panel A of Table 6 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 mutual funds participate more in front-running. Column 2 shows that the interaction term between $Ptrade_{i,q-1}$ and the indicator variable denoting flow volatility ranked in the top quartile in the quarter 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 6 reports the results for hedge funds. Unlike mutual funds, assets under management of a hedge fund (besides distressed MHFs) do not significantly predict whether it will front run its distressed peers. However, hedge funds with above-median redemption period 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. Like mutual funds, hedge funds with higher return volatility and turnover also exhibit greater anticipatory trading. Finally, the coefficient is negative on the interaction variable between $Ptrade_{i,q-1}$ and the indicator variable for above-median fund leverage, suggesting that anticipatory trading is lower among highly leveraged hedge funds that presumably have more exposure to funding liquidity risk.

Overall, the extent of front-running against distressed MHFs varies with fund characteristics: more active 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 adversely impacts its performance during periods of distress. Intense front-running by other institutions could negatively impact underlying stock prices, leading to lower liquidation values and worse performance for distressed MHFs. Such performance deterioration could become a downward spiral as the result of margin calls and persistent outflows.

We use the amount of downloading of a MHF's 13F filings to proxy for its exposure to anticipatory trading. We adopt this simple yet intuitive proxy of exposure to anticipatory trading from other institutions learning about a MHF's stock positions as revealed through its public disclosures such as Form 13F. A greater number of Form 13F downloads would indicate that the MHF is more closely watched by potential front-runners. In Panel A of Table 7, we summarize the number of downloads of the Form 13F filings of funds in different size quintile groups. We follow Cao et al. (2021) and exclude so-called robo-downloads by identifying downloads from institutions with more than 50 downloads on a particular day. These robo-downloads are likely to be a poor proxy for the amount of attention a hedge fund has attracted during the period. As expected, we find that the 13F filings of larger hedge funds, which include MHFs, attract more downloads than smaller funds.

Next, we sort hedge funds into three groups based on their performance in the quarter. Following our classification of distressed MHFs in earlier analyses, distressed funds have returns that are in the bottom quartile and negative; good-performing funds have returns that are in the top quartile and positive; and all other funds are in the middle group. Panel B of Table 7 shows that, among non-MHFs, good performing funds tend to attract the most downloads. This is consistent with the idea that hedge funds are watched by other institutions due to their perceived strong investment skill. However, among MHFs, distressed funds attract more attention. The finding is consistent with the idea of distressed MHFs attracting more investor attention due to the prospect of large price impacts as the result of their liquidating trades and those of other institutions that mimic these trades (Cao et al., 2021).

In the second stage, we use the number of downloads of a fund's Form 13F filings to proxy for its exposure to anticipatory trading and examine its effect on hedge fund performance. In Table 8, we regress hedge fund performance on dummy variables indicating different levels of downloading activities (i.e., Download H and Download M) and their interaction terms with the distress dummy. Download H (M) indicates fund quarters ranked in the top (middle) tercile with the bottom tercile being the omitted group. $Distress_{f,q}$ is an indicator variable denoting financial distress.

We measure hedge fund performance using both reported quarterly raw returns and style-adjusted returns during quarter q+1 or quarters q+1 through q+4. From the regression, we can infer the marginal impact that greater investor attention has on the performance of distressed versus other MHFs. Significantly negative coefficients of the interaction terms between $Distress_{f,q}$ and the downloading dummies would indicate that hedge funds that are closely watched by other institutions are associated with worse performance following periods of distress. Such a difference-in-differences specification allows us to isolate the effect of exposure to anticipatory trading on the performance of distressed MHFs while controlling for unobserved common factors that affect the performance of all MHFs as well as the effect of distress itself. We also control for various observable factors that could affect hedge fund performance, including the logarithm of its assets under management, quarterly flows, incentive fees (in percent), management fees (in percent), and the logarithm of fund age. We include time fixed effects and compute *t*-statistics after clustering standard errors by fund. This analysis is done separately for MHFs and non-MHFs.

Table 8 reports the results. The coefficients on the dummy variables indicating moderate and strong downloading activity are almost all insignificant. However, the coefficients of their interaction terms with the distress dummy are significantly negative. This implies that a larger exposure to anticipatory trading does not adversely affect MHFs in the absence of distress, but the performance of *distressed* MHFs is significantly hurt by such trading. Similarly, in the absence of strong downloading activities, a MHF that is currently distressed does not continue to have poor performance in the future. We obtain similar results using raw returns and style-adjusted returns. In terms of economic magnitudes, relative to distressed MHFs with the lowest downloads, those that experience medium or high downloads are associated with 2.39% and 2.21% lower abnormal returns, respectively, in the following quarter. An examination of average fund performance over quarters q+1 through q+4 suggests that larger exposure to anticipatory trading also hurts the performance of distressed MHFs over the longer term. Lastly, in sharp contrast to distressed MHFs, their distressed non-MHF counterparts do not experience worse future performance when they are exposed to downloading of their 13F filings by other institutions. This is consistent with the finding in Panel B of Table 7 that these funds are followed less closely by other institutions and have lower exposure to anticipatory trading to begin with.

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 by institutional investors seeking to benefit from predatory trading against distressed selling by MHFs as well as mitigating the negative return shocks to their portfolios as the result of such selling. However, institutions that do not hold stocks that distressed MHFs are expected to sell can also benefit from shorting these stocks, while closing out the shorts promptly when prices are depressed.[23] While data limitations preclude us from analyzing short selling at the individual fund level, we use aggregate short interest data to provide some evidence along these lines.

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.[24] If anticipated selling of stocks by distressed MHFs motivates institutions to engage in front-running,

[23] For example, 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).

[24] 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).

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 *ABSI* in quarter q on $Ptrade_{i,q-1}$ with firm fixed effects. We also control for lagged market returns that account for the effect of overall market conditions on short interest.

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 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 predicted to be sold by distressed MHFs, but also short sell these stocks.

The remaining columns in Table 9 examine the effect of predicted trades by distressed MHFs on abnormal short interest at longer horizons. We find that the negative effects of $Ptrade_{i,q-1}$ on abnormal short interest decline during quarters q+1 through q+4, with the effect eventually turning insignificant in quarter q+5. Therefore, the absence of significant relation between *Ptrade* and abnormal short interest at long horizons indicates a *reversal* in the higher abnormal short interest of stocks that are anticipated to be sold more by distressed MHFs. In summary, short sellers tend to open short positions in stocks that are anticipated to be sold by distressed MHFs in the following quarter, and then cover those short positions in the quarters following 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 be associated with 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 Panel A of Table 10, we report the results from Carhart (1997) four-factor regressions of quarterly value-weighted returns of portfolio 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 –1.69% in quarter q that reverses to a positive and significant alpha of 1.50% in quarter q+4. This evidence is consistent with our hypothesis that anticipatory trading is associated with a temporary decline in stock prices.

We note that despite the temporary nature of the negative effects of anticipatory trading on stock returns, distressed MHFs will nevertheless tend to suffer a permanent deterioration in performance. When being in distress, they may need to liquidate assets in their portfolios in response to margin calls or redemptions and have to sell their portfolio assets at temporarily depressed prices. As a result, they do not get to participate in the gains when stock prices recover.

Panel B reports the estimates of alphas for different subsamples of stocks. Panel B1 shows that the price effects of anticipatory trading are primarily driven by stocks with above-median ownership by distressed MHFs in q-1 and, therefore, instances where distressed MHFs' liquidating trades are expected to have larger price impacts and thus there may be greater benefits from anticipatory trading.[25]

To further assess whether selling by front-runners is responsible for the observed return patterns rather than just the selling by distressed MHFs, 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. Panel B2 of Table 10 shows that the return patterns observed in Panel A are driven by the group of stocks that are subject to stronger anticipatory trading. In contrast, stocks that are not subject to strong anticipatory trading do not experience any negative abnormal returns in quarter q. This finding suggests that the price pressure and subsequent reversal patterns that we observe are attributable to the anticipatory trading by other institutions instead of just the selling activity of distressed MHFs. Overall, the evidence

[25] In untabulated analyses, we find that the initial negative price impacts experienced by stocks expected to be sold by distressed MHFs and the subsequent return reversals are also more pronounced among stocks that carry larger portfolio weight among distressed MHFs.

supports our interpretation that institutions engaging in anticipatory trading are responsible for the negative returns in stocks targeted for selling by distressed MHFs.

A possible concern is that the quarter q poor performance of stocks held by distressed MHFs simply reflects these stocks' poor fundamental value and explains why MHFs become distressed. As a result, the return patterns observed in Panel A have little to do with anticipatory trading by front-runners. To address this concern, we divide stocks projected to be sold by distressed MHFs into two groups by their quarter q-1 abnormal short interest and separately examine their future abnormal returns. Panel B3 of Table 10 shows that while stocks that have above-median abnormal short interest and are anticipated to be sold by distressed MHFs in quarter q+1 experience negative abnormal returns in quarter q, they do not show patterns of return reversals. That is, the negative abnormal returns in quarter q are consistent with stock fundamentals. In contrast, Panel B3 shows that the pattern of significantly negative abnormal returns in quarter q and subsequent reversals observed in Table 10 is mostly driven by the subsample of stocks with below-median abnormal short interest. This finding indicates that this return pattern is more likely to be attributed to anticipatory trading again distressed MHFs as opposed to stock fundamentals.

Overall, the evidence in Table 10 suggests that front-running against distressed MHFs is associated with 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 and liquidity protection, 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 we find no evidence of front-running against the confidential stock positions of distressed MHFs that, if were known to the public, would be targets for front-running. This is also consistent with our finding 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 increase short positions in stocks that are anticipated to be sold more by distressed MHFs in the following quarter and then cover those short positions 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. We attribute these price patterns to the anticipatory trading of 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 cut the time for investors passing the 5% threshold for reporting from ten to five business days. Furthermore, it has also 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.[26] 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, especially when disclosure becomes more timely. Our study also relates to other examples of changes in mandatory disclosure requirements that include SEC's recent proposal requiring activists to reveal their positions in target firms once they cross 5% threshold in a timelier fashion (five instead of ten business days) and SEC's recent ruling about the mandated disclosure of short position data and short activity data for equity securities.[27]

[26] See https://www.sec.gov/news/press-release/2020-152 for details.
[27] https://www.sec.gov/comments/s7-06-22/s70622-20123623-279866.pdf
and https://www.sec.gov/files/rules/final/2023/34-98738.pdf for details on the disclosure of activist and short positions, respectively.

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, 2023, Redemption in kind and mutual fund liquidity management, Review of Financial Studies 36, 2274–2318.

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.

Cao, Sean, Zhi Da, Daniel Jiang, and Baozhong Yang, 2023, Do Hedge Funds Strategically Misreport Their Holdings? Evidence from 13F Restatements, Working Paper, Georgia State University

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.

Jiang, Wenxi, 2023. Leveraged speculators and asset prices. Forthcoming, Review of Finance.

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.

van Kervel, Vincent, and Albert J. Menkveld, 2019, High-frequency trading around large institutional orders, Journal of Finance 74, 1091−1137.

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.

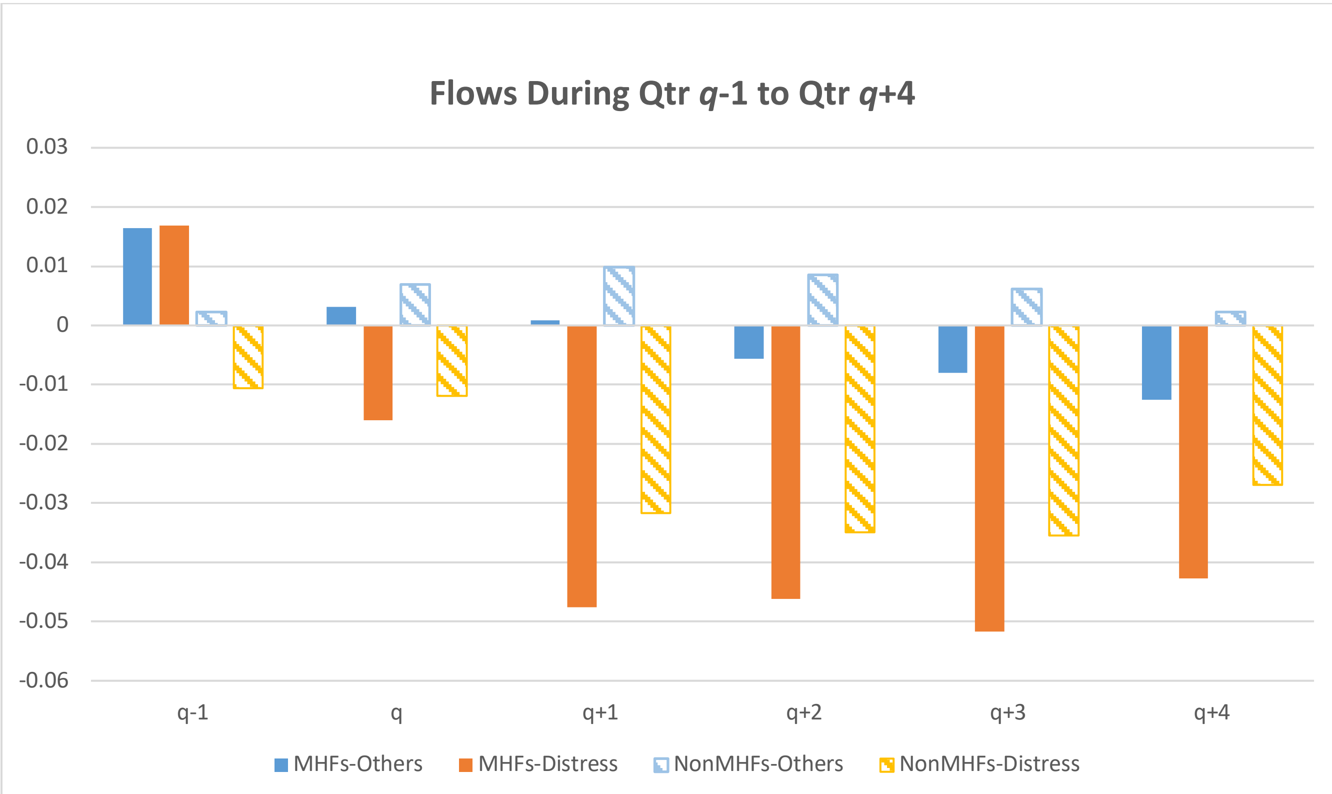


Figure 2: Timeline of Anticipatory Trading Activities

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

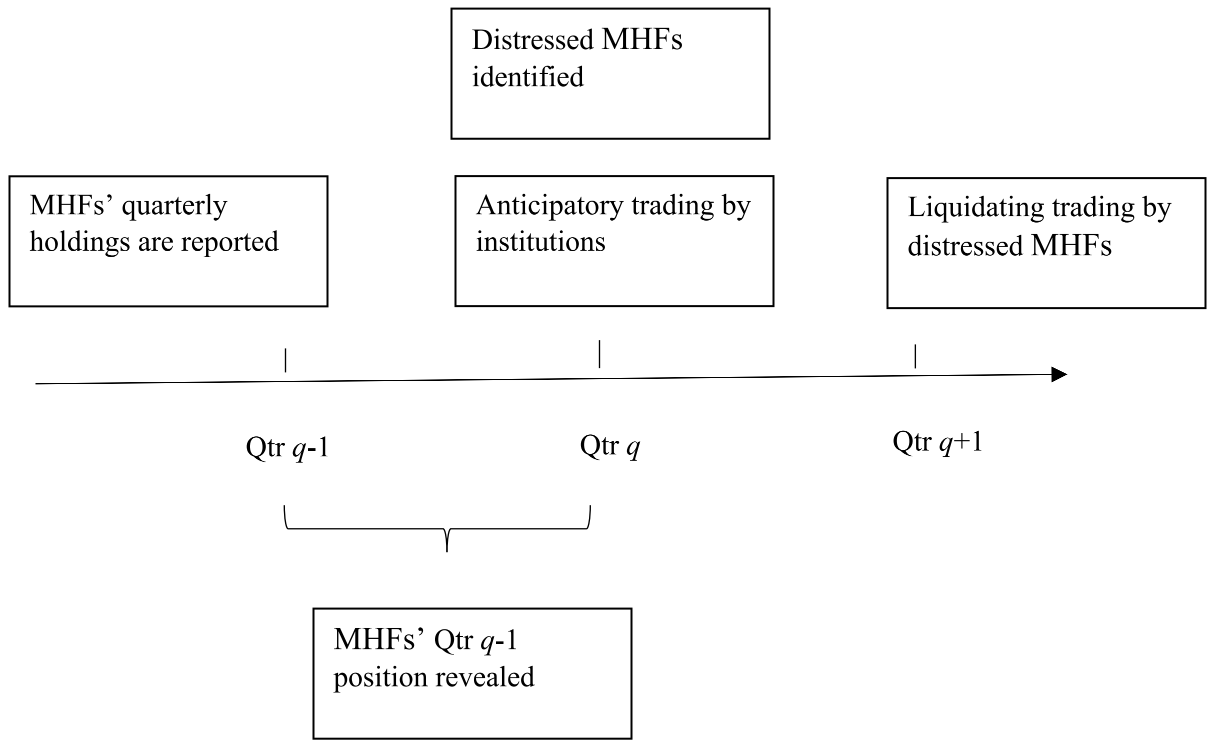
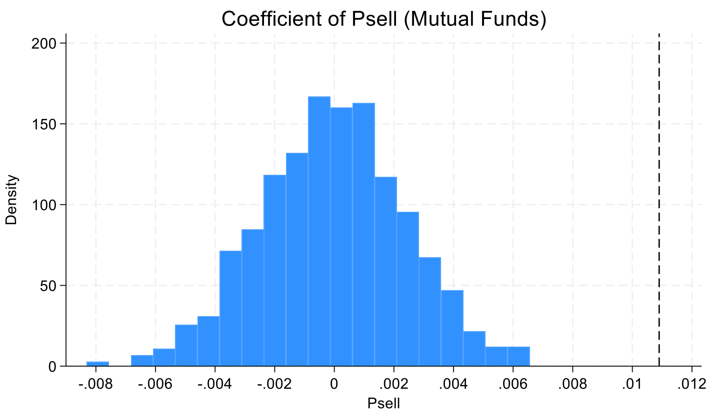


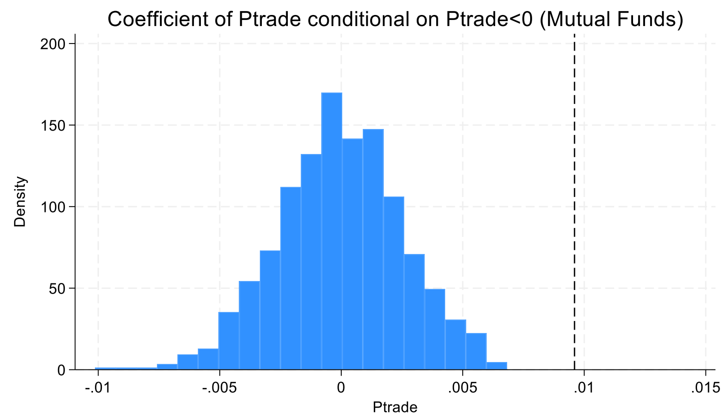
Figure 3: Bootstrapped Distribution of Anticipatory Trading

This figure plots the distribution of bootstrapped coefficients of *Psell* (Panels A and C) in Equation 1 or *Ptrade* (Panels B and D) in Equation 2 among mutual funds (Panels A and B) and hedge funds (Panels C and D). The vertical lines indicate value of the estimated coefficients in the corresponding regressions run using our sample observations as reported in Panel A of Table 5.

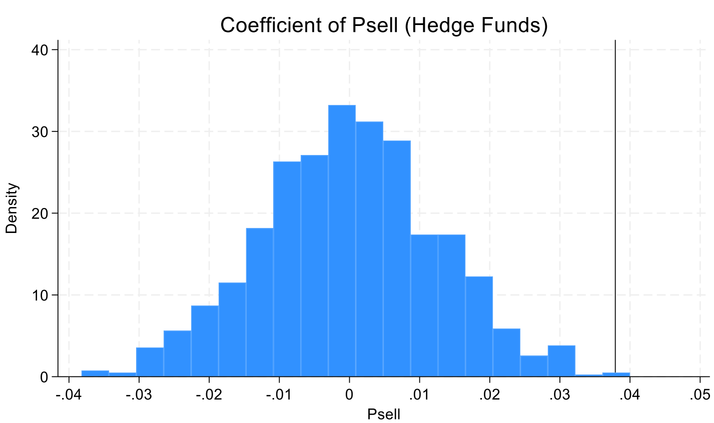
Panel A



Panel B



Panel C



Panel D

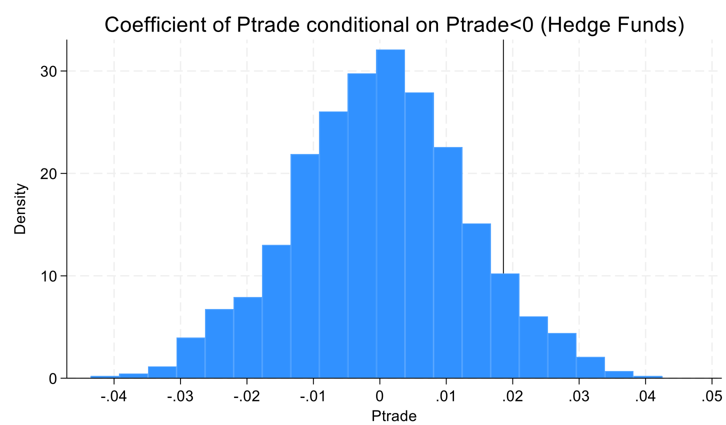


Table 1: Summary Statistics

This table provides summary statistics for our sample of 13F institutions and subsamples of hedge funds and mutual funds. Panel A provides the average quarterly 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 based on dollar of 2006Q2. 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 holdings data. *Independent Investment Advisors* are type 4 institutions of Thomson Reuters. *Other Institutions* include banks, insurance companies, investment banks, and pension funds. 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. *Trade* is the quarterly change of fund holdings standardized by total shares outstanding of the stock in bps. *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. *Total Vol* is the standard deviation of monthly fund returns in the past 12-month period. *Turnover* is measured as sum of dollar purchases and sales divided by the mean of prior- and current-quarter dollar holdings. *Leverage* is the extrapolated leverage ratio of gross asset value to net asset value of a fund as in Jiang (2023). *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*, *Trade*, *AUM*, *Fund Return*, *Quarterly Flows*, *Fund Age*, and *Total Vol* 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 12-month period. In Panel D, we provide summary statistics for stocks held by distressed MHFs including predicted *Ptrade* as defined in Section 2, total ownership by MHFs, quarterly returns, cumulative returns in the four-quarter period ending as of the current quarter, market capitalization, book-to-market ratio and Amihud illiquidity ratio.

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

Institutions	No. of Obs	Average Number	Mean	Median	P25	P75	Std Dev
Distressed MHFs	723	8.03	7168	1019	299	3256	28424
Non-distressed MHFs	3759	38.75	10688	975	331	2769	54625
Non-mega hedge funds	13598	140.19	1313	285	128	772	5037
Mutual funds	249675	2547.70	809	102	21	447	3457
Independent Inv. Advisors	120874	1233.41	2416	323	142	1081	11780
Other Institutions	35204	359	10603	569	184	3157	50763

Panel B: Summary statistics for hedge funds

Variable	**Mean**	**Median**	**P25**	**P75**	**Std Dev**
Mega	0.2479	0	0	0	0.4318
Distress	0.1987	0	0	0	0.3990
Equity Value	3497	368	146	1191	26201
Trade	–1.3553	–0.0490	–3.0089	0.8651	31.5306
AUM	1265	293	99	970	4220
Fund Return	0.0188	0.0187	–0.0104	0.0491	0.0777
Abnormal Return	0.0014	–0.0001	–0.0263	0.0264	0.0658
Quarterly Flow	0.0703	0.0001	–0.0477	0.0519	1.7985
Fund Age	10	9	5	14	7
Total Vol	0.0540	0.0474	0.0343	0.0659	0.0286
Turnover	0.6802	0.6140	0.3681	0.9356	0.3984
Leverage	1.7641	1.6083	1.4735	1.8239	0.5644
Lockup Fund	0.56	1	0	1	0.50
Restriction Period	143	120	83	155	107
Incentive Fees (%)	18.36	20.00	20.00	20.00	4.72
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	809	102	21	447	3457
Trade	–0.6432	0.0000	–0.1332	0.0281	5.7184
AUM	1333	202	52	794	5452
Fund Return	0.0210	0.0301	–0.0231	0.0764	0.0999
Abnormal Return	–0.0008	–0.0008	–0.0026	0.0010	0.0039
Quarterly Flow	0.0585	–0.0111	–0.0419	0.0335	3.7433
Fund Age	13	10	5	17	13
Total Vol	0.0454	0.0407	0.0292	0.0558	0.0228
Turnover	0.8708	0.6388	0.3400	1.0900	1.0854
Flow Volatility	0.0367	0.0196	0.0098	0.0415	0.0493

Panel D: Summary statistics for stocks held by distressed MHFs

Variable	**Mean**	**Median**	**P25**	**P75**	**Std Dev**
Ptrade (bps)	5.3428	3.2367	–3.5938	11.1110	30.7240
Ownership (%)	1.2741	0.3865	0.1192	1.2954	2.5417
Quarterly Ret	0.0254	0.0166	–0.0941	0.1267	0.2577
Cumulative Ret	0.1600	0.0967	–0.1440	0.3403	0.6562
Market Cap ($M)	8351	1366	363	4952	27652
B/M	0.6086	0.4877	0.2726	0.7940	0.6357
Amihud	0.3706	0.0017	0.0003	0.0124	4.1525

Table 2: Predicting Trades by Mega Hedge Funds

This table presents the results from regressions of aggregate trading by mega hedge funds (MHFs) of a stock on stock characteristics. The dependent variable is a dummy variable indicating aggregate buying (column 1), selling (column 2) or the aggregate hedge fund dollar trades (column 3) of a stock (standardized by the stock's market capitalization) in quarter *q*+1. The independent variables include quarter *q*-1 hedge fund ownership of the stock measured by the total dollar holdings of the stock by 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		
VARIABLES	Buy (*q*+1)	Sell (*q*+1)	Trade (*q*+1)
Ownership	–0.5190***	0.8314***	–0.0458***
	(–4.83)	(7.94)	(–13.72)
Return (*q*-1)	0.0798***	–0.0732***	0.0034
	(3.39)	(–3.98)	(1.63)
Return (*q*-4, *q*-1)	–0.0209***	0.0224***	–0.0007
	(–3.15)	(3.91)	(–1.40)
Log (Size)	0.0021	0.0213***	0.0000
	(0.76)	(8.68)	(0.54)
BM Ratio	0.0022	0.0006	0.0001
	(0.45)	(0.14)	(0.44)
Amihud	–0.0053***	–0.0072***	–0.0000
	(–3.97)	(–5.42)	(–0.64)
Lagged Trade	0.4617***	–0.0956	–0.0148***
	(3.51)	(–0.75)	(–3.23)
Constant	0.4370***	0.3414***	0.0007**
	(17.18)	(17.51)	(2.41)
Observations	288,129	288,129	288,129
Adj. R-square	0.0046	0.0164	0.0291

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 trading by distressed mega hedge funds (MHFs) of the stocks they hold 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), using a rolling window estimation of the predictive model of MHF trading in Table 2. The regression is run separately for different institutional groups. *Other Institutions* include banks, insurance companies, investment banks, and pension funds. In Panel A, *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 separately for each institution type. In Panel B, we re-run the model using the subsample with negative *Ptrade*. In Panel C1, *Ptrade* is the projected trading of distressed MHFs using an alternative rolling window estimation of the predictive model in Table 2 where the model is estimated on all distressed hedge funds rather than all MHFs. Panel C2 presents the results of regressing individual institutions' trading (in basis points, bps) of stocks in quarter *q* on dummy variables indicating top holdings of distressed mega hedge fund (MHF) quarter *q*-1, *Top* is set to 1 if a stock's portfolio weight in the aggregate portfolio held by distressed MHFs in ranked in the top quartile, and 0 otherwise. In Panel C3, *Top* is set to 1 if a stock's portfolio weight in the aggregate portfolio held by distressed MHFs in ranked in the top decile, and 0 otherwise. Panels C1-C3 include all control variables that are in Panels A and B. All regressions include fund and quarter fixed effects. *t*-statistics are 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: Anticipatory buying versus selling

	Non-Distressed MHFs	**Non-MHFs**	**Mutual Funds**	**Independent Inv. Advisors**	**Other Institutions**
Dep. Variable	Trade	Trade	Trade	Trade	Trade
Psell	0.0401***	0.0255***	0.0056***	0.0174***	0.0091***
	(3.06)	(3.35)	(3.15)	(4.23)	(3.28)
Pbuy	–0.0473	–0.0049	0.0003	–0.0017	–0.0018
	(–0.88)	(–0.51)	(0.25)	(–0.46)	(–0.72)
Log (Equity)	–4.6696	–1.2056***	–0.5071***	–0.4247***	–0.3715
	(–1.53)	(–5.92)	(–16.82)	(–8.54)	(–1.19)
Return (*q*-1)	2.2039	0.9633	0.0123	0.1250	0.9981***
	(1.45)	(1.20)	(0.20)	(0.62)	(4.55)
Return (*q*-4, *q*-1)	0.2322	–0.2983	0.0169	–0.0794	0.2789***
	(0.84)	(–1.62)	(0.78)	(–0.86)	(3.82)
Log (Size)	0.3902	1.1997***	0.3644***	0.4138***	0.1208***
	(0.92)	(12.29)	(19.98)	(16.32)	(6.28)
BM Ratio	–0.5645*	–0.0571	0.0035	0.0875**	0.0012
	(–1.76)	(–0.49)	(0.13)	(2.09)	(0.03)
Amihud	–0.1812	0.0383	0.0192***	–0.0225	–0.0174*
	(–1.43)	(0.95)	(3.57)	(–1.12)	(–1.80)
Lagged Trade	0.0392	–0.0005	0.0998***	0.1053***	–0.0043
	(0.60)	(–0.02)	(11.71)	(6.74)	(–0.14)
Observations	469,677	713,668	8,556,859	9,381,914	6,675,337
Adj. R-square	0.0635	0.0346	0.0650	0.0361	0.0081

Panel B: Anticipatory selling only

	Non-Distressed MHFs	Non-MHFs	Mutual Funds	Independent Inv. Advisors	Other Institutions
Dep. Variable	Trade	Trade	Trade	Trade	Trade
Ptrade (<0)	0.0167**	0.0191***	0.0055***	0.0161***	0.0074***
	(2.17)	(2.85)	(3.23)	(4.10)	(2.67)
Log (Equity)	0.2033	–1.5287***	–0.5653***	–0.5157***	–0.5080*
	(0.40)	(–5.67)	(–16.09)	(–8.44)	(–1.72)
Return (*q*-1)	1.8432	1.6073*	0.1541	0.2351	1.0895***
	(1.03)	(1.66)	(1.33)	(0.93)	(3.92)
Return (*q*-4, *q*-1)	0.2315	–0.1918	0.0129	–0.0936	0.2775***
	(0.77)	(–0.83)	(0.39)	(–0.74)	(2.87)
Log (Size)	0.8940***	1.2539***	0.3756***	0.4475***	0.1543***
	(3.01)	(8.69)	(14.41)	(12.34)	(5.88)
BM Ratio	–0.4230	–0.0822	–0.0186	0.0365	–0.0049
	(–1.27)	(–0.66)	(–0.39)	(0.85)	(–0.08)
Amihud	–0.0016	0.0379	0.0138	–0.0183	–0.0200
	(–0.03)	(0.47)	(1.47)	(–0.86)	(–1.49)
Lagged Trade	0.0078	–0.0190	0.0774***	0.0949***	–0.0154
	(0.12)	(–0.87)	(7.84)	(6.05)	(–0.55)
Observations	156,657	254,881	2,667,961	3,338,963	2,366,529
Adj. R-square	0.0102	0.0411	0.0662	0.0355	0.00964

Panel C: Robustness using alternatives to baseline *Ptrade*

	Non-Distressed MHFs	Non-MHFs	Mutual Funds	Independent Inv. Advisors	Other Institutions
Dep. Variable	Trade	Trade	Trade	Trade	Trade
Panel C1: *Ptrade* based on alternative predictive model using all distressed HFs					
Ptrade (<0)	0.0350*	0.0187***	0.0041***	0.0116***	0.0059***
	(1.95)	(3.51)	(3.04)	(4.73)	(2.72)
Controls?	Yes	Yes	Yes	Yes	Yes
Observations	394,165	584,458	7,048,009	7,548,800	5,450,838
Adj. R-square	0.0736	0.0357	0.0658	0.0363	0.0078
Panel C2: *Top* indicates a top quartile position of distressed MHFs					
Top	–0.4723	–0.1409*	–0.0219*	–0.0507**	–0.1195***
	(–0.87)	(–1.81)	(–1.91)	(–2.26)	(–4.23)
Controls?	Yes	Yes	Yes	Yes	Yes
Observations	469,661	713,629	8,556,434	9,381,313	6,675,071
Adj. R-square	0.0634	0.0345	0.0650	0.0360	0.00811
Panel C3: *Top* indicates a top decile position of distressed MHFs					
Top	–0.5961	–0.3391***	–0.0802***	–0.1726***	–0.1561***
	(–1.36)	(–3.79)	(–5.56)	(–6.94)	(–5.25)
Controls?	Yes	Yes	Yes	Yes	Yes
Observations	469,661	713,629	8,556,434	9,381,313	6,675,071
Adj. R-square	0.0634	0.0345	0.0650	0.0360	0.0081

Table 4: Placebo test using confidentially-held positions

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 in confidential filing of distressed mega hedge funds (MHFs). *Ptrade* is the projected quarter *q*+1 trading of stocks that were held by distressed MHFs in quarter *q*-1 (in bps), using a rolling window estimation of the predictive model of MHF trading in Table 2. The table presents the results from using the subsample with negative *Ptrade*. *Other Institutions* include banks, insurance companies, investment banks, and pension funds. 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-Distressed MHFs	**Non-MHFs**	**Mutual Funds**	**Independent Inv. Advisors**	**Other Institutions**
Dep. Variable	Trade	Trade	Trade	Trade	Trade
Ptrade (<0)	0.0524	–0.0321*	0.0310	0.0053	–0.0050
	(1.48)	(–1.97)	(1.47)	(0.49)	(–0.30)
Log (Equity)	–0.4404	–2.8443	–1.2912***	–1.8900***	–2.4359**
	(–0.12)	(–1.57)	(–3.28)	(–5.12)	(–2.75)
Return (*q*-1)	–8.9038	1.0101	0.2806	2.1144**	–1.9024**
	(–1.52)	(0.23)	(0.41)	(2.47)	(–2.72)
Return (*q*-4, *q*-1)	–1.4589	–0.4994	–0.2605	–0.4601	0.9336
	(–0.70)	(–0.67)	(–1.30)	(–1.63)	(1.34)
Log (Size)	0.8059	2.2642***	1.2027***	0.8343***	0.4919***
	(1.18)	(3.07)	(3.89)	(5.71)	(4.32)
BM Ratio	–1.7358	0.0962	–0.1206	0.1982	–1.3471
	(–0.44)	(0.05)	(–0.42)	(0.27)	(–1.75)
Amihud	–0.5904	9.4516	1.5099***	–2.9264**	1.6522***
	(–0.12)	(1.60)	(3.02)	(–2.48)	(3.21)
Lagged Trade	–0.1052*	–0.0543	0.1017***	0.0793***	–0.0021
	(–2.09)	(–1.10)	(8.72)	(4.58)	(–0.05)
Observations	2,237	2,793	18,164	21,992	23,494
Adj. R-square	0.0495	0.113	0.155	0.0402	0.0174

Table 5: Anticipatory Trading and Stock Characteristics

This table presents the results of regressing mutual funds' and hedge funds' trading (in bps) of stocks in quarter q on the predicted quarter q+1 trading (*Ptrade*) of the stocks held by distressed mega hedge fund (MHF) in quarter q-1. Panel A compares anticipatory trading by mutual funds versus hedge funds and provides the difference in the coefficients of *Psell* (Columns 1 and 2) or *Ptrade* (columns 3 and 4), as defined in Table 3, 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 among the subsample of observations with negative *Ptrade* 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 above-median ownership by distressed MHFs with lockup periods and greater than 120-day restriction periods, respectively, an indicator variable denoting above-median ownership by funds with above-median total return volatility, an indicator variable denoting above-median ownership by distressed MHFs with high leverage (extrapolated leverage ratio of gross asset value to net asset value as measured in Jiang, 2023), or an indicator variable denoting above-median portfolio weight of a stock in the fund (*Position*). 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**	**Mutual Funds**	**Hedge Funds**
Dep. Variable	Trade	Trade	Trade	Trade
Psell	0.0109***	0.0379***		
	(3.66)	(3.53)		
Pbuy	0.0040	–0.0295		
	(1.37)	(–1.44)		
Ptrade (<0)			0.0096***	0.0186***
			(3.75)	(3.25)
Fund Abret	54.5960***	1.6489	54.9121***	4.6787
	(5.72)	(0.45)	(4.71)	(1.48)
Log (AUM)	–0.4377***	0.4811	–0.4277***	0.0846
	(–16.10)	(1.47)	(–12.34)	(0.81)
Flow	5.0148***	1.3542**	5.0647***	1.7928**
	(15.91)	(2.46)	(13.58)	(2.47)
Return (*q*-1)	–0.0395	1.4693	0.2307	1.5549
	(–0.35)	(1.52)	(1.16)	(1.59)
Return (*q*-4, *q*-1)	–0.0820**	–0.3302	–0.1355**	–0.3685
	(–2.08)	(–1.50)	(–2.09)	(–1.40)
Log (Size)	0.4158***	0.8185***	0.4230***	1.0148***
	(15.26)	(4.60)	(12.75)	(6.44)
BM Ratio	0.1714***	–0.1883	0.1311*	–0.1593
	(3.78)	(–1.09)	(1.80)	(–1.07)
Amihud	0.0473***	0.0147	0.0456***	0.0328
	(5.61)	(0.31)	(2.88)	(0.91)
Lagged Trade	0.0807***	0.0077	0.0552***	–0.0190
	(7.57)	(0.20)	(4.30)	(–0.54)
Observations	5,718,912	1,183,605	1,798,490	411,647
Adj. R-square	0.0279	0.00815	0.0273	0.0080
χ^2 **test (HF-MF)**	0.0270**		0.0090***	

Panel B: Anticipatory trading by mutual funds and stock characteristics

Rank	Size	Amihud	Lockup	Restriction	Total Vol	Leverage	Position
VARIABLES	Trade	Trade	Trade	Trade	Trade	Trade	Trade
Ptrade (<0)×Rank	–0.0114***	0.0115***	–0.0079*	–0.0105**	–0.0049*	0.0102***	.0219***
	(–2.64)	(2.81)	(–1.81)	(–2.63)	(–1.69)	(2.88)	(4.78)
Ptrade (<0)	0.0171***	0.0067***	0.0123***	0.0130***	0.0104***	0.0028	–0.0010
	(3.52)	(3.20)	(3.30)	(3.72)	(3.82)	(1.13)	(–0.43)
Rank	0.2188**	0.2107***	–0.0571	–0.1484***	–0.1441***	0.0887	–1.6284***
	(2.39)	(2.71)	(–1.14)	(–4.11)	(–3.12)	(1.58)	(–16.97)
Controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,798,490	1,798,490	1,766,530	1,765,841	1,765,235	1,793,964	1,794,638
Adj. R-square	0.0275	0.0274	0.0273	0.0273	0.0278	0.0274	0.0401

Panel C: Anticipatory trading by hedge funds and stock characteristics

Rank	Size	Amihud	Lockup	Restriction	Total Vol	Leverage	Position
VARIABLES	Trade	Trade	Trade	Trade	Trade	Trade	Trade
Ptrade (<0)×Rank	–0.0274*	0.0021	–0.0271**	–0.0223*	–0.0259**	0.0466*	0.0861***
	(–1.85)	(0.15)	(–2.44)	(–1.69)	(–2.21)	(1.99)	(4.95)
Ptrade (<0)	0.0334***	0.0179**	0.0277***	0.0242***	0.0256***	–0.0200	–0.0267***
	(2.80)	(2.58)	(3.31)	(3.06)	(3.56)	(–1.05)	(–3.14)
Rank	0.9050**	0.1915	–0.2884	–0.7638***	–0.5980***	0.2435	–6.9151***
	(2.36)	(0.54)	(–1.59)	(–4.66)	(–3.51)	(1.09)	(–10.69)
Controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	411,647	411,647	408,100	407,770	404,078	237,449	411,551
Adj. R-square	0.0082	0.0080	0.0081	0.0082	0.0081	0.0077	0.0247

Table 6: 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 stocks that distressed mega hedge funds (MHFs) hold in quarter *q*-1 and are anticipated to sell 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, number of funds in the family, total return volatility during the past 12-month period, and fund turnover. We also examine whether a mutual fund's flow volatility, computed using monthly flows during the past 12-month period, is ranked in the top quartile, In Panel B, *Rank* represents indicator variables denoting above-median AUM, fund having lockup periods, the total length of redemption and notification periods exceeding 120 days, above-median total return volatility during the past 12-month period, above-median turnover (computed as the sum of total dollar purchases and sales divided by the mean of prior- and current-quarter dollar holdings), and leverage as defined in Jiang (2023). 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)×Rank	0.0166***	–0.0075**	0.0064	0.0108**	0.0192***
	(4.40)	(–2.28)	(1.61)	(2.55)	(3.80)
Ptrade (<0)	–0.0012	0.0111***	0.0058*	0.0032	–0.0009
	(–0.52)	(4.06)	(1.95)	(1.41)	(–0.34)
Rank	0.3941***	–0.1747***	0.1584**	–0.4577***	–0.4069***
	(3.55)	(–2.87)	(2.24)	(–5.05)	(–4.99)
Other controls?	Yes	Yes	Yes	Yes	Yes
Observations	1,798,490	1,346,376	1,758,281	1,346,376	1,723,386
Adj. R-square	0.0275	0.0316	0.0277	0.0325	0.0293

Panel B: Hedge funds

	AUM	**Lockup**	**Restriction**	**Return Vol**	**Turnover**	**Leverage**
Dep Variable	Trade	Trade	Trade	Trade	Trade	Trade
Ptrade (<0)×Rank	–0.0027	0.0152	0.0295*	0.0377**	0.0174	–0.1051***
	(–0.22)	(0.97)	(1.80)	(2.47)	(1.65)	(–2.77)
Ptrade (<0)	0.0203*	0.0110*	0.0064	0.0089	0.0062	0.1028***
	(1.77)	(1.72)	(0.97)	(1.13)	(0.96)	(2.85)
Rank	–0.8358	–0.9720***	–1.0756**	–1.2145***	–1.3093***	1.4103*
	(–1.64)	(–2.68)	(–2.31)	(–3.50)	(–3.93)	(1.83)
Other controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	411,647	407,360	405,941	411,250	403,561	122,076
Adj. R-square	0.0081	0.0086	0.0087	0.0087	0.0089	0.0259

Table 7: Downloads of Form 13F Filings

This table summarizes the average number of non-robo downloads of 13F filings for each hedge fund in a quarter. Panel A presents the mean and median of non-robo downloads for hedge funds in each quintile by AUM. Panel B reports the statistics for hedge fund groups by both MHF status and current quarter performance. Distressed funds are those hedge funds with returns ranked in the lowest quartile during the quarter and returns below zero. Good performing funds are those hedge funds with returns ranked in the highest quartile during the quarter and returns above zero. Mid funds are all other funds.

Panel A: Downloading for Hedge Funds in AUM Groups

AUM	Mean	Median
Q1	49.08	30
2	80.48	34
3	80.97	40
4	98.09	51
Q5	197.93	78

Panel B: Downloading for Hedge Funds in AUM and Performance Groups

AUM	Performance	Non-Robo Mean	Non-Robo Median
Non-MHF	Distressed	83.32	37
Non-MHF	Mid	69.41	36
Non-MHF	Good Performing	86.76	40
MHF	Distressed	219.11	78
MHF	Mid	163.56	72
MHF	Good Performing	178.40	72

Table 8: Downloading and Fund performance

This table examines whether a hedge fund's exposure to anticipatory trading is related to its performance during periods of distress. In Panel A, fund performance is measured as the raw or style adjusted return during quarter q+1. In Panel B, fund performance is measured as the cumulative raw or style adjusted return over quarters q+1 to q+4. *Distress* is a dummy variable indicating MHFs with performance being negative and ranked in the bottom quartile during quarter q. A MHF's exposure to anticipatory trading is measured by *Download*. *Download (M)* and *Download (H)* are dummy variables indicating funds with non-robot downloads of their 13F filings ranked in the middle and top terciles, respectively, in quarter q. Results are reported separately for mega hedge funds (MHFs) and non-MHFs. Control variables (not tabulated) include the logarithm of a fund's AUM, quarterly flows, 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.

	Panel A: Qtr t+1				**Panel B: Qtr t+1 to Qtr t+4**			
Fund Type	**MHFs**	**Non-MHFs**	**MHFs**	**Non-MHFs**	**MHFs**	**Non-MHFs**	**MHFs**	**Non-MHFs**
Performance	**Raw return**	**Raw return**	**Abnormal return**	**Abnormal return**	**Raw return**	**Raw return**	**Abnormal return**	**Abnormal return**
Distress	0.0134*	–0.0073**	0.0112	–0.0073**	0.0051	–0.0022	0.0040	–0.0021
	(1.70)	(–2.07)	(1.52)	(–2.10)	(1.23)	(–1.03)	(1.02)	(–1.00)
Distress*Download (M)	–0.0269***	0.0092*	–0.0239**	0.0089*	–0.0094*	0.0080***	–0.0074	0.0077**
	(–2.65)	(1.92)	(–2.47)	(1.86)	(–1.87)	(2.62)	(–1.51)	(2.55)
Distress*Download (H)	–0.0247***	–0.0018	–0.0221**	–0.0027	–0.0101**	–0.0003	–0.0099**	–0.0014
	(–2.69)	(–0.32)	(–2.55)	(–0.49)	(–2.06)	(–0.11)	(–2.14)	(–0.47)
Download (M)	0.0051	0.0020	0.0046	0.0017	0.0031	0.0010	0.0029	0.0011
	(1.62)	(1.02)	(1.46)	(0.87)	(1.11)	(0.73)	(1.05)	(0.74)
Download (H)	0.0067*	0.0017	0.0053	0.0012	0.0047	0.0025	0.0041	0.0025
	(1.81)	(0.67)	(1.50)	(0.48)	(1.51)	(1.31)	(1.35)	(1.25)
	(0.06)	(–0.52)	(–0.33)	(–0.96)	(1.00)	(–1.36)	(0.44)	(–1.75)
Control variables?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,038	8,228	3,038	8,228	3,038	8,228	3,038	8,228
Adj R-square	0.371	0.303	0.0264	0.0413	0.337	0.302	0.00793	0.0384

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

This table examines the relation between abnormal short interest during each quarter from quarters *q* through *q+5* and the predicted quarter *q*+1 trading of stocks that distressed mega hedge funds (MHFs) hold in quarter *q*-1 and are anticipated to sell in quarter *q*+1 (*Ptrade*<0). Abnormal short interest (*ABSI*) is estimated according to *ABSI (1)* of Karpoff and Lou (2010). ABSI in quarters *q* through *q+5* is regressed on *Ptrade* among the subsample with negative *Ptrade*. *Lagged Market Ret* denotes market return in the prior quarter. All models include firm fixed effects. *t*-statistics computed with standard errors clustered by stock are reported in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

Dependent variable: Abnormal short interest

Quarter	*q*	*q*+1	*q*+2	*q*+3	*q*+4	*q*+5
Ptrade (<0)	–0.8187***	–0.8321***	–0.7589***	–0.6626***	–0.2974*	0.0851
	(–5.64)	(–5.80)	(–5.13)	(–4.32)	(–1.82)	(0.50)
Lagged Market Ret	–0.0003	0.0040**	0.0068***	–0.0058***	–0.0072***	–0.0025
	(–0.13)	(2.13)	(3.79)	(–2.75)	(–2.94)	(–1.11)
Constant	–0.0055***	–0.0055***	–0.0053***	–0.0047***	–0.0044***	–0.0046***
	(–21.68)	(–21.38)	(–20.16)	(–17.25)	(–15.30)	(–15.49)
Observations	33,213	33,201	32,452	31,392	30,617	29,978
Adj. R-square	0.455	0.440	0.435	0.447	0.433	0.440

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 portfolios of stocks held by distressed mega hedge funds (MHFs) in quarter *q*-1 but are expected to be sold in quarter *q*+1 during quarters *q* through *q*+5. 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 (Panel B1), stocks subject to strong versus weak anticipatory trading by mutual funds and hedge funds (Panels B2), and stocks with high and low levels of short interest (Panel B3). We separately report results for stocks with above-median (high) versus below-median (low) abnormal short interest (ABSI) in quarter *q*-1 as estimated according to ABSI (1) of Karpoff and Lou (2010). *t*-statistics are reported in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A: Full sample alphas and beta coefficients

Qtr	Qtr *q*	Qtr *q*+1	Qtr *q*+2	Qtr *q*+3	Qtr *q*+4	Qtr *q*+5
$Alpha_t$	–0.0169**	–0.0066	–0.0061	–0.0073	0.0150**	0.0081
	(–2.63)	(–1.00)	(–0.80)	(–1.06)	(2.58)	(1.18)
$(MKT\text{-}RF)_t$	1.0063***	1.0782***	1.0547***	1.0919***	0.9086***	0.9736***
	(12.27)	(12.81)	(10.74)	(12.63)	(12.47)	(10.72)
SMB_t	0.9430***	0.6781***	0.6419***	0.6304***	0.7291***	0.7348***
	(6.73)	(4.73)	(3.85)	(4.00)	(5.71)	(4.80)
HML_t	0.1586	0.1209	0.2424**	0.3431***	0.1888**	0.0715
	(1.59)	(1.19)	(2.07)	(3.21)	(2.15)	(0.68)
MOM_t	–0.2097***	–0.2388***	–0.3788***	–0.2622***	–0.2841***	–0.3273***
	(–2.76)	(–3.11)	(–4.22)	(–3.24)	(–4.25)	(–4.08)

Panel B: Subsample alphas

Qtr	Qtr *q*	Qtr *q*+1	Qtr *q*+2	Qtr *q*+3	Qtr *q*+4	Qtr *q*+5
Panel B1: Level of distressed MHF ownership						
$Large_t$	–0.0184***	–0.0083	–0.0061	–0.0073	0.0191***	0.0066
	(–2.71)	(–1.22)	(–0.76)	(–1.01)	(3.12)	(0.87)
$Small_t$	0.0010	0.0121*	0.0042	0.0091	0.0117*	0.0056
	(0.16)	(1.68)	(0.53)	(1.08)	(1.67)	(0.78)
Panel B2: Level of anticipatory trading						
$Strong_t$	–0.0353***	–0.0077	–0.0101	–0.0055	0.0235**	0.0108
	(–5.36)	(–0.90)	(–1.08)	(–0.66)	(2.02)	(1.00)
$Weak_t$	0.0067	0.0058	0.0058	–0.0028	0.0167**	0.0108
	(0.85)	(0.79)	(0.73)	(–0.40)	(2.60)	(1.63)
Panel B3: Level of short interest						
$High_t$	–0.0159*	–0.0002	–0.0081	–0.0106	0.0081	0.0040
	(–1.88)	(–0.03)	(–0.96)	(–1.40)	(1.11)	(0.40)
Low_t	–0.0153*	–0.0043	0.0121	0.0054	0.0208***	0.0029
	(–1.81)	(–0.52)	(1.19)	(0.74)	(2.78)	(0.32)